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DISCUSSION PAPER SERIES

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ABSTRACT

Timetables, Attendance and Academic Achievement in Higher Education*

Managing schedules is an important aspect of student success. In this paper, we identify the impacts of a student's timetable on their attendance, study time and academic achievement. We use detailed administrative and survey data from a public UK university across that includes students from a broad range of degree programmes. Our data features quasi-random assignment of students to their timetables and measures their individual, hourly, attendance decisions. We consider multiple, related, aspects of timetables including back-to-back classes, single-class days, time-of-day, day-of-instruction and long hours. Findings indicate that across-day and within-day student attendance is highly dependent on timetable structure. Single-class days reduce attendance and back-to-back classes raise it. Time-of-day and day-of-week also exhibit meaningful differences in attendance. We are able to show that students compensate for marginal non-attendance at some events with in- creased attendance at others within the same module and that more conscientious students compensate with increased study time. Net of all behavioural responses to the timetable, however, these timetable features and changes in attendance rates have little impact on academic attainment.

JEL Classification: I23, I24, J24, C81, C91

Keywords: human capital, higher education, timetables, schedules, education production, attendance, effort

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1 Introduction and Background

The move from secondary to higher education presents students with a number of new challenges. Among them is adjusting to new schedules that typically feature fewer in-class hours and less oversight on their whereabouts. A weekday with no obligations can seem too good to be true. Identifying the factors that support or hinder students in staying on track is critical for improving academic outcomes. In this paper, we examine how the structure of a student's daily timetable: the sequencing, spacing, and distribution of classes, as well as their timing (start-time and day-of-week); affects class attendance and academic performance at university.

We study this question using rich adminsitrative and survey data from a large UK public university. The BOOST2018 study (Delavande *et al.*, 2022) tracks an entire cohort of undergraduate students and includes over 300,000 individual student attendance decisions linked to module-level academic outcomes (course-level in the US) across a wide range of programs. For a subset of respondents, we additionally observe detailed survey data on study time, study habits, and personality traits, enabling us to explore mechanisms and heterogeneity. This is a representative higher education setting where students have significant autonomy in organizing their time. While this autonomy can help optimize time allocation, it may also lead to procrastination and present bias, hindering academic success.

Our identification strategy exploits quasi-random variation in students' timetables during their first year at university. Students within the same programme (or major) enroll in multiple compulsory modules. Each module includes a large-group lecture - scheduled at the same time for all students - and a smaller teaching event(s) (e.g., lab, tutorial, seminar) for which students are randomly assigned to different time slots in smaller groups. This random allocation generates exogenous variation in key features of student timetables including event start times, whether sessions are back-to-back, and total daily event loads. We use this variation to estimate causal effects of timetable structure on both attendance and academic performance.

Our first key finding is showing that students' daily attendance decisions are highly influenced by their timetable structure. Students are significantly more likely to attend classes when events are scheduled back-to-back, with attendance increasing by 1.5 percentage points relative to a mean attendance rate of 65%. In contrast, isolated events, those occurring alone on a given day, reduce attendance by 0.9 percentage points. While students are less likely to attend isolated events, they appear to compensate by attending other sessions for the same module at above-average rates, leading to higher overall attendance at the module level. We interpret this as evidence of strategic time management: students make deliberate trade-offs in their attendance decisions based on convenience and opportunity cost. We also find that events held in the afternoon or on Mondays are associated with higher attendance rates.

Our second key finding is that timetable structure has no meaningful or consistent effect on academic achievement, despite its effect on attendance. Timetables could plausibly affect performance through multiple channels other than attendance, including in-class learning productivity, fatigue, or incentives. Our results suggest that students appear to effectively adjust their behavior in response to less-than-optimal schedules. In particular, their ability to compensate for marginal non-attendance, presumably through increased out-of-class effort, suggests that autonomy in time management plays a protective role.

To explore mechanisms, we consider heterogeneity by student- and module-type and further use linked survey data on time use, study behavior, and non-cognitive traits. We find that average study hours are not systematically affected by timetable structure. However, students differ in how effectively they respond to scheduling constraints. In particular, more conscientious students, who may have a lower "cost of focused effort" (Lundberg, 2013), are better able to take advantage of scheduling features—such as back-to-back events that create longer uninterrupted blocks for study—by reallocating time toward more productive self-directed learning. In contrast, less conscientious students reduce study time in response to dispersed or isolated events. We also find that off-campus residents are more responsive to back-to-back scheduling. This pattern is consistent with the presence of commuting costs: students living farther from campus are more likely to attend when they can consolidate their activities into fewer, more time-efficient trips.

Our paper contributes to the literature examining the role of class timing on academic performance. Prior research on start times consistnently finds early morning classes lower achievement (Carrell *et al.*, 2011; Diette & Raghav, 2017; Edwards, 2012; Groen & Pabilonia, 2019; Heissel & Norris, 2017). Studies on broader intervals - such as morning vs afternoon find that timing impacts not just achievement, but also choice of major (Cortes *et al.*, 2012; Cotti *et al.*, 2018; Dills & Hernandez-Julian, 2008; Haggag *et al.*, 2021; Lusher & Yasenov, 2018). Afternoon courses are typically associated with better performance, but the evidence is not unanimous (Pope, 2015).

We extend this literature by moving beyond timeing to study the causal impact of the *structure* of timetables - the order, spacing, and arrangement of classes - on attendance and performance. This dimension of scheduling remains largely understudied. The most closesly related work to ours is Williams & Shapiro (2018), who find that fatigue brought on by prior (especially back-to-back) classes earlier in the day offset the benefit of afternoon events. Their findings are similar to those on the negative impacts of block-scheduling (Rice *et al.*, 2002), but both are limited to a setting with mandatory attendance. In contrast, we examine a generalizable higher education context where students have considerable autonomy, allowing us to capture behavioral responses to scheduling constraints more directly.

We also contribute to the literature on the relationship between attendance and and academic achievement. Our paper distinguishes itself by observing specific attendance choices both made with autonomy and across a broad range of departments. Prior studies measuring detailed attendance focus on a single module or department (often economics) and find a positive association between attendance and achievement (Andrietti & Velasco, 2015; Chen & Lin, 2008; Cohn & Johnson, 2006; Dobkin *et al.*, 2010). Arulampalam *et al.* (2012) use the time in the week that a class meets as an IV for attendance and find attendance improves marks by 1.5 marks out of 100. In contrast, Kapoor *et al.* (2021), exploits a university-wide attendance policy and finds no impact of attendance for a locally-treated group of students while Bratti & Staffolani (2013) find that attendance only matters in mathematics-heavy courses. The effect of attendance may depend on the institutional context and ability for students to exercise autonomy (Delavande *et al.*, 2021; Goulas *et al.*, 2023). Like Goulas *et al.* (2023), we also find that students take advantage of the autonomy offered by non-compulsory attendance to adjust the composition of their attendance and study; but unlike them we find no evidence that timetable structures that provide more scope for this reallocation improve grades, even among highly conscientious students.

Section 2 will describe our institutional setting. Section 3 summarizes our data and explains our measures of timetable structure. Section 4 describes our empirical model, identification, and balance checks. Results are discused in Section 5. Section 6 concludes.

2 Institutional background

The structure of the academic year, organization and assessment of degree courses at this university is representative of most universities in England. Students apply and are accepted for a specific degree programme (i.e. major), which can be for one subject (e.g. Economics), or a combination (e.g. Politics, Philosophy and Economics). There is limited scope to switch programmes without re-starting studies, meaning students effectively make their programme choice before arriving at university.

Undergraduate degrees typically last three years. An illustrative timeline of an academic year is shown on the left-hand side of Figure 1. Within an academic year, teaching takes place during an Autumn term (interchangeably: semester) from October to December and a Spring term (semester) from January to March, both lasting 10 weeks and followed by a four week vacation. There is a shorter Summer term starting late-April lasting three weeks in which revision lectures take place, before an exam period in May and early June. Teaching takes place from 0900-1800 on Mondays, Tuesdays, Thursdays and Fridays, and from 0900-1300 on Wednesdays.[1]

2.1 Module and timetable structure

Material is taught and assessed in *modules* (courses in the US). First year students must take modules worth 120 'Level 4' credits in the UK Credit Accumulation and Transfer Scheme. These are typically arranged as 8 single-term 15-credit modules, 4 two-term 30-credit modules, or some combination of the two. Students from multiple degree programmes may be present within one module. For example, Politics, Philosophy and Economics programme students may be required to take the same introductory microeconomics module as those on the plain Economics programme.

The timing of a module's timetabled events repeat weekly during a term. An unique event is identified by the date, time, and location of its occurrence.

Each week, most modules have a single *lecture*, for which all enrolled students are assigned to be taught at the same time in the same room by the lead instructor. Modules also have

[1] This is in common with most universities in the UK, to accommodate the majority of inter-university sports fixtures, under the aegis of British Universities and Colleges Sport (BUCS), that take place on Wednesday afternoons.

more practical or interactive sessions. Depending on the subject these are structured as a class, lab, seminar or workshop, for which the enrolled students are split into smaller groups. We collectively refer to these as *group events*. A module will host several group events each week, with each student assigned to attend a single one of each type. These group events are potentially taught by different instructors within a module. The assignment of students into their smaller groups taught at different times provides our main source of identification, described in detail in section 3.3.

Our smallest unit of analysis is the *student-event*, which refers to an event on a particular student's timetable that they are assigned to attend. A student's weekly timetable is the set of all student-events on their timetable for a given week. Figure 2 shows two example fictional weekly timetables for students enrolled in the same programme. While their lectures are all at common times, they are assigned to different group events, creating variation in timetable structure. Section 3.3 discusses how we convert timetables into measurable characteristics.

2.2 Assignment to timetables

The university's overall timetable of teaching events is generated by a computer algorithm designed to fulfill a set of constraints submitted in advance by administrators for the department administering each module. These specifications include a list of modules that are core or compulsory[2] for each relevant degree programme (whole-intake events for these therefore should not clash), the frequency and duration of each module's weekly events, the maximum number of students that may be accommodated, the equipment required (e.g. a computer laboratory as opposed to a lecture theatre), and the order or gaps of weekly events within each module (e.g. that group events should occur after the corresponding module's lecture). Allocation to group events is done randomly, subject to avoiding clashes with students' other teaching events. Students should not be taught for more than 5 consecutive hours.

It is important to note several features of this system and the context of higher education admissions and progression in England, that support a causal interpretation for the effects of course timetables on attendance and performance.

First, students specialize early. The decision over institution and field of study must be made jointly, meaning students arrive at university to study an intended degree programme

[2]Compulsory modules must be attempted, but the student can fail these and still proceed to the next year if their average across all modules exceeds 40%. Core modules must be passed in order to proceed to the next year.

lasting a specified period of time. There is no process of major selection. Hence, the decision over university and programme of study will have been made before the timetable has been constructed or made available to students. Also, the vast majority of modules each student takes in the first year will be compulsory for their programme.[3]

Second, within a module, students cannot normally select into their smaller groups on the basis of their own preferences or expectations about productivity. Nor can any group event be filled up by more proactive students registering their preferred slot.

Third, in general, class instructors are unable to request a specific time of day to teach. The exception to this is staff employed on part-time contracts, in which case their designated working days and hours can be included in the constraints. This means that there is no reason why more senior or more effective teaching staff should be teaching at certain times or that staff characteristics should otherwise be correlated with student timetables.

However, there exist two potential threats to random assignment. First, the "exceptional circumstances" under which students can request a change in their group event assignment within a module include caring responsibilities, university sports fixtures, or (for those not living on the campus only) excessive commutes.. This introduces the possibility that some students' teaching group assignment is endogenous to their preferences, or to how costly the student finds it to request a change.

Second, approximately 20% of student-modules are 'optional', in that they are not core for the student's intended degree programme, and can be chosen by student after the timetable is published. Students are encouraged to choose complementary courses, or those which are pre-requisites for degree courses they may consider switching on to for the second year. Some choices may not be feasible where teaching events clash with those for their compulsory modules. However, students choosing optional modules have no control over which teaching group they will get assigned to for group events, which provide our identifying variation.

We present a comprehensive set of balancing checks in Section 4.1 that support the assignment of students to timetable characteristics being quasi-random in practice. Specifically, we show that conditional on the fixed effects we include in our models, timetable characteristics are orthogonal to both student and module characteristics.

[3] It is possible to change degree programme and still complete on time, but only if pre-requisites for all the second and third-year modules on the alternative degree scheme have been studied before commencing them. More commonly this entails repeating a year.

2.3 Attendance policy

Across the university, attendance is strongly encouraged, but is not compulsory. Attendance at teaching events is recorded through an electronic swipe-card system, which we describe in more detail in section 3.1, below. The university only intervenes, with an email enquiring whether the student requires any support, after 10 consecutive events of non-attendance, or if overall attendance falls below 50% across at least half a term. Escalations or sanctions beyond this are rare, being only applied in the case of extended non-engagement, including long-term low or non-attendance in combination with repeated non-completion of course requirements.[4] This means that in this context students have considerable autonomy over their attendance decisions.

Figure 3 shows student attendance across the school year. There are large differences between the start and end of a term and between fall and spring terms. Attendance is above 70% for most of the fall term. In spring, it is never above 70% and declines steadily throughout the term. The lower panel shows the likelihood that a student attends no events in a given week. This is below 5% throughout the fall except for the final week. In the spring, complete absences are worse, starting off below 5%, but creeping up to between 5% and 10%, and close to 25% in the final week.

2.4 Marks

Each student receives an overall mark for each module, which is a weighted average of a coursework mark from an end-of-term exam or a submitted piece of independently produced work, and an exam mark obtained during the summer exam period. All marks are awarded on a positive scale between 0 and 100. An overall mark of 40/100 is required to pass a module, with thresholds of 60 and 70 constituting Upper Second Class and First Class marks respectively. Assessments are moderated by external examiners, with the intention that grading standards are comparable within subjects, across universities (Naylor, Smith and Telhaj, 2016). Students must pass a sufficient number of first-year modules (Level 4 difficulty in the UK's National Qualifications Framework) to be allowed to progress into the second year. A final Degree Class is awarded based on a weighted average of second year (Level 5) and third year (Level 6) module overall marks, and the number of modules meeting each class threshold.

[4]These sanctions are potentially more serious for international students, for whom extended periods of non-engagement may be deemed non-compliant with their visa conditions.

We restrict our analysis to first-year marks. These are strongly predictive of students' final degree class. In our cohort, 64% of those receiving a First Class mark in their first year completed their programme on schedule *and* received a First Class Degree, compared with only 23% of those receiving an Upper Second Class mark in their first year, and 3% of those initially receiving a Lower Second. Final degree class plays a similar role to the GPA in the United States as a summary measure of performance in UK universities, being the main measure of acacademic performance seen by prospective employers, and there is a well established and significant degree class premium in graduate earnings (Feng & Graetz, 2017; Naylor *et al.*, 2016; Walker & Zhu, 2011).

3 Data description

3.1 Data collection and sample selection

The BOOST2018 Study is a longitudinal survey of undergraduate students who enrolled to begin undergraduate (Bachelors) courses at one UK university in the academic year 2015/16 (Delavande et al., 2022). As shown in the study timeline in Figure 1, students were recruited into the study during their registration processes before the start of the first term in October 2015, and through the first half of term. They were offered £5 as a thank-you for consenting to receive invitations to take online surveys through their university email addresses, and to the research team accessing and linking administrative records on their demographic and educational background, attendance and academic performance held by the university.[5]

In this paper we restrict our analysis to the 2015-16 academic year, our cohort's first year at university. For this period, all students in our cohort were enrolled on courses at the same level of study within the UK's system of qualification credits, and of the same total credit value. Students are not yet retaking any modules that add to their timetable burden and the vast majority (80%) of modules are core or compulsory for their chosen degree programme.

We use administrative data on each student's timetable linked with records of their attendance obtained through the electronic swipe-card system which is used for administrative records of student engagement. The attendance data are very detailed, recorded at the level of student

[5]The surveys generally took about one hour. Participation was compensated by between £10 and £24.50 for online surveys and on average £30 for the laboratory sessions. The surveys were designed to collect information on students' academic investments (hours of study), non-academic investments (working for pay, participation in volunteering groups, etc), and a range of non-cognitive indicators.

by module by week by event-type, enabling us in most cases to identify (non-)attendance for every student at every unique timetabled student-event (including the date, start-time, finish-time, and room), on every day of every week of the academic year.[6]

This swipe-card system was put in place to record non-EU students' compliance with their visa and immigration requirements. Some departments might monitor attendance much more closely than others and can make attendance to some classes effectively compulsory, but this is accounted for by our programme fixed-effects. These data are not subject to any of the recall or approximation biases inherent in self-reported data. They may have some measurement error, since students may either forget to swipe their card or give their card to a classmate to swipe on their behalf. We have no data on the extent of either problem, though the former we expect quickly to become a minimal concern as swiping in becomes part of students' routine, while the latter requires a degree of effort to co-ordinate, making this unlikely to happen on a large scale. There is no reason to expect that this error is correlated with the class timetabling characteristics.

In our data, attendance is a positively-selected characteristic. Figure 4 shows the relationship between average attendance marks by decile. Students in the bottom decile of average attendance earn notably lower marks than those in the second decile and there are incremental increases thereafter. The correlation need not be causal, but it is clear why a university looking at similar raw data may want to encourage attendance. The majority of students attend somewhere between 50-85% of their events. For a median student, a 6 percentage point increase/decrease in attendance would move them +/- 10 percentiles.

3.2 Student characteristics

The characteristics of the population of students in the cohort and institution we study are summarized in Column 1 of Table 1. Column 2 summarizes students enrolled in the study who form the primary sample for all estimates involving administrative data. These variables form the majority of our set of individual control covariates in estimation. An exception is field of study, which is further disaggregated by fixed-effects for each degree programme and module being studied.

[6] In rare cases where students have two events on a module of the same narrow type (NB: seminars, labs, classes, tutorials are all different here) we only know how many of the events were attended. Where this corresponds to neither 100% or 0% attendance, we impute attendance at specific events on a proportional basis.

Here British ("Home") students are classified by socioeconomic status (SES) according to parental occupation, where "High SES" corresponds to a "Managerial or Professional" or "Intermediate" occupation in the UK National Statistics Socio-Economic Classification (categories 1-3) and "Low SES" corresponds to all other categories.[7] Non-UK students are divided into those from the European Union, who at the time paid the same fees and had access to the same income-contingent loans for tuition and living costs as UK students, and non-EU, who pay higher fees. Ethnicity is self-identified at the time of enrolment at the university, and parental experience of higher education at time of application. Students' entry tariff score is a measure of performance in qualifications from school or college. These we divide into quintiles within this institution's population (unequal numbers are due to ties). We also distinguish between those arriving with academic A-Level qualifications or other primarily vocational qualifications. The population and the enrolled or responding sample are mostly well-balanced with a marginally higher proportion of black students in the latter group. The enrolled sample is also more likely to have A-Level qualifications rather than missing or Level 3 qualifications, but this is not unusual in a longitudinal study (see e.g. Lynn and Borkowska, 2018; Department for Education, 2011).

These administrative data are supplemented by variables from the BOOST waves 1-3 surveys, that by definition are not recorded for BOOST non-participants. In our balance checks for the validity of random assignment (section 4.1) we consider two non-cognitive traits we assume to be time-invariant, namely students' conscientiousness and experimentally-elicited discount factor (recorded for 1469 and 1202 students, 80% and 65% of enrolled sample respectively).

3.3 Timetable characteristics

We derive measures of what we describe as the *daily structure* of each student's timetable. These measures capture interdependence across events meeting on the same day and vary even among students sitting in the same group event of a module. We also consider event timing, including the *start-time* and *day-of-week* and event takes place. For students enrolled in the same module, these measures will vary across, but not within, group events.

Our three primary daily structure characteristics are: *Only* events, *Back-to-Back* events, and *Cumulative Hours.* These are features of a student's timetable that may affect their attendance

[7] Where SES is missing, those living in neighbourhoods in the top 40% for young adults' higher education participation are classified as High SES, with a small proportion still unknown.

choices, alertness, and achievement. Each of these measures is generalizable to the timetable structure of any higher education setting.

Only is a dummy variable indicating that an event is the student's only one that particular day. *Only* events are characterized by low expected cognitive fatigue for attenders, but also by a higher average cost of attendance (e.g. commuting for a single event).

Back-to-Back is a dummy for any events occurring in immediate succession with other(s) and with only a short break for the student to move between classrooms. These events are efficient to attend, but may cause cognitive fatigue by expecting students to be focused for long stretches of time. The time it takes for cognitive fatigue to impact a subject's performance is context-specific, but in situations similar to a classroom setting it has been shown to be anywhere from 20 minutes to two hours (Ackerman & Kanfer, 2009; Jackson *et al.*, 2014). In Figure 2 we distinguish between *First of Back-to-Back*, a dummy that indicates the first event in a back-to-back sequence and *Later in Back-to-Back* which takes a values of 1 for all subsequent events in such a sequence. We do not disaggregate further because there is comparatively little additional variation to exploit.[8]

Our hypotheses are that *Back-to-Back* events are efficient for students to attend with lower average fixed costs of leaving accommodation or stopping other activities; and that conditional on attending, *First of Back-to-Back* will be more productive for marks than *Later in Back-to-Back* events because the student will be less fatigued.

Cumulative Hours measures the total hours of event time a student has had up to that point of the day. The first event of a student's day always has a value of 0.

A default event, our omitted category where all three *daily structure* measures equal 0, would be one that is the first of the day on a student's schedule, but where they have at least one more event occurring later on that day, not immediately after the first. 23% of events in our main sample are default events.

Figure 2 conveys how our measures of student's timetables are constructed and how even two students in the same programme can have variation in the timetable characteristics. For example, both students attend the same Maths lecture at 1000 on Mondays. Due to the assignment of Student 1 and Student 2 to different group events for this module, it is an *Only*

[8] 84% of back-to-back sequences are just two in a row before a break and 14% are three in a row. Sequences of four or more events in a row represent less than 2% of events in our data.

event for student 2, but not student 1. Their Maths group event is a *Back-to-Back* for Student 2 (at 1400 on Tuesday) but not Student 1 (at 1400 on Monday). The assignment to different Maths group events also affects the timetable characteristics of the Micro lecture they are both scheduled to attend at 1300 on Tuesday. This is the *First of Back-to-Back* sequence for Student 2 but not Student 1, and the *Only* event of the day for Student 1 but not Student 2. The 0900 Wednesday Stats lecture is an example of a default event for both students. It is their first of the day, but each student has subsequent events that day after a break.

Student timetables are summarized in Table 2. Our data set spans 170 modules, 11,346 events and 307,488 student-events. Columns 1 and 2 summarize student-events weighted equally (Column 1) and giving each student equal weight (Column 2). Column 3 reports totals of student-events aggregated into a representative week. The average student has 8.8 events per week on their timetable. Students attend 65% of events on average, or 5.8 events per week.

Since students' academic performance or marks are defined only at the student-module level, we will also analyse the impact of timetable structure on both attendance and marks with data aggregated to the student-module level. Column 4 shows that on average, each student has 33 scheduled events per module, of which they attend 20. Similarly, since our survey-elicited study-related behaviours are only elicited once per term and cannot be attributed to any particular module being studied then, we will analyse the impact of timetable features on these behaviours at the student-term level. Students have on average 84 events per term, of which they attend 52.

14% of all student-events are their *Only* event that day, an average of one per week. 21% of events are *First of Back-to-Back* events 27% are *Later in Back-to-Back*. The average student has 1.2 *Only* events per week, 4.4 per module, and 11.6 per term. Correspondingly, they have 1.8 back-to-back sequences per week, 6.9 per module and 17.3 per term. In subsequent module- and term-level analysis our explanatory variables will be the share of that students' events that have each of these characteristics.

We also measure event timing. This includes the hour that instruction begins, which we capture with start-time dummies. Around 15% of events begin in each of the three morning hours (beginning 0900-1100) and roughly 10% of events begin in each hour from 1200 onward.[9]

[9] Over 99% of observations begin at the start of an hour. We treat those starting at half-past the hour as *Later in Back-to-Back* if they follow an event finishing on the hour (which is, hence, treated as either *First of Back-to-Back* or *Later in Back-to-Back* as appropriate). However, we use the actual timetabled duration to construct *Cumulative Hours* for subsequent events.

Not shown is a summary of class distribution across the week. Events occur with similar frequency on each day of the week, around 23% each with the exception of Wednesdays (whose afternoons are reserved for extra-curricular activities), with only 9% of total events. Event timing variables vary across students enrolled in the same module but assigned to different group events.

The most common event types are lectures, accounting for 56% of all student-events, with sudents having around 5 lectures per week, 18 per module, and 47 per term. The average size for a lecture is 211 students. In all but six modules with lectures, the whole student intake meets together. This means for most students in the same programme-module, lectures only exhibit variation in daily structure due to the arrangement of other events on each student's timetable. In a few modules with intakes above approximately 400, lectures are split into two roughly-equal sized groups.

Classes and other types of small teaching group events (tutorials, seminars, workshops) make up 36% of observations. Labs, which are the most likely event type to be longer than an hour, account for an additional 8% of student-events. The average size for these group events is 31 students. Since students on the same module are split into these smaller groups, these events all feature within programme-module variation in our daily structure variables as well as variation in event timing.

4 Empirical strategy

Timetable effects are identified on the assumption that timetables are conditionally quasi-randomly assigned. Section 4.1 will empirically test this assumption. Section 4.2 presents our primary models of analysis. In our analysis we utilize three levels of data aggregation:

Student-event level: An individual lecture or group event for a student on a particular date. This is the level that students make attendance decisions. See Column 1 of Table 2.

Student-module level: Aggregated to averages of timetable characteristics for the student across all their student-events on a specific module. This is the level of variation for student marks. See Column 4 of Table 2.

Student-term level: Aggregated to averages of timetable characterstics for the student across all their student-events in a given term. This is the level of variation for surveyed outcomes (such as study time) that are elicited in surveys, and not specific to a module.

4.1 Validity of random assignment

Our primary specification compares students enrolled in the same programme and module, but whose timetables differ due to the random assignment of group events. It is therefore important to check that students' characteristics are not systematically correlated with their timetables. We test the assumption of conditional random assignment of students to courses using the following model:

$$Structure_{ipmt} = \gamma_0 + \gamma_1 \mathbf{X}_i + \rho_w + \mu_h + \lambda_p + \tau_m + \upsilon_{ipmt} \tag{1}$$

We first focus on the specification where our unit of observation is a student-event. A student i is enrolled in program p and assigned to take module m. t represents the date, time and place of a particular event. The dependent variable $Structure_{ipmt}$, represents one of our *daily structure* variables, namely *Only*, *First of Back-to-Back*, *Later in Back-to-Back*, or *Cumulative Hours.*

$\mathbf{X}_i$ are background student characteristics which are used to test the validity of quasi-random assignment. ρ_w and μ_h are fixed effect controls for the *day-of-week* the event takes place and the *start-time* of instruction respectively. λ_p is a vector containing programme fixed effects, and τ_m a vector containing module fixed-effects. These account for the non-random sorting of students into programmes and modules. υ_{ipmt} is an student-event-level idiosyncratic error, that we cluster at the student level since this is the level at which the individual characteristics $\mathbf{X}_i$ vary.

In the top panel A of Table 3 we regress the *daily structure* characteristics on individual characteristics, with programme plus module fixed-effects, giving each person equal weight, and each student-event an equal weight within person. Our test for quasi-random assignment is the F-statistic for joint significance of all the individual characteristics shown in the table, plus (omitted only for reasons of space) the student's entry university qualification type and quintile of standardized university entry qualification scores.

We exclude from this calculation of joint significance the indicator for whether the student lives off campus, since these students are permitted to request timetable changes. We note that off-campus residents have more events in longer back-to-back sequences, as indicated by the positive coefficient on this variable in Column 3. This may reflect an ability of off-campus residents to request events in back-to-back sequences that are convenient for their longer commutes. In Table 4 we replicate all the tests shown in Table 3, for the campus-resident population only.

After correcting for multiple hypothesis testing, we fail to reject F-test of joint non-effects in any column, with just a marginally 10%-level significant unadjusted F-statistic for the *Later in Back-to-Back* Column in Table 3, and no such concerns in Table 4. This supports the claim of conditional random assignment among students enrolled in the same programme and suggests that there not meaningful correlations between student timetables and their background observable characteristics.

The lower panels of Tables 3 and 4 test the quasi-random assignment using different levels of aggregation. Individual coefficients are omitted for reasons of space, with just the F-statistic and p-values reported. Panel B reports test statistics where the equation has been aggregated to the student-module level, hence the superscript m on all coefficients, and again with standard errors clustered at the student level:

$$\overline{Structure}_{ipm} = \gamma_0^m + \gamma_1^m \mathbf{X}_i + \rho_w^m + \mu_h^m + \lambda_p^m + \tau_m^m + \upsilon_{ipm}^m \tag{2}$$

In Panel C we aggregate to the student-term (superscript i) level:

$$\overline{Structure}_{ip} = \gamma_0^i + \gamma_1^i \mathbf{X}_i + \rho_w^i + \mu_h^i + \lambda_p^i + \upsilon_{ip}^i \tag{3}$$

Finding only a single jointly significant association of individual characteristics with any *daily structure* characteristic across all of the person-event, or person-module, and person-term level of aggregation, and single significant association at the person-level (and then only at the 10% level, and disappearing after adjusting for multiple testing), supports our assumption of quasi-random assignment to timetables.[10]

These tests cannot completely ensure an effective natural experiment. There may still be endogenous correlation among module characteristics and timetables. For example, if the best group event instructors typically teach late in the day, the estimates on the effects of *Cumulative Hours* may be biased. We do not directly observe instructor quality or module difficulty.

[10] We additionally tested for balance including our measures of the Big 5 personality traits. Across the board p-values were similar or slightly higher and so we are confident student timetables are not correlated with measurable personality traits.

To examine the relationship between modules and timetables, Table 5 estimates a version of Equation 1 with module and event-level characteristics, Mod_{mt} replacing student ones. We cluster standard errors instead at the event level, because the characteristics Mod_{mt} do not differ across students assigned to attend the same event. These characteristics include: the number of registered students for a module, the share of contact hours on the module that are of the same type as the present event (which may be a proxy for the relative importance of a particular event), the relative size of the group (compared to an even allocation of students registered for the module), the weighting given to coursework (versus examinations) in calculating marks, and whether the course is *Compulsory* or *Core*. Larger teaching groups may be a function of students being moved between groups to accommodate timetabling clashes - outside the control of the student - but also students invoking exceptional circumstances. Table 5 again shows no jointly-significant association of module characteristics with timetable characterisics, and only one statistically significant coefficient, and only at the 10% level, from the 24 coefficients shown.

4.2 Empirical specifications

Our two primary outcomes of interest are event attendance and module marks. These outcomes vary at different levels of granularity. For each of our estimated models below, we explain the level of aggregation with careful distinctions in how coefficients in each model should be interpreted.

4.2.1 Attendance

We first investigate the impact of timetables on daily attendance, at the student-event level, by estimating Equation 4:

$$Att_{ipmt} = \beta_0 + \beta_1 Structure_{ipmt} + \lambda_p + \tau_m + \beta_2 \mathbf{X}_i + \beta_3 Mod_{mt} + \rho_t^w + \mu_t^h + \epsilon_{ipmt} \tag{4}$$

Here Att_{ipmt} is an indicator for whether the student i in programme p attended the event for module m with timing t. Attendance varies at the student-event level and estimates can be interpreted as the marginal impacts on attendance. The vector $Structure_{ipmt}$ contains *Only*, *Back-to-Back*, and *Cumulative Hours*. β_1 is the vector of interest, containing the relationships between a student's timetable's *daily structure* and their attendance. We scale all variables such that the coefficients can be interpreted as the percentage point impact on probability of attendance at that event.

λ_p and τ_m represent programme and module fixed effects which control for student selection into programmes and average module difficulty. We discuss our results under the assumption that timetables are random, conditional on λ_p and τ_m. $\mathbf{X}_i$ contains time-invariant individual controls shown in Table 3. Mod_{mt} contains module and teaching group controls shown in Table 5. μ_h and ρ_w are time-of-day and day-of-week fixed effects, respectively. To aid parsimony while capturing key differences, we group start times and days as follows: For start-time, 0900 is omitted category, other events grouped in 1000-1200, 1300-1400, and 1500-1800; For day-of-week, Monday is omitted category, other events grouped into 'midweek' (Tuesday-Thursday) and Friday. ϵ_{ipmt} is an error term, which, if identifying assumptions are met, will be conditionally uncorrelated with the vector $Structure_{ipmt}$. Standard errors are clustered at the individual level.

We also investigate the impact of timetable characteristics on attendance at the student-by-module level, by estimating Equation 5:

$$\overline{Att}_{ipm} = \beta_0^m + \beta_1^m \overline{Structure}_{ipm} + \lambda_p^m + \tau_m^m + \beta_2^m \mathbf{X}_i + \overline{\rho}_{ipm}^{mw} + \overline{\mu}_{ipm}^{mh} + \epsilon_{ipm} \tag{5}$$

Here $\overline{Att}_{ipm}$ is the student's rate of attendance across all events in module m. The vector $\overline{Structure}_{ipm}$ contains the *share* of person i's events on module m that are the *Only* event person i has in the day, and that are *First of Back-to-Back* or *Later in Back-to-Back*, and average number of preceding hours on the same day in total (the module-level average of *Cumulative Hours*), across person person i's events on module m. $\overline{\rho}_{im}^{mw}$ and $\overline{\mu}_{im}^{mh}$ captures the share of events for person i on module m in each block of the week and the day respectively.

The coefficients β_1^m represent the impact of a one unit change in each component of $\overline{Structure}_{ipm}$, at face-value the impact of *all* events on a module being *Only* or *Back-to-Back*, versus none, for example.

This specification captures spillover effects across events within a student's module. For example, students may be more likely to skip Friday events because they are more inconvenient. If this is a conscious decision, they may exercise some autonomy and undertake intertemporal substitution by being more likely to attend other non-Friday events on the module. This pattern of behaviour would show up in a negative coefficient in the event-level Equation 4, but a less-negative, zero, or even positive coefficient in the module-level specification depending on the degree of cross-event substitution.

4.2.2 Academic performance

Students' academic performance is measured by their marks, out of 100, for each module (Y_{ipm}). We therefore estimate the impact of timetable characteristics on marks at the student-by-module level, by estimating Equation 6:

$$Y_{ipm} = \theta_0^m + \theta_1^m \overline{Structure}_{ipm} + \lambda_p^m + \tau_m^m + \theta_2^m \mathbf{X}_i + \overline{\rho}_{ipm}^{mw} + \overline{\mu}_{ipm}^{mh} + \epsilon_{ipm} \tag{6}$$

The coefficients θ_1^m here represent the reduced-form impact of a one unit change in each component of $\overline{Structure}_{ipm}$, on marks in the corresponding module. This will be driven by a combination of their impacts on attendance, the productivity of these events conditional on attendance, and the impact of timetable characteristics on the student's other study time and study habits invested in the module.

4.2.3 Other uses of time

Students have autonomy over the allocation of their time in this university environment and this autonomy has been shown to increase productivity, especially for high-ability students (Bratti and Staffolini, 2013; Dolton et al., 2003; Goulas et al., 2023; Kapoor et al., 2021). Students who struggle with self-discipline or with understanding how to be productive on their own time may struggle with this autonomy (Fryer, 2011; Beattie et al. (2019)). The BOOST2018 survey data, which includes self-reported measures of student allocation of time allows us to consider this question in combination with our main data set of quasi-experimentally assigned timetables.

To investigate this last component, we use data from the BOOST2018 survey waves 1 and 3. These were launched at the start of the 9th week of the autumn/fall and spring terms respectively, and elicit self-reports of study habits, including overall time per week they usually study, propensity to cram, and other time investments including working for pay. We treat this as student-by-term level data on these time use. We estimate the following specification:

$$I_{ips} = \theta_0^s + \theta_1^s \overline{Structure}_{ips} + \lambda_p^s + \theta_2^s \mathbf{X}_i + \overline{\rho}_{ips}^{sw} + \overline{\mu}_{ips}^{sh} + \epsilon_{ips} \tag{7}$$

Here, I_{ips} represents student i on programme p's investment in term (semester) s; and other variables are the student-term counterparts to the student-module-level variables in Equation 5 and 6. We include programme and term fixed-effects.

In all specifications for attendance and marks, we weight observations such that each individual has an equal weight, each module within an individual has equal weight, and each event within a module has equal weight. Results are not significantly or qualitatively different to the unweighted specifications, in which each student-event is implicitly given equal weight. In specifications using survey data, we use non-response weights to weight observations to the characteristics of the estimation sample for attendance and academic performance.

5 Results

5.1 Attendance and marks

Table 6 shows estimates of timetable impacts on attendance at the student-event level (Equation 4, Columns 1-3), attendance at the student-module level (Equation 5, Cols 4-6), and marks at the student-module level (Equation 6, Cols 7-9). For each model, three columns include different combinations of the daily structure characteristics in the vector *Structure*, to check for robustness to different specifications. All models include a control for an *Only* event in the day, *start-time*, and *day-of-week*. These are dummy variables in the event-level model and shares in module-level models. The impact of *Back-to-Back* and *Cumulative* events are incorporated in three different ways. The first column of each model (cols 1,4,7) includes a control for whether or not an event is in a back-back sequence (*Back-to-Back Event*) and does not include *Cumulative hours*. The second columns (2,5,8) add in *Cumulative hours* and the third columns (3,6,9) separate out the *First of Back-to-Back* and *Later in Back-to-Back* events, due to their hypothesized differential effects on marks. Overall, when considering the different versions of our *Structure* vector, the main coefficients of interest are not meaningfully changed and we focus on interpretation of the middle columns for each outcome as our preferred specification.

At the event-level (Col 2), student attendance decisions are clearly influenced by their timetables. Students are less likely to attend *Only* events on a given day by 0.9pp. Perhaps due to the desire to have a "day off" or the fixed-cost of commuting, when there is a single event on a student's timetable they are more likely to skip it. *Back-to-Back* events, meanwhile, increase attendance at the event-level by 1.5pp.

Time-of-day and day-of-week have larger effects on attendance. Attendance is notably lower in early-morning classes relative to all others (5.8-9.1pp), Monday is the best-attended day of the week and Friday the worst (5pp lower than Monday).

Module-level estimates on attendance (Col 5) represent impacts of the average characteristics of a student's timetable structure (e.g. share of events that are *Only* or *Back-to-Back*) on overall attendance across all events in a module. These results therefore capture substitution on the part of students across events in the same module. Here, *Only* events show an interesting pattern. The sign of the coefficient on *Only* events switches from negative in Column 2 (-0.92pp) to positive in Column 5 (2.8pp). So while students attend *Only* events less frequently, they make up for that missed attendance by attending the other events in that module at an increased rate such that their overall attendance for the module is higher-than-average. We interpret this as strategic and deliberate time use choices on the part of students. Skipping an individual *Only* event provides a large perceived benefit (a day with no events), but students then make sure not to miss the other weekly event(s) for that module.

Other timetable features (*Back-to-Back*, start-time and day-of-week) have module-level estimates similar to their event-level ones. *Back-to-Back* events, for example, increase attendance at the event itself and that passes through to the module-level, but it does not seem to affect the attendance at the other weekly event(s) for that module. This implies that students are not perfectly strategic or elastic in their attendance choices. There are timetable features that can be built-in to increase a programme or university's overall attendance. Multiple events scattered across a day result in absolute lower attendance.

Column (8) shows module-level impacts on marks. *Only* and *Back-to-Back* events, which both have significant impacts on attendance at the event- and module-level do not show any significant impact on student marks. Students are perhaps able to compensate for their attendance choices with their allocation of effort outside the classroom, or there may be other offsetting mechanisms, such as lower engagement or productivity conditional on attendance in *Back-to-Back* events

For *start-time* and *day-of-week*, we see significant impacts on marks. However, the coefficient patterns do not point towards attendance being the driving mechanism. Time-of-day, which has been studied in numerous settings (see Introduction), is known to have a direct impact on learning above-and-beyond attendance. Afternoon classes typically exhibit higher achievement than morning ones. In our results all three *start-time* categories show higher attendance relative to early morning classes, but only the late afternoon classes show positive impacts on marks. For *day-of-week* students attend classes at the highest rate on Mondays and the lowest rate on Fridays. Yet students with a Friday event earn marks that our insignificantly different from their counterparts with Monday events. Meanwhile, students with middle-of-the-week events - which are attended at a rate in between Mondays and Fridays - do earn lower marks relative to students with Monday events. Like with time-of-day, these results cannot identify the precise mechanism that is driving the results on marks, but attendance does not appear to be the primary mechanism. If it were, we would expect stronger impacts of Friday events relative to midweek ones.

5.2 Reallocation of effort

We are interested in better understanding why timetables strongly impact attendance, but have inconsistent or non-existent resulting impacts on marks in our setting. We first use survey data to assess the reallocation of time away from other investments based on timetables. The next subsection proceeds to evaluate whether these overall effects are disguising significant heterogeneity across students and modules.

Table 7 shows the impact of the timetable characteristics on study time, cramming, and engagement in working for pay. Because these are measured at the student-term level, but we have so far looked at the event or module level, in the first column we show an additional specification for attendance at the term level. Although we lose precision, the positive signs on *Only* and *Back-to-Back* events match those in Table 6, with the magnitudes inflated. We can then compare variation in attendance measured at the same level as these other habits.

There are no significant impacts of *Only* or *Back-to-Back* events on any of these activities, so these cannot help explain why the significant positive impacts of these types of event on module-level attendance do not pass through to marks. The finding that events scheduled later in the day significantly reduce study time, combined with the small positive effects of later events on marks documented in Table 6, lends further credibility to later-in-day events being good for both attendance, and for in-class productivity conditional on attendance.

There are no significant impacts of any timetable features on proclivity to cram. Although the *daily structure* of students' timetables do not impact students' ability to work for pay, it is intuitive that that those whose events are predominantly first thing in the morning are more able to take up employment hence the stable negative coefficients on the later time-of-day dummies. For our heterogeneity analysis, we retain study time in our analyses, as a potential driver of impacts on marks for sub-groups of the population.

5.3 Heterogeneous responses

Tables 8 - 10 examine our main result broken down by event and student characteristics that we would expect, *a priori* to drive differential responses by students, and hence have differential impacts on performance.

We first assess heterogeneity by event type, since this relates to whether students are expected to learn through active interaction. We break these down into lectures, labs and other group teaching. Second, we assess heterogeneity by students' residence type, since off-campus residents face greater fixed costs of attending any classes, and lack a private space to study between classes, on a given day. Third, we assess heterogeneity by students' conscientiousness, which we argue is the most relevant noncognitive trait affecting students' cost of attendance or substituting study for attendance.[11]

Each table shows the effects of *Only* and *Back-to-Back* events on a baseline group of the population, and the interaction term showing the difference in the impact of this timetable characteristic between the specified group and baseline. A dummy for the specified group is always included elsewhere in the model. The model is not fully interacted, meaning that the effects of all other covariates (including *Cumulative Hours*, start-time and day-of-week) in the model are assumed to be the same across groups.

Table 8 interacts the daily structure variables with event type, splitting these into lectures (the baseline category), labs, and other group teaching events.[12] The most striking finding is that while students are significantly more likely to attend lectures scheduled back-to-back, relative to this they are significantly less likely to attend lab events scheduled back-to-back

[11]We undertake further assessment of heterogeneity by sex, reported in Appendix Table A1. Despite females attending significantly more, engage in significantly longer hours of private study, and achieve significantly higher marks, we find no significant differential effects.

[12]We carry this out interaction *after* collapsing to module (or term), meaning that the coefficients for these aggregated specifications are deliberately interpreted as relating to the impact of daily structure in modules with a greater or lesser share of events that are labs.

(-5pp) and marginally less likely (-1.6pp) to attend other small-group events. This suggests that students anticipate fatigue for lab events scheduled back-to-back, which outweighs their relative convenience. This interpretation applies at the event-level, and is also reflected in overall attendance at the module-level.[13] Moreover, although not significant, the reduction in study hours and in marks in response to having back-to-back events in modules with labs, suggests that the overall coefficients are masking important heterogeneity. A similar picture emerges for *Only* events, with positive and large, though again insignificant, coefficients on this interaction term for module-level attendance and term-level study. The common direction of attendance, study and marks here is suggestive of complementarities between study and attendance being more important for the predominantly-quantitative modules taught through labs, than in other fields.[14]

Table 9 interacts by residence type. The baseline are on-campus residents and the interaction group is off-campus residents. Off-campus students represent 12% of the enrolled population and these students face higher fixed-costs of attending university on a given day, and are more constrained in the space available to them between classes, in that they cannot return to their residence to study if they wish. Note that students wanting to reside on campus must book their accommodation before the timetable is revealed. We use the location of residence recorded at time of initial registration at the university, to prevent this cut of the data being affected by endogenous re-sorting of students in response to experiencing their timetable in practice. Table 9 clearly shows that off-campus residents' attendance is highly positively responsive to *Back-to-Back* events, consistent with our hypothesis that these students are more responsive to the efficiency of their timetable. This effect is seen at the event level and carries through to the module level. The interaction terms for off-campus residents are significant and over twice as large as the impact for on-campus students. Off-campus students do not appear significantly more deterred from attending *Only* events, but in Column (3), we have suggestive evidence (p-value of 0.15) that *Only* events reduce study for off-campus students. If the student has 10 events per week, the coefficient is consistent with an extra *Only* event reducing study time by 1.23 hours per week, which is a plausible duration for a round-trip commute to crowd-out study

[13] The large coefficient of 21.7 in column 2 should be interpreted in light of an average value of this variable of 0.037. A one standard deviation (0.084) increase in this characteristic is predicted to reduce attendance by 1.8 percentage points.

[14] For example, if we classify as quantitative all modules taught in the departments of Biology, Business, Computer Science, Economics, Maths or Psychology, then 12.7% (1.8%) of quantitative (non-quantitative) teaching events are labs; and 65% (17%) of quantitative (non-quantitative) modules conduct at least some teaching in labs.

time. Like with our main result, there are no corresponding significant impacts on marks.

Table 10 shows results by conscientiousness. We restrict the sample to study participants who provided responses to the battery eliciting the Big 5 personality traits, and define conscientious students as those with conscientiousness above the sample median.[15] There are no significant differences in impacts of timetable structure on conscientious students' attendance or marks. However, while non-conscientious students significantly reduce study time in response to having *Only* events, the interaction term is such that conscientious students do not respond at all to this timetable feature. Moreover, while non-conscientious students' do not respond to *Back-to-Back* events, conscientious students respond by significantly increasing their study time, making use of this feature that will, other things equal, result in more uninterrupted time before and after the day's timetabled events. Both these findings indicate that the structure of the timetable again has meaningfully different impacts on different students' effort allocations according to their characteristics, albeit here in terms of study rather than attendance. Again, these timetable features do not have a significant overall or differential effect on marks.

For completeness, heterogeneous effects by the other Big 5 personality traits are reported in Appendix Tables A3-A6. Attendance by students who are more neurotic, agreeable, extraverted, and open to experience are all less responsive to back-to-back scheduling. This intuitively may reflect the psychic costs of *not* attending, for neurotic students; and lower psychic costs of attendance, and hence relative unimportance of convenience, for the others. However, like conscientiousness, none of these lead to any significant differential effects on marks, but remarkably none show any significant differential effects on study, a behavioural response which for conscientiousness were quite striking.

6 Discussion and conclusion

We use linked timetable, daily attendance, and administrative data from a representative public UK university to understand the impacts of daily structure on student decisions and achievement. We exploit quasi-random assignment to timetables of students enrolled in the same degree programs and taking the same modules and show balance tests supporting our pseudo-

[15] Conscientiousness was measured as the sum of "I am someone who does a thorough job", "... does things efficiently" and "tends to be lazy", all elicited on a fully-labelled 7-point scale from Strongly Disagree to Strongly Agree, with the last item reverse-coded. Table A2 shows that conscientiousness is the only one of the Big 5 traits to correlate with all four of our main outcomes, with coefficients at least twice as large as the others.

experimental setting. Our primary model is supplemented with time-use and survey data that allows us to consider mechanisms such as conscientiousness as a drivers of our results.

We cleanly identify six related findings. Each of these is either novel to the field or is strengthened by our granular, event-level, data and our ability to observe students across a representative set of programmes.

First, we show that student daily attendance choices are dependent on their timetable structure and timing. *Only* events decrease event-level attendance while *Back-to-Back* ones increase it, both novel results. Time-of-day and day-of-week have even larger attendance impacts, broadly consistent with prior literature (Carrell *et al.*, 2011; Diette & Raghav, 2017; Edwards, 2012).

Second, students offset marginal non-attendance at some events by increasing attendance or varying their study time. We are not the first to document that student's are strategic in their time-use decisions (Delavande *et al.*, 2021), but are the first to causally document this sort of strategic attendance substitution with event-level evidence. This leads the impacts of students' timetables on marks to be relatively innocuous.

Third, following from above, timetable-induced attendance decisions do not broadly pass-through to marks. In other words, consistent with existing literature (e.g. of Bratti and Staffolani, 2013; Goulas et al., 2023) we show that allowing autonomy can be beneficial for students. Overall attendance rate is a positively-selected trait among students, but they are able to adjust around the margins.

Fourth, we causally show that there are clear methods for universities to raise absolute attendance. *Back-to-Back* are more convenient to attend and raise event-level and overall attendance for a module and we show that this is especially true for off-campus students. The vast majority of *Back-to-Back* sequences in our data are two-event, two-hour sequences and we would not extrapolate our results beyond that length. Likewise, early-morning classes depress attendance, consistent with prior work (Arulampalam *et al.*, 2012; Chen & Lin, 2008). Schools could raise overall attendance with later start times. We also show decreased attendance for Friday events. While four-day school weeks have shown some promise Anderson & Walker (2015), we cannot be sure of the spillover effects of reducing or eliminating Friday events.

Fifth, we see suggestive evidence that impacts on overall attendance rates and marks are larger for modules taught with lab sessions, the majority of which are in quantitative fields.

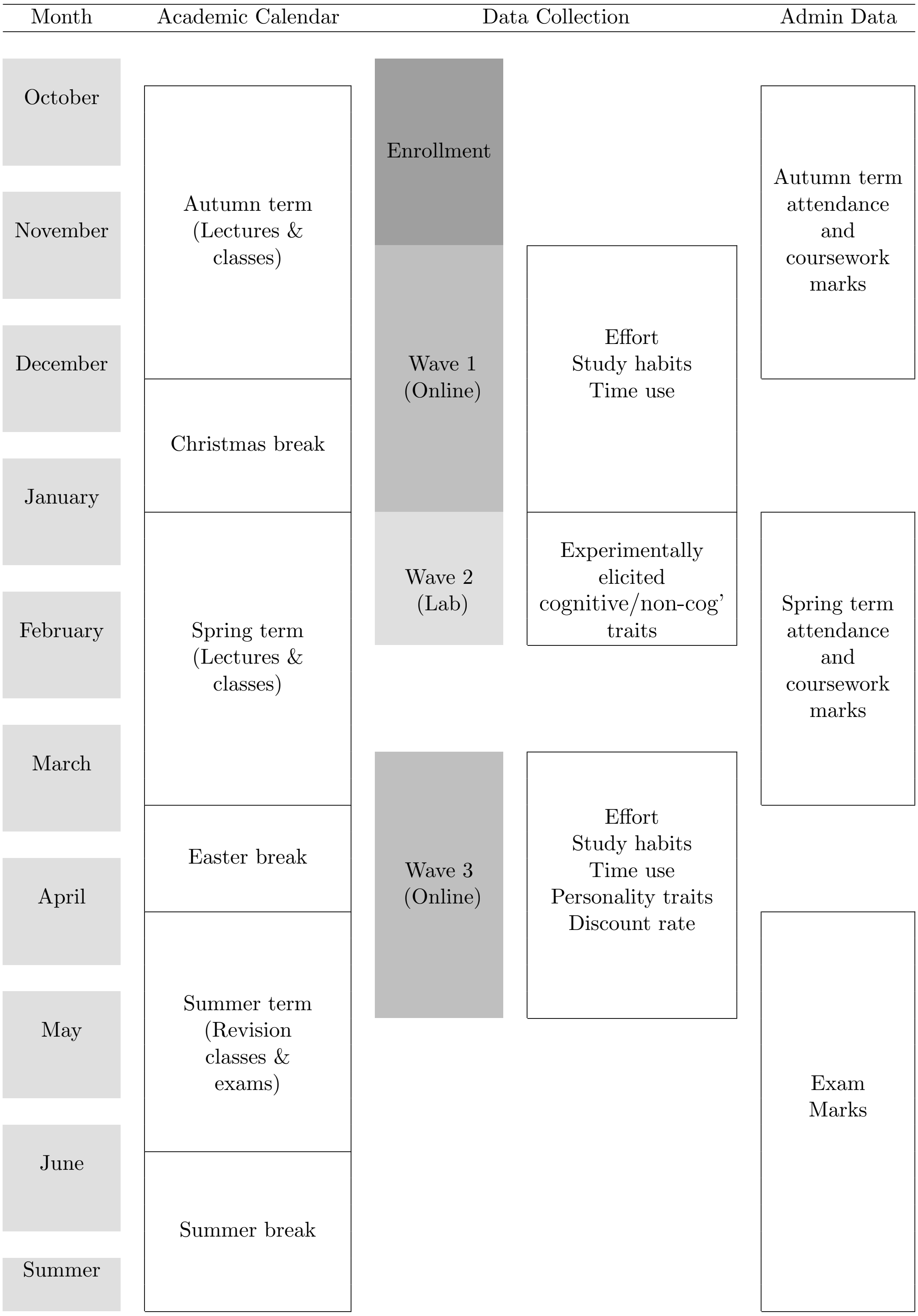
This may be a reason that numerous papers focusing on a single quantitative department find positive effects (Andrietti & Velasco, 2015; Chen & Lin, 2008; Cohn & Johnson, 2006; Dobkin *et al.*, 2010) of attendance on marks.

Sixth, we document how timetables affect study habits as well as attendance in heterogeneous ways. For example, we show that *Only* events alter the study patterns for students with below-median conscientiousness meaningfully more than ones with above-median levels. Hence, the right timetable may be different depending on the student.

Our results have implications for both university administrations as well as students and their advisers. We have focused on attendance as an outcome in its own right because it is typically thought of as an input for human capital accumulation, that crucially is malleable by these agents. Our findings suggest that to increase overall attendance, one-event days should be avoided, and classes should be scheduled in short back-to-back sequences (i.e. 2×1 hour consecutively, then a break). A university looking to maximize student on-campus attendance could try to avoid early morning events and group daily events close together. In many Higher Education settings students have control over their timetables and could enroll in a way to set themselves up for increased expected attendance.

7 Figures and Tables

Figure 1: Timeline of the Study



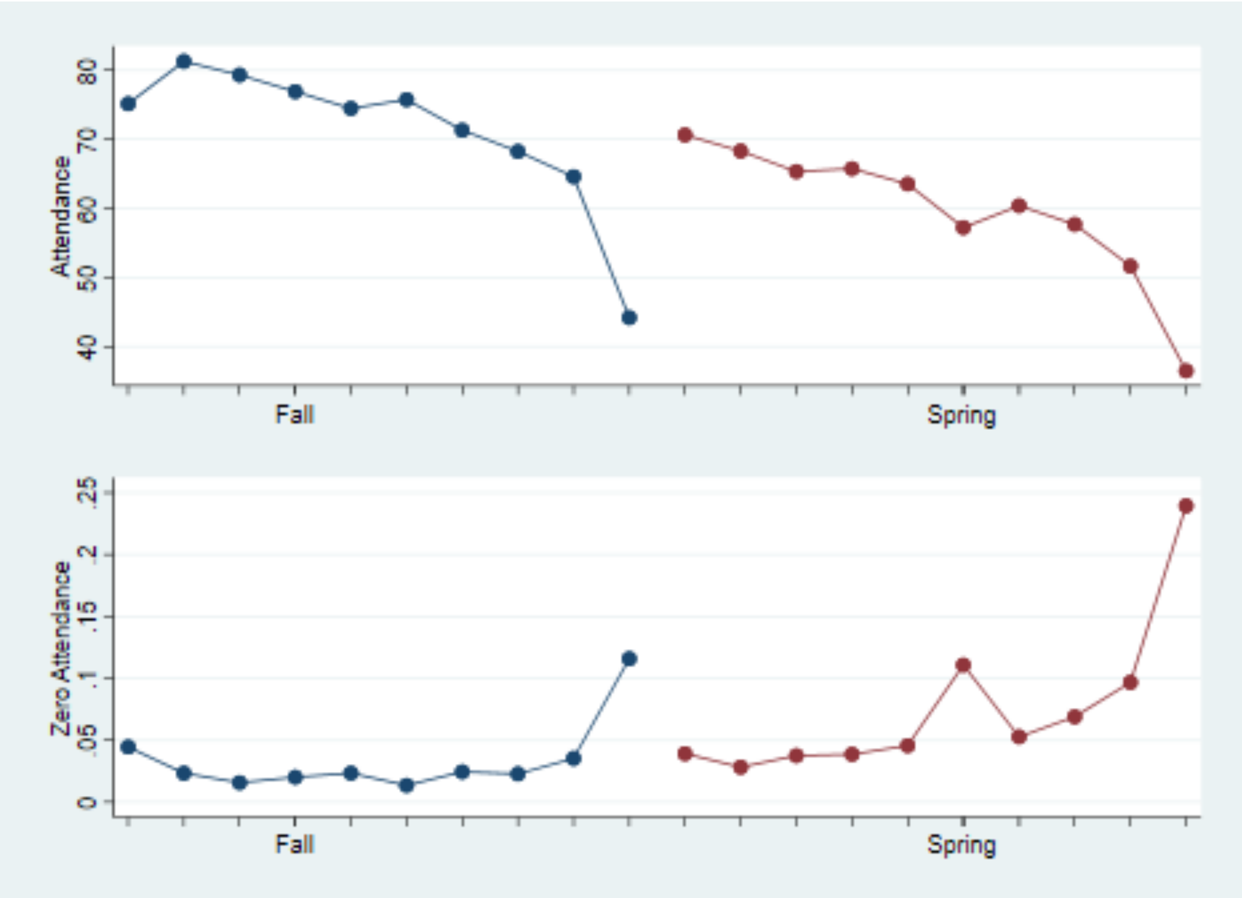
Notes: Representation of the timeline of the first year of data collection.

Figure 2: Example Timetables

Student 1:	**Economics programme**					
	0900	1000	1100	1200	1300	1400
Monday		Maths 0, 0, 0 ,0 Lecture				Maths 0, 0, 0, 1 Class 1
Tuesday					Micro 1, 0, 0, 0 Lecture	
Wednesday	Stats 0, 0, 0, 0 Lecture		Macro 0, 1, 0, 1 Class 1	Stats 0, 0, 1, 2 Class 1	Micro 0, 0, 1, 3 Class 1	
Thursday			Macro 1, 0, 0, 0 Lecture			
Student 2:	**Economics programme**					
	0900	1000	1100	1200	1300	1400
Monday		Maths 1, 0, 0, 0 Lecture				
Tuesday					Micro 0, 1, 0, 0 Lecture	Maths 0, 0, 1, 1 Class 2
Wednesday	Stats 0, 0, 0, 0 Lecture		Macro 0, 0, 0, 1 Class 1		Micro 0, 0, 0, 2 Class 1	
Thursday			Macro 0, 1, 0, 0 Lecture	Stats 0, 0, 1, 1 Class 2		
Figures shown are *Only*, *First of Back-to-Back*, *Later in Back-to-Back*, *Cumulative*						

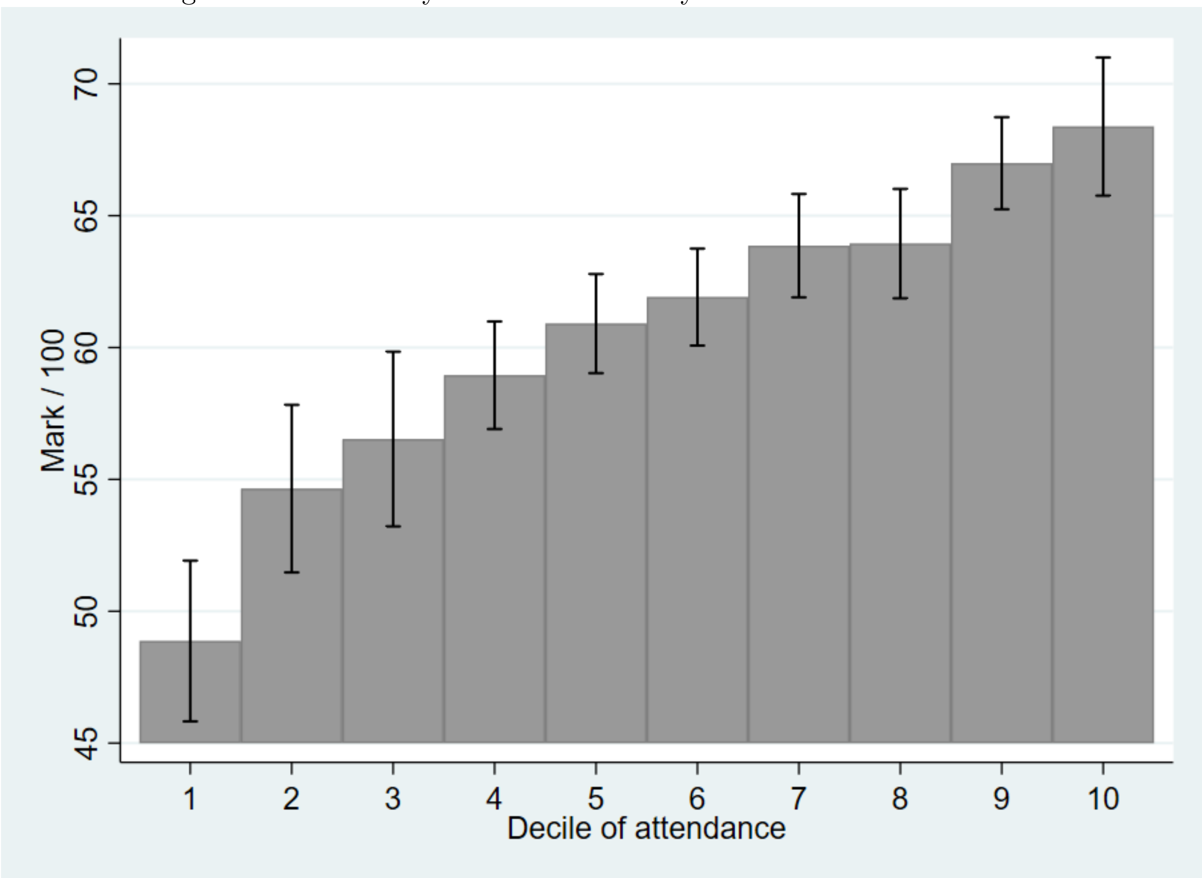
Notes: Shows fictional extract from a weekly timetable for two students. Common shading represents a given module. Figures shown are: *Only* (student's only event on a given day); *First of Back-to-Back* (event does not immediately follow another event, but does immediately precede another event); *Later in Back-to-Back* (another event immediately precedes this event, without a break); and *Cumulative* (number of hours of event that precede this event over the whole day). A 'default' event for which all of these characteristics take the value zero, would be the first of the day, but each student has subsequent events that day after a break.

Figure 3: Overall Attendance Pattern



Notes: Top panel plots mean percentage of events attended each week in fall and spring semester. Each person weighted equally, and within each person, each event equally. Bottom panel plots proportion of individuals with at least one timetabled event who attend zero events, each week in fall and spring semester.

Figure 4: Mean first-year overall marks by decile of overall attendance



Notes: Unconditional margins, with 95% confidence intervals derived from standard errors clustered by programme, N=1820 first-year students with valid first-year overall mark. Decile upper bounds (%): p1 (sample minimum): 0; p10 (upper bound of decile 1): 37.7, p20: 48.5, p30: 54.8, p40: 61.6, p50: 67.0, p60: 73.4, p70: 78.6, p80: 83.9, p90: 90.2, p100 (sample maximum): 100

Table 1: Summary: Population and sample composition

	(1) Population	(2) Enrolled in BOOST	(3) Difference	(4) (p-value)
Female	0.502	0.524	-0.021	(0.164)
Mature (age 21+)	0.095	0.078	0.017	(0.053)
Nationality/SES grouping:				
Home High SES	0.402	0.415	-0.013	(0.385)
Home Low SES	0.272	0.279	-0.007	(0.621)
Home SES Unclassified	0.009	0.005	0.004	(0.130)
EU	0.164	0.159	0.005	(0.630)
Overseas	0.152	0.142	0.010	(0.335)
Parents' education:				
Parent has degree	0.465	0.476	-0.011	(0.474)
Neither parent has degree	0.333	0.337	-0.003	(0.827)
Parents' ed' unknown	0.201	0.187	0.014	(0.245)
Ethnicity:				
White	0.588	0.560	0.029	(0.056)
Asian	0.160	0.165	-0.005	(0.652)
Black	0.159	0.184	-0.024*	(0.033)
Ethnicity unknown/refused	0.009	0.007	0.002	(0.402)
Mixed ethnicity	0.059	0.065	-0.006	(0.374)
Other ethnicity	0.024	0.020	0.005	(0.282)
Entry qualifications:				
A-Levels and Highers	0.559	0.587	-0.028	(0.065)
International Baccalaureate	0.030	0.028	0.002	(0.717)
Other Level 3 or HE Level	0.180	0.145	0.035**	(0.002)
Other Level 2	0.085	0.086	-0.001	(0.922)
Entry quals missing / unknown	0.146	0.154	-0.009	(0.423)
Students' entry tariff score:				
Lowest Quintile	0.145	0.151	-0.006	(0.566)
2nd	0.161	0.168	-0.007	(0.556)
3rd	0.132	0.131	0.001	(0.913)
4th	0.155	0.162	-0.006	(0.575)
Highest Quintile	0.145	0.153	-0.008	(0.461)
Missing	0.261	0.235	0.026*	(0.050)
Field of Study:				
Humanities	0.269	0.271	-0.002	(0.883)
Social Science	0.411	0.413	-0.002	(0.875)
Science and Health	0.320	0.315	0.004	(0.760)
Residence:				
Live on campus	0.841	0.887	-0.046***	(0.000)
Observations	2,621	1,837		

Notes: Summarizes composition of students in first-year cohort (Column 1) vs those enrolled in our study (Column 2). Column 3 shows the difference in means between Columns 1 and 2 and Column 4 has the corresponding t-test's p-value.

Table 2: Summary: timetables and attendance rates

	(1) All mean/sd	(2) Weighted mean/sd	(3) Avg. student-week mean/sd	(4) Avg. student-module mean/sd	(5) Avg. student-term mean/sd
N Events Attended			5.84	19.99	51.51
			(2.21)	(8.14)	(18.33)
N Events Scheduled			8.82	32.90	83.69
			(1.50)	(9.31)	(13.24)
Total duration, minutes			698.38	2612.46	6646.98
			(124.55)	(727.48)	(1126.24)
Only Event	0.14	0.15	1.16	4.43	11.55
	(0.34)	(0.36)	(0.79)	(2.85)	(7.03)
First of Back-to-Back	0.21	0.20	1.83	6.85	17.27
	(0.40)	(0.40)	(0.91)	(3.47)	(7.67)
Later in Back-to-Back	0.27	0.26	2.40	9.11	22.34
	(0.44)	(0.44)	(1.22)	(5.15)	(10.33)
Cumulative Hours	1.12	1.09	9.98	37.08	93.46
	(1.28)	(1.27)	(4.48)	(18.96)	(37.93)
0900	0.15	0.14	1.33	5.10	12.70
	(0.36)	(0.35)	(0.97)	(3.99)	(8.94)
1000	0.14	0.14	1.22	4.82	11.51
	(0.34)	(0.35)	(0.95)	(4.34)	(9.05)
1100	0.15	0.16	1.32	5.17	12.86
	(0.36)	(0.37)	(0.83)	(3.65)	(7.90)
1200	0.09	0.08	0.77	2.88	7.27
	(0.28)	(0.28)	(0.74)	(2.77)	(6.88)
1300	0.10	0.10	0.84	3.28	8.13
	(0.30)	(0.30)	(0.71)	(3.03)	(6.69)
1400	0.10	0.10	0.87	3.08	8.41
	(0.30)	(0.30)	(1.09)	(3.55)	(9.97)
1500	0.11	0.11	1.02	3.48	9.18
	(0.31)	(0.32)	(1.06)	(3.20)	(8.66)
1600	0.09	0.09	0.78	2.84	7.52
	(0.29)	(0.28)	(0.74)	(2.78)	(6.68)
Lecture	0.56	0.55	4.92	18.06	47.13
	(0.50)	(0.50)	(1.82)	(6.93)	(17.45)
Lab	0.08	0.08	0.70	2.38	6.69
	(0.27)	(0.26)	(0.81)	(2.74)	(8.58)
Class / other	0.36	0.37	3.19	12.47	29.87
	(0.48)	(0.48)	(1.69)	(7.90)	(15.77)
Module Size	226.35	216.63			
	(133.97)	(138.59)			
Attendance, %	65.41	65.99			
	(45.03)	(45.23)			
Observations:					
N students	1,837	1,837	1,837	1,837	1,837
N events	11,346	11,346			
N student-events	307,488	307,488			
N student-weeks			36,740		
N student-modules				15,162	
N student-terms					3,592

Notes: Shows summary of primary analysis sample. Col. 1 summarizes all student-events, providing equal weight to each. Col. 2 weights events so that each student is given equal weight. Col. 3 summarizes the timetable load for a student's typical week, based on third week of the autumn/fall and spring terms. Column 4 summarizes the timetable load for an average student-module, giving each student equal weight. Column 5 summarizes the timetable load for an average student-term, giving each student equal weight. Additional timetable controls in primary specification include: day of week dummy variables, relative teaching group size, and event share type.

Table 3: Balance test: Regression of daily structure on student characteristics across levels of aggregation. All students

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Panel A: Student-Event level data: Programme + Module Fixed Effects				
Female	-0.003	-0.001	0.002	0.018
	(0.004)	(0.003)	(0.004)	(0.011)
Home Low SES	-0.002	0.006*	0.007	0.014
	(0.004)	(0.004)	(0.005)	(0.012)
Home Unclassified	-0.000	0.014	0.007	-0.011
	(0.017)	(0.018)	(0.017)	(0.033)
EU	-0.004	-0.007	-0.008	-0.010
	(0.008)	(0.006)	(0.008)	(0.022)
Overseas	0.006	0.005	-0.001	0.012
	(0.007)	(0.006)	(0.008)	(0.022)
Mature (age 21+)	-0.000	0.010*	0.011	0.014
	(0.007)	(0.006)	(0.007)	(0.018)
Parents' ed' unknown	0.0019	-0.005	0.011**	0.011
	(0.005)	(0.004)	(0.005)	(0.015)
Parent has degree	-0.006	-0.004	0.003	0.010
	(0.004)	(0.004)	(0.005)	(0.012)
Asian	0.001	-0.004	-0.009	-0.009
	(0.006)	(0.005)	(0.007)	(0.018)
Black	0.005	-0.001	-0.003	0.003
	(0.005)	(0.004)	(0.005)	(0.014)
Ethnicity unknown/refused	-0.008	-0.009	0.015	0.002
	(0.025)	(0.010)	(0.022)	(0.055)
Mixed ethnicity	-0.002	0.000	-0.003	-0.037*
	(0.006)	(0.005)	(0.007)	(0.020)
Other ethnicity	-0.021*	-0.012	-0.018	0.030
	(0.012)	(0.011)	(0.013)	(0.040)
Conscientiousness	-0.001	-0.000	0.003	-0.005
	(0.002)	(0.002)	(0.002)	(0.005)
Discount factor	-0.004	-0.000	-0.004	0.011
	(0.003)	(0.003)	(0.004)	(0.009)
Live off campus	-0.004	0.003	0.030***	0.017
	(0.006)	(0.005)	(0.011)	(0.017)
F	1.037	0.933	1.403	1.260
$p(F)$	0.413	0.555	0.093	0.179
adjusted p	0.797	0.867	0.243	0.427
Observations	307,488	307,488	307,488	307,488
Panel B: Student-Module level data: Programme + Module Fixed Effects				
F	0.947	1.087	1.242	1.041
$p(F)$	0.536	0.350	0.193	0.408
adjusted p	0.897	0.637	0.446	0.774
Observations	15,162	15,162	15,162	15,162
Panel C: Student-term level data: Programme Fixed Effects				
F	0.837	0.925	1.291	0.838
$p(F)$	0.671	0.567	0.157	0.690
adjusted p	0.976	0.838	0.337	0.905
Observations	3592	3592	3592	3592

Notes: Singleton observations dropped. Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. "Lives on campus" is excluded from calculation of F-test for joint significance. Additional individual-level controls included in F-test for joint significance: Entry qualification type (2 dummies); entry qualification total tariff score (5 quintile dummies). Additional module and group controls in event-level specification: Event type, event-type share, and relative size of teaching group. Omitted categories are: male, Home High-SES, mature (age 21+), neither parent has a university degree, White ethnicity, entry qualifications are A-Level, and entry tariff Q1 (lowest). Adjusted p-values account for testing of multiple hypotheses using the following modified Bonferroni Adjustment: $p_{adj} = 1 - (1 - p(k))^{g(k)}$ *where* $g(k) = M^{1-r(.k)}$, where M is the number of outcomes being tested (here 4 timetable characteristics), $p(k)$ is the unadjusted p-value for the k^{th} outcome and $r(.k)$ is the mean of the (absolute) pairwise correlations between all the outcomes other than k.(See Sankoh, Huque and Dubey, 1997, pp.2534-2535, for discussion).

Table 4: Balance test: Regression of daily structure on student characteristics across levels of aggregation. Students living on campus only

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Panel A: Student-Event level data: Programme + Module Fixed Effects				
Female	-0.001	-0.002	0.001	0.014
	(0.004)	(0.004)	(0.004)	(0.012)
Home Low SES	-0.004	0.006	0.007	0.018
	(0.004)	(0.004)	(0.005)	(0.013)
Home Unclassified	-0.006	0.020	0.016	-0.013
	(0.023)	(0.025)	(0.022)	(0.045)
EU	-0.004	-0.009	-0.011	-0.012
	(0.008)	(0.006)	(0.009)	(0.023)
Overseas	0.003	0.007	0.001	0.025
	(0.007)	(0.006)	(0.008)	(0.022)
Mature (age 21+)	0.006	0.011	0.008	-0.023
	(0.007)	(0.008)	(0.009)	(0.021)
Parents' ed' unknown	0.004	-0.007	0.010	0.014
	(0.005)	(0.005)	(0.006)	(0.016)
Parent has degree	-0.006	-0.006	-0.000	0.006
	(0.004)	(0.004)	(0.005)	(0.013)
Asian	-0.003	-0.008	-0.009	-0.004
	(0.006)	(0.005)	(0.007)	(0.019)
Black	0.002	-0.003	-0.004	0.002
	(0.005)	(0.004)	(0.005)	(0.015)
Ethnicity unknown/refused	0.004	-0.015	0.017	0.028
	(0.029)	(0.011)	(0.025)	(0.060)
Mixed ethnicity	-0.003	-0.003	-0.001	-0.039*
	(0.006)	(0.006)	(0.008)	(0.021)
Other ethnicity	-0.024*	-0.016	-0.021	0.029
	(0.014)	(0.012)	(0.014)	(0.045)
Conscientiousness	-0.000	-0.001	0.002	-0.005
	(0.002)	(0.002)	(0.002)	(0.006)
Discount factor	-0.004	0.001	-0.001	0.010
	(0.003)	(0.003)	(0.004)	(0.0105)
F	0.944	1.062	1.160	1.260
$p(F)$	0.541	0.381	0.269	0.179
adjusted p	0.903	0.694	0.592	0.427
Observations	273,731	273,731	273,731	273,731
Panel B: Student-Module level data: Programme + Module Fixed Effects				
F	0.768	1.231	1.039	1.055
$p(F)$	0.781	0.203	0.410	0.390
adjusted p	0.989	0.414	0.766	0.754
Observations	13,465	13,465	13,465	13,465
Panel C: Student-term level data: Programme Fixed Effects				
F	0.852	0.982	1.156	0.831
$p(F)$	0.670	0.487	0.273	0.699
adjusted p	0.971	0.767	0.537	0.910
Observations	3184	3184	3184	3184

Notes: Singleton observations dropped. Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Additional individual-level controls included in F-test for joint significance: Entry qualification type (2 dummies); entry qualification total tariff score (5 quintile dummies). Additional module and group controls in event-level specification: Event type, event-type share, and relative size of teaching group. Omitted categories are: male, Home High-SES, mature (age 21+), neither parent has a university degree, White ethnicity, entry qualifications are A-Level, and entry tariff Q1 (lowest). Adjusted p-values account for testing of multiple hypotheses using the following modified Bonferroni Adjustment: $p_{adj} = 1 - (1 - p(k))^{g(k)}$ $where$ $g(k) = M^{1-r(.k)}$, where M is the number of outcomes being tested (here 4 timetable characteristics), $p(k)$ is the unadjusted p-value for the k^{th} outcome and $r(.k)$ is the mean of the (absolute) pairwise correlations between all the outcomes other than k.(See Sankoh, Huque and Dubey, 1997, pp.2534-2535, for discussion).

Table 5: Balance test: Regression of daily structure on module and event characteristics

	(1) Only Event	(2) First of Back-to-Back	(3) Later in Back-to-Back	(4) Cumulative Hours
Module Size (100s of students)	-0.006	-0.010	0.021	0.008
	(0.011)	(0.014)	(0.016)	(0.058)
Event Type Share	-0.050	0.062	0.047	0.314
	(0.044)	(0.065)	(0.068)	(0.219)
Relative Teaching Group Size	-0.041	-0.036	-0.073	-0.238
	(0.062)	(0.066)	(0.090)	(0.266)
Coursework Weight (1=100%)	-0.047	0.051	0.088	0.225
	(0.072)	(0.100)	(0.113)	(0.413)
Compulsory module	-0.052	0.015	-0.009	0.274*
	(0.036)	(0.045)	(0.053)	(0.161)
Core module	-0.015	0.030	-0.058	0.101
	(0.020)	(0.041)	(0.049)	(0.114)
F	0.984	0.701	1.067	1.047
$p(F)$	0.435	0.649	0.380	0.393
adjusted p	0.819	0.925	0.745	0.756
Observations	307,476	307,476	307,476	307,476

Notes: Standard errors clustered by event in parentheses. ***: p <0.01, **: p <0.05, *: p <0.1. Additional controls not included in joint-F test: Duration of teaching event; event type (lecture, lab, etc...), programme fixed-effects . Adjusted-p values calculated as described in Table 3.

Table 6: Effect of timetable characteristics on attendance and performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Attendance, %, event-level			Attendance, %, module-level			Mark, /100, module-level		
	Convenience only	Convenience +day-long fatigue	+ consecutive fatigue	Convenience only	Convenience + day-long fatigue	+ consecutive fatigue	Convenience only	Convenience +day-long fatigue	+ consecutive fatigue
Default = First-in-day, with other events to follow after a break									
Only Event	-0.802*	-0.920*	-0.881*	2.224*	2.815**	2.645**	0.328	0.0907	0.140
	(0.466)	(0.482)	(0.485)	(1.276)	(1.323)	(1.344)	(0.734)	(0.761)	(0.777)
Back-to-Back Event	1.394***	1.456***		3.015***	2.705**		0.698	0.823	
	(0.374)	(0.378)		(1.051)	(1.053)		(0.674)	(0.677)	
First of Back-to-Back			1.616***			2.008*			1.023
			(0.406)			(1.214)			(0.756)
Later in Back-to-Back			1.277***			3.397***			0.625
			(0.430)			(1.204)			(0.824)
Cumulative Hours		-0.177	-0.130		1.005**	0.792		-0.404	-0.343
		(0.168)	(0.178)		(0.510)	(0.569)		(0.298)	(0.345)
Start-time: *Omitted = 0900 start*									
1000-1200	5.695***	5.783***	5.805***	9.146***	8.627***	8.541***	0.393	0.602	0.626
	(0.569)	(0.587)	(0.587)	(1.679)	(1.728)	(1.730)	(1.088)	(1.115)	(1.116)
1300-1400	8.459***	8.709***	8.676***	12.58***	11.08***	11.06***	1.199	1.804	1.809
	(0.675)	(0.734)	(0.738)	(2.030)	(2.245)	(2.245)	(1.259)	(1.387)	(1.386)
1500-1800	8.675***	9.057***	9.033***	13.84***	11.95***	12.19***	1.978	2.738*	2.669*
	(0.634)	(0.775)	(0.777)	(1.968)	(2.316)	(2.350)	(1.305)	(1.528)	(1.544)
Day-of-week: *Omitted = Monday*									
Midweek	-2.731***	-2.711***	-2.712***	-4.980***	-4.665***	-4.730***	-1.772**	-1.899**	-1.880**
	(0.418)	(0.421)	(0.421)	(1.391)	(1.382)	(1.386)	(0.894)	(0.892)	(0.895)
Friday	-5.166***	-5.137***	-5.146***	-8.743***	-8.657***	-8.710***	-0.0870	-0.121	-0.106
	(0.491)	(0.493)	(0.493)	(1.546)	(1.547)	(1.553)	(1.032)	(1.034)	(1.036)
Dep var mean	65.40	65.40	65.40	65.32	65.32	65.32	60.31	60.31	60.31
(standard dev')	(45.03)	(45.03)	(45.03)	(24.89)	(24.89)	(24.89)	(14.48)	(14.48)	(14.48)
Observations	289,325	289,325	289,325	14,982	14,982	14,982	14,982	14,982	14,982

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: Programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Event-level specifications in columns 1, 4, 7 also includes event type dummy variables, event type share, and relative teaching group size. In all module-level columns, all timetable characteristics are the within-person mean across all their events on the module.

Table 7: Effect of timetable characteristics on term-level attendance, study habits and competing time uses

	(1) Attendance, %	(2) Study hours per week	(3) Cramming - often or always	(4) Work for pay
Default = First-in-day, with other events to follow after a break				
Only Event	3.576	-3.762	0.104	-0.0535
	(3.975)	(2.523)	(0.113)	(0.0868)
Back-to-Back Event	6.874***	0.732	0.0119	0.0467
	(2.658)	(1.550)	(0.0785)	(0.0582)
Cumulative Hours	-1.953	-0.921	-0.0274	0.0221
	(1.813)	(0.887)	(0.0532)	(0.0387)
Start-time: *Omitted = 0900 start*				
1000-1200	1.075	-3.858	0.180	-0.284***
	(4.925)	(2.544)	(0.135)	(0.107)
1300-1400	-1.094	-6.157*	0.234	-0.239*
	(5.958)	(3.357)	(0.162)	(0.124)
1500-1800	6.489	-5.693*	0.0286	-0.299**
	(6.067)	(2.930)	(0.164)	(0.123)
Dayof-week: *Omitted = Monday*				
Midweek	-9.262***	-0.990	0.105	-0.099
	(3.493)	(1.788)	(0.102)	(0.0737)
Friday	-13.909**	-4.868*	0.0720	0.107
	(5.553)	(2.953)	(0.152)	(0.113)
Dependent variable mean	65.56	11.76	0.411	0.196
(std.dev if continuous)	(21.66)	(10.44)		
Observations	3654	2,365	2,365	2,365

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. Observations for each wave/term are weighted to profile of BOOST2018 participants. Additional controls in all columns: Programme fixed effects, dummy variables for individual characteristics shown in Table 1, term/wave. All timetable characteristics are the within-person mean across all their events on the term. The outcome variable in Columns 2-4 is equal to one if the student "often" or "always" has this habit. Outcome in Column 5 is binary.

Table 8: Heterogeneity by event type

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-1.317**	2.578	-9.617*	-0.652
	(0.627)	(2.954)	(5.560)	(1.748)
Only Event × Lab	0.793	12.640	19.102	5.815
	(1.719)	(11.478)	(31.588)	(7.861)
Only Event × Other group teaching	0.100	-0.079	8.951	1.148
	(1.000)	(4.729)	(9.194)	(2.703)
Back-to-Back Event	2.463***	5.359**	2.890	1.014
	(0.427)	(2.337)	(3.977)	(1.437)
Back-to-Back Event × Lab	-4.966***	-21.670**	-7.984	-6.438
	(1.240)	(10.229)	(17.957)	(6.424)
Back-to-Back Event × Other group teaching	-1.636**	-4.422	-4.009	-0.075
	(0.765)	(4.099)	(7.437)	(2.316)
Dependent variable means (std.dev)				
Lectures	70.74			
	(41.69)			
Labs	62.08			
	(48.24)			
Other group teaching	57.57			
	(48.15)			
Observations	289,325	14,982	2,365	14,982

Notes: Standard errors clustered by individual in parentheses. ***: p <0.01, **: p <0.05, *: p <0.1. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). In this specification event types are split between Lectures (omitted category), Labs, and all others.

Table 9: Heterogeneity by campus residence

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-0.992**	2.914**	-2.530	0.232
	(0.499)	(1.334)	(2.558)	(0.769)
Only Event × off-campus	0.868	-0.310	-9.778	-1.227
	(1.824)	(4.328)	(6.986)	(2.318)
Back-to-Back Event	1.108***	2.154*	1.034	0.727
	(0.409)	(1.108)	(1.531)	(0.710)
Back-to-Back Event × off-campus	3.297**	5.284*	-3.911	0.896
	(1.326)	(2.751)	(4.882)	(1.812)
Dependent variable means (std.dev)				
On-campus	65.0	65.0	11.43	60.11
	(45.1)	(24.8)	(10.19)	(14.4)
Off-campus	68.4	67.9	14.33	61.95
	(43.3)	(25.3)	(11.98)	(15.2)
p-value (t-test of difference)	0.000	0.000	0.000	0.000
Observations	289,325	14,982	2,365	14,982

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term).

Table 10: Heterogeneity by Conscientiousness

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-1.486**	1.160	-6.892**	0.675
	(0.653)	(1.693)	(2.823)	(0.944)
Only Event × conscientious	1.139	2.570	7.178**	-1.520
	(0.972)	(2.184)	(2.803)	(1.069)
Back-to-Back Event	0.857	1.565	-0.948	-0.008
	(0.577)	(1.387)	(1.722)	(0.699)
Back-to-Back Event × conscientious	0.392	0.309	3.556***	0.604
	(0.725)	(1.938)	(1.120)	(1.173)
Dependent variable means (std.dev)				
Not conscientious	64.8	67.7	10.33	59.7
	(45.3)	(24.9)	(10.13)	(14.2)
Conscientious	69.8	69.8	13.81	63.5
	(43.1)	(23.5)	(10.66)	(12.8)
p-value (t-test of difference)	0.000	0.000	0.000	0.000
Observations	231,544	11,950	2,282	11,950

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). "Conscientious" here is a dummy for above-median conscientiousness among BOOST2018 participants.

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A Appendix

Table A1: Heterogeneity by sex

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-0.650	4.639**	-6.439*	0.041
	(0.698)	(1.845)	(3.595)	(1.161)
Only Event × female	-0.477	-3.214	4.361	0.174
	(0.930)	(2.240)	(3.828)	(1.356)
Back-to-Back Event	1.473**	3.516**	-0.177	-0.093
	(0.576)	(1.512)	(2.119)	(1.004)
Back-to-Back Event × female	-0.038	-1.535	1.676	1.787
	(0.767)	(1.785)	(2.469)	(1.156)
Dependent variable means (std.dev)				
Male	62.3	62.3	10.36	59.1
	(45.8)	(25.8)	(10.20)	(15.5)
Female	68.4	68.2	12.80	61.4
	(44.1)	(23.6)	(10.50)	(13.3)
p-value (t-test of difference)	0.000	0.000	0.000	0.000
Observations	289,325	14,982	2,365	14,982

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term).

Table A2: Associations of attendance, study and marks with the Big 5 personality traits

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-1.834***	1.514	-4.037	-0.022
	(0.510)	(1.408)	(2.487)	(0.780)
Back-to-Back Event	1.510***	1.644	0.610	0.309
	(0.403)	(1.111)	(1.572)	(0.706)
Cumulative Hours	-0.324*	0.639	-1.173	-0.361
	(0.179)	(0.554)	(0.909)	(0.330)
Conscientiousness	4.363***	4.247***	2.131***	2.006***
	(0.592)	(0.612)	(0.272)	(0.343)
Neuroticism	1.140***	1.194***	0.140	0.296
	(0.368)	(0.384)	(0.205)	(0.223)
Extraversion	-1.786***	-1.707***	-0.241	-0.583**
	(0.375)	(0.404)	(0.206)	(0.240)
Agreeableness	0.575	0.550	-0.060	0.129
	(0.463)	(0.486)	(0.277)	(0.280)
Openness	-1.330***	-1.543***	-0.334	-0.247
	(0.488)	(0.503)	(0.322)	(0.293)
Bonferroni-adjusted p-values for significance of the Big 5				
Conscientiousness	0.000	0.000	0.000	0.000
Neuroticism	0.010	0.010	1.000	0.926
Extraversion	0.000	0.000	1.000	0.076
Agreeableness	1.000	1.000	1.000	1.000
Openness	0.033	0.011	1.000	1.000
Observations	231,189	11,934	2,281	11,934

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term).

Table A3: Heterogeneity by neuroticism

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-0.746	1.194	-3.684	0.146
	(0.666)	(1.752)	(2.789)	(0.933)
Only Event × neurotic	-0.426	1.600	-0.927	-0.070
	(0.943)	(2.114)	(2.664)	(1.093)
Back-to-Back Event	1.776***	2.165*	0.531	0.565
	(0.491)	(1.177)	(1.626)	(0.692)
Back-to-Back Event × neurotic	-2.324***	-2.279	0.110	-1.384
	(0.674)	(2.803)	(1.116)	(1.947)
Dependent variable means (std.dev)				
Not neurotic	64.8	64.9	11.60	60.7
	(45.0)	(24.8)	(11.07)	(14.0)
Neurotic	69.8	69.4	11.94	13.7
	(43.6)	(23.8)	(9.72)	(13.5)
p-value (t-test of difference)	0.000	0.000	0.442	0.000
Observations	231,544	11,950	2,282	1,1950

Notes: Standard errors clustered by individual in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). "Neurotic" here is a dummy for above-median neuroticism among BOOST2018 participants.

Table A4: Heterogeneity by extraversion

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-0.570	2.174	-4.286	-0.145
	(0.672)	(1.745)	(3.107)	(0.997)
Only Event × extraverted	-0.863	-0.502	0.437	0.555
	(0.935)	(2.102)	(2.828)	(1.153)
Back-to-Back Event	1.723***	2.129*	0.359	0.565
	(0.490)	(1.176)	(1.708)	(0.692)
Back-to-Back Event × extraverted	-2.300***	-2.322	0.511	-1.389
	(0.677)	(2.834)	(1.128)	(1.953)
Dependent variable means (std.dev)				
Not extraverted	68.0	67.8	11.68	61.6
	(44.2)	(24.7)	(10.90)	(14.0)
Extraverted	65.2	65.3	11.86	60.8
	(44.9)	(24.2)	(9.86)	(13.4)
p-value (t-test of difference)	0.000	0.000	0.674	0.002
Observations	231,544	11,950	2,282	11,950

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). "Extraversion" here is a dummy for above-median extraversion among BOOST2018 participants.

Table A5: Heterogeneity by agreeableness

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-2.039***	0.335	-5.059*	-0.000
	(0.658)	(1.723)	(2.844)	(0.930)
Only Event × agreeable	2.613***	3.980*	2.074	0.332
	(0.945)	(2.155)	(2.668)	(1.079)
Back-to-Back Event	1.744***	2.125*	0.160	0.554
	(0.491)	(1.176)	(1.674)	(0.692)
Back-to-Back Event × agreeable	-2.331***	-2.302	0.959	-1.394
	(0.677)	(2.834)	(1.119)	(1.952)
Dependent variable means (std.dev)				
Not agreeable	66.3	66.3	11.26	61.0
	(44.7)	(24.8)	(10.96)	(14.0)
Agreeable	67.5	67.4	12.40	61.6
	(44.2)	(24.0)	(9.81)	(13.4)
p-value (t-test of difference)	0.000	0.012	0.010	0.024
Observations	231,544	11,950	2,282	11,950

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). "Agreeable" here is a dummy for above-median agreeableness among BOOST2018 participants.

Table A6: Heterogeneity by openness to experience

	(1) Attendance, %, event-level	(2) Attendance, %, module-level	(3) Study hours per week, term-level	(4) Mark /100 module-level
Only Event	-1.602**	0.708	-5.391*	-0.295
	(0.656)	(1.713)	(2.811)	(0.916)
Only Event × open to experience	1.602	3.041	2.590	0.974
	(0.977)	(2.220)	(2.623)	(1.159)
Back-to-Back Event	1.733***	2.007*	1.014	0.537
	(0.491)	(1.167)	(1.725)	(0.693)
Back-to-Back Event × open to experience	-2.338***	-2.089	-0.992	-1.354
	(0.676)	(2.806)	(1.130)	(1.951)
Dependent variable means (std.dev)				
Not open to experience	67.0	66.8	11.51	61.2
	(44.4)	(24.5)	(11.02)	(14.0)
Open to experience	66.5	66.6	12.12	61.4
	(44.6)	(24.5)	(9.62)	(13.4)
p-value (t-test of difference)	0.011	0.578	0.178	0.344
Observations	231,368	11,942	2,282	11,942

Notes: Standard errors clustered by individual in parentheses. ***: $p<0.01$, **: $p<0.05$, *: $p<0.1$. All specifications weight each person equally, and within each person each event equally. Additional controls in all columns: *Cumulative Hours*, programme plus module (or term) fixed effects, dummy variables for individual characteristics shown in Table 1. Column 1 also includes event type dummy variables, event type share, and relative teaching group size. In Columns 2, 3 and 4, all timetable characteristics are the within-person mean across all their events on the module (or term). "Open to Experience" here is a dummy for above-median openness to experience among BOOST2018 participants.