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Are Students Time Constrained? Course Load, GPA, and Failing

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Are Students Time Constrained? Course Load, GPA, and Failing

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Abstract

Given the simultaneous rise in time-to-graduation and college GPA, it may be that students reduce their course load to improve their performance. Yet, evidence to date only shows increased course loads *increase* GPA. We provide a mathematical model showing many unobservable factors – beyond student ability – can generate a positive relationship between course load and GPA unless researchers control student schedules. West Point regularly implements the ideal experiment by randomly modifying student schedules with additional training courses. Using 19 years of administrative data, we provide the first causal evidence that taking more courses reduces GPA and increases course failure rates, sometimes substantially.

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1 Introduction

From the beginning, Gary Becker put time costs at the center of human capital decisions (Becker, 1964; Gary S. Becker, 1965). An additional year in college has substantial costs in tuition, living expenses, and foregone earnings. On the other hand, time in college provides human capital development and increased future earnings (Arteaga, 2018; Justicz-Simmons et al., 2022). What is less understood is how students may take lighter course loads – and potentially delay graduation – in order to obtain a higher grade point average (GPA) and create better opportunities after graduation (Jones and Jackson, 1990; Rumberger and Thomas, 1993; Røberg and Helland, 2017; Mueller and Essilfie, 2020). The result is a conflict for students between their observed performance and the time it takes to complete their degree. Indeed, time-to-degree continues to rise in the U.S. (Bound et al., 2012; Shapiro et al., 2016), as do average grades (Denning et al., 2022). Yet, while students clearly see a trade-off between course load and GPA (Cornwell et al., 2005), no direct evidence exists showing course load and performance are substitutes.

Researchers have confirmed that time spent studying improves college performance (Dolton et al., 2003; Stinebrickner and Stinebrickner, 2004, 2008; Pu et al., 2020), which would imply heavier course loads should decrease GPA if students have less time to dedicate to each course. However, studies to date have found higher course loads have a positive effect on GPA, even when controlling for student ability (Szafran, 2001; Jackson et al., 2003; Huntington-Klein and Gill, 2020). Given these results, it may be that course load and performance are complements (at least at standard course load levels): increased course load can crowd out non-academic commitments or generate positive externalities by requiring students to spend more time on campus (Attewell et al., 2012). Similarly, studies examining how work or competitive sports affect college GPA have been mixed, though the majority also find no – or very few – negative effects (Ehrenberg and Sherman, 1987; Darolia, 2014; Maloney and McCormick, 1993; Robst and Keil, 2000; Emerson et al., 2009). Given these results, perhaps students are in an inefficient equilibrium where they have chosen too light a course load given the costs of extending graduation by a year or more (Baum et al., 2011; Babcock and Marks, 2011).

Some policy makers have taken steps to push students towards higher course loads. The PROMISE program in West Virginia linked financial aid with adequate course completion, which increased on-time graduation (Scott-Clayton, 2011). More recently, the California State University system, the University of Hawaii, the University of South Dakota, and Oklahoma State University have also made increasing student course load a central part of their policy (Huntington-Klein and Gill, 2020). Many of these policies are motivated by research finding higher freshman course loads correlate with higher five-year graduation rates, among other outcomes (Attewell et al., 2012; Attewell and Monaghan, 2016). While we do not test the general equilibrium effects of increased course load over the full college experience, we do provide the first causal evidence on increased course load and college student performance.[1]

Disentangling how students respond to changes in their time commitments requires an experiment that is nearly everywhere infeasible given student control over how many and which classes they take. To illustrate the problem, we provide a mathematical model in which students face trade-offs between leisure time, timely graduation (which is dictated by course load), and higher GPA. A key takeaway is that course load and GPA are highly endogenous, potentially depending on unobservable and changing factors (Yue and Fu, 2017). We show how these unobservable factors generate a positive correlation between course load and GPA, even after controlling for individual ability and fixed effects. As a result, researchers seeking to measure the time constraints on college students would need both exogenous variation in student time commitments while also preventing students from altering their course schedule.

While such an experiment is usually infeasible, the United States Military Academy at

[1] One important caveat is that these policy recommendations focus on increasing what is considered a full-time course load from 12 credits to 15 credits, but all of the students in our sample have 15 or more credits.

West Point routinely replicates the ideal experiment. Students are randomly assigned zero, one, or two additional 1.5-credit courses *after* they've set their schedule for the school year. Given students are unable to modify their schedule, we can identify the causal effect of additional courses on student performance. We estimate that having two of these courses (roughly the equivalent of an additional 3-credit course) has the equivalent effect of reducing their semester GPA by 0.07-0.11 points, or about 10% of a standard deviation. This is the equivalent of reducing two of their other course grades by half a letter (e.g. from a B+ to a B). The effect is double for students who are already enrolled in six courses, signifying fairly steep increasing marginal costs to course load. We also look at how additional courses increase the probability a student fails a course. The average effect is fairly marginal: increasing the course load by three credits increases the probability of a course failure by roughly 0.5 percentage points on an average of 3.4%. However, when looking at the effects by current course load, students who already have a full course load (six classes) increase their likelihood of failing at least one class from 2.5% to 6.0%. Overall, students at a standard full load of five classes experience performance losses that we would consider moderate, but students who are already time constrained experience fairly severe performance losses.

All else equal, increased course loads have modest performance costs. Our setting does not allow us to comment strongly on the optimal policy regarding student course load. Our results do demonstrate students can be quite time constrained, especially if they are enrolled in six courses in a single semester, which is generally considered a maximum course load. In light of existing research, our results also underscore how college students are able to moderate their schedules and maintain their desired GPA in response to non-academic time demands, like work, at the expense of on-time graduation (Ehrenberg and Sherman, 1987; Darolia, 2014). As such, policies aimed at increasing average course load should also consider ways to reduce other demands on student time.

2 Literature Review

2.1 Literature Linking Course Load to GPA

One key input in the education production function is the time students dedicate to class and studying (Hanushek, 1979, 2020). Several studies show a clear link between student study time and collegiate performance (Dolton et al., 2003; Stinebrickner and Stinebrickner, 2004, 2008; Pu et al., 2020). What is less clear is how students substitute between study time and other non-academic activities in conjunction with their course load and desired GPA. Students appear to *believe* their is a link between their course load and GPA. The HOPE scholarship at the University of Georgia required students to maintain a GPA of 3.0 or higher. Researchers found this requirement reduced overall credit completions each year, which we would expect if students viewed higher course loads as a threat to maintaining the required GPA (Cornwell et al., 2005). But directly testing whether there is a causal link between course load and GPA is not usually feasible.

Researchers have relied on rich administrative data to control for individual student characteristics when measuring how course load might affect GPA. Szafran (2001) uses administrative data from a public state university to control for high school performance, SAT score, and course difficulty. He finds increasing course load by one class correlates with an increase of 0.076 in semester GPA. More recently, Huntington-Klein and Gill (2020) conduct a similar analysis but are able to also include individual fixed-effects. When controlling for observable characteristics only (without fixed-effects), the authors find that a full course load – 15 or more credits relative to students with only 12-14 – correlates with an increase in GPA of 0.069 points. However, when the fixed-effects are added, they find a statistically significant increase of only 0.008 points. To put this effect size in perspective, it is roughly the equivalent of a student taking 10 courses over the year and increasing one of her course grades by half a letter grade. Such a dramatic change in the estimated effect of course load illustrates the substantial self-selection into higher course loads.

Another strand of literature evaluates the idea of Academic Momentum: there could be an increase in student performance – on-time graduation in particular but possibly GPA as well – as students move from low course loads to more standard, 15-credit course loads (Adelman, 1999, 2006). Attewell et al. (2012) provides three theoretical reasons why this might be. First, higher intensity enrollment will enable students more frequent contact with professors and students. Second, faster credit accumulation can act as motivation as students improve their sense of efficacy. And finally, heavier course load may have positive externalities on their time use, crowding out other attachments. Martin et al. (2013) build on the theory by underscoring how early course completion provides better foundations for later learning given the cumulative nature of many course sequences. Empirically, most of this literature has focused on graduation rates rather than GPA and finds a positive relationship between heavier early course loads and re-enrollment the second year (Szafran, 2001) as well as six-year graduation rates (Attewell et al., 2012; Attewell and Monaghan, 2016). It is unclear, however, whether these studies have adequately dealt with the potential selection bias, even with propensity score matching.

2.2 The Effects of other Time Substitution in College

Researchers have also considered how other non-academic activities in college may affect student performance. Of particular interest to policy makers is whether working while in college substantively impairs students. Here – as with course load – researchers struggle to identify the causal effect because course load, work load, and course performance are all part of the student's decision. In fact, both Ehrenberg and Sherman (1987) and Darolia (2014) find working students did not have lower GPAs but did graduate later, which is consistent with students choosing to reduce their course load and maintain their GPA while slightly delaying graduation in order to work. Other research finds working decreases high school studying (Kalenkoski and Pabilonia, 2012) and college student study time (Babcock and

Marks, 2011), which could be a reduction in course load or a reduction in performance. Looking at high school student performance, Ruhm (1997) uses NLSY data and a large battery of observable characteristics to control for potential self-selection but finds work commitments have no detrimental effect on future earnings. Rothstein (2007) uses NLSY data but attempts to control for self-selection with the Heckman correction and instrumental variables based on local labor market conditions. She finds ten more hours of work reduce annual GPA by between 0.06-0.08 points. However, once the author uses student fixed-effects, the effect of additional work hours drops to nearly zero. Other research also finds employment has either no or very small negative effects on high school performance (Eckstein and Wolpin, 1999; Oettinger, 1999; Tyler, 2003).

On the other hand, Stinebrickner and Stinebrickner (2003) find that higher work loads cause lower GPA. Their setting is one in which *all* students are required to participate in work-study, but students can select into additional work hours for extra income, though this flexibility is limited depending on the job students were assigned to. Using job assignment as an instrumental variable, the authors find an additional hour of work per week reduces semester GPA by 0.162 points. Their result suggests a single additional hour of work per week reduces a student's grade in one class by a full letter. It is also possible that students who select into additional work hours differ systematically along dimensions that correlate with lower course performance. While the authors do not find low-ability students (measured by standardized test scores) self-select into additional work, our model illustrates that equilibrium GPA is affected by several other factors beyond ability alone, a hypothesis confirmed in more recent studies (Yue and Fu, 2017).

College students also may invest significant time in organized athletic activities, which could detract from study time and performance. While reduced studying may negatively impact academic performance, there is also research finding increased physical activity improves performance, particularly among previously sedentary students. Two recent studies conducted RCTs in which college students are incentivized to use school athletic and exercise facilities and participate in intramural sports (Fricke et al., 2018; Cappelen et al., 2017). Both studies find that the incentives increased physical activity and improved student performance, particularly for students who previously exercised little.[2]

However, highly competitive Division I athletics can induce time constraints that go well beyond the potential benefits of exercise, especially among a population already likely to exercise. The evidence, however, is mixed. Maloney and McCormick (1993) find athletes in revenue-generating sports do worse even after accounting for their preparation, and the effects are concentrated during the athletic season. Looking instead at the less competitive Division III athletes, Robst and Keil (2000) find competitive athletes perform as well as or better than non-athlete counterparts, and Emerson et al. (2009) find non-recruited Division III athletes perform as well or better than non-athletes even at highly selective colleges.

2.3 What Affects GPA

In all, the evidence on how time-consuming activities may reduce student performance is quite mixed and sometimes counter-intuitive. Here we describe various student characteristics that are known to affect GPA in an effort to understand the severity of self-selection when looking at how students substitute between study and leisure. As shown earlier, studies that include individual fixed effects show fairly dramatic changes in the estimated effect of work or course load on student performance (Rothstein, 2007; Huntington-Klein and Gill, 2020).

Elements that should be accounted for in fixed-effect specifications are those that are relatively time invariant. These include high school preparation measured through high school GPA and SAT scores. Academic ability generally accounts for substantial variation in college GPA, as we would expect (Cohn et al., 2004; Schmitt et al., 2009; Cyrenne and Chan, 2010; Danilowicz-Gösele et al., 2014; Caviglia-Harris and Maier, 2020). Characteristics measured

[2]Evidence among K-12 students is somewhat mixed. Some studies find high school athletics or physical education improve school performance or future earnings (Barron et al., 2000; Lipscomb, 2007; Lechner, 2009; Knaus et al., 2020), while others find no effect or negative effects (Ransom and Ransom, 2018; Guo et al., 2018; Packham and Street, 2019).

outside high school performance have also been shown to predict college performance. These traits include complex problem solving (Stadler et al., 2018), grit (Credé et al., 2017; Fosnacht et al., 2019), and other personality traits like conscientiousness, goals, and motivation (Schmitt et al., 2009; Heckman and Kautz, 2012; Richardson et al., 2012; Kautz et al., 2014; Caviglia-Harris and Maier, 2020; Sweet et al., 2019; Martínez et al., 2019).

There are several other time varying characteristics that significantly correlate with student performance such as choice of major and inclusion of a minor (Yue and Fu, 2017). Student peers and mentors can change major or career choice (Kofoed and McGovney, 2019), and peers themselves also influence performance (Berthelon et al., 2019; Pu et al., 2020). Health (Larson et al., 2016) and substance abuse (Wallis et al., 2019) can change over time and have known effects on student performance.

Major choice, peers, and external circumstances may affect a student's required course load or how she values higher GPA, on-time graduation, or leisure time, which are likely not captured in observable characteristics and may not be captured by individual fixed effects. In the next section, we illustrate how students will endogenously choose course load and study time to optimize across how they value higher GPA and on-time graduation. We find this framework helpful in understanding the diversity of results we've outlined here and in highlighting the need for evidence based on a natural experiment.

3 Theoretical Model of Student Time Allocation

We provide a basic theoretical framework of student time allocation between studying and leisure. The basic features we capture are to demonstrate student trade-offs between on-time graduation, GPA, and leisure. While we use a specific functional form, the results are robust and quite general with basic assumptions that we highlight.

The student's utility function depends on her GPA G, leisure L, and time-to-graduation T. We think of valuing time-to-graduation as incorporating the net present value of earnings from completing college earlier rather than later. Her GPA is affected by her ability $a \in [0, 1]$, her study time $s \in [0, 1]$, and her course load $c \in [0, 1]$.[3] We enforce the time constraint such that all non-study time is leisure time, which means $L = 1 - s$. We assume a simple GPA production function, $G(s, c; a) = 1 + as - c$, and her time-to-graduation is simply $T(c) = 1 - \kappa c$. κ captures the marginal contribution of course load c to the present discounted value of future earnings. Of course, given the non-linear nature of course requirements, this function could be quite complicated. However, to keep the model tractable, we've assumed time-to-graduation is locally linear, which is reasonable for choices made on the margin.

Her Cobb-Douglas utility is $U(G, L, T) = G^{\delta} L^{\gamma} (1 - T)^{\alpha}$ where $\delta \in [0, 1]$, $\gamma \in [0, 1]$ and $\alpha \in [0, 1]$. We can substitute and obtain the log-utility function:

$$\ln U(G(s, c; a), L(1 - s), T(c)) = \delta \ln(1 + as - c) + \gamma \ln(1 - s) + \alpha \ln(\kappa c)$$

The parameter δ captures the utility weight given to improving GPA. It is helpful also to think of δ reflecting the potential increases in future earnings from achieving higher grades in college. The term γ is the weight given to improving leisure, and α captures the potential utility gains from our student accelerating her graduation timeline by increasing her current course load.

The general assumptions required are first that there are diminishing marginal returns to studying, leisure, and course load. Less obvious is that this framework assumes the marginal value of studying grows with course load.[4]

[3] Because we will assume time is divided between "leisure" L and study time s, it must be the case that "study time" also includes class time. This choice is purposeful because students can opt to miss some classes. Course load c, then, captures commitments rather than classes attended. This also underscores the importance of ensuring the marginal benefit of s is increasing in c so that s necessarily increases with c in equilibrium. This assumption also simplifies the analysis without detracting from the results.

[4] This is apparent by looking at the partial derivative of utility with respect to study time:

$$\frac{\partial U}{\partial s} = \frac{\delta a}{1 + as - c} - \frac{\gamma}{1 - s}$$

which is always increasing in c (recall $c \in [0, 1]$).

3.1 Case 1: Choosing Study Time and Course Load

We first consider the usual case in which college students have control (at the margins) over their course load. The first-order conditions are

$$s = \frac{\delta a - \gamma}{\delta a + \gamma a} + \frac{\gamma}{\delta a + \gamma a} c$$

$$c = \frac{\alpha}{\delta + \alpha}(1 + as)$$

Substituting and simplifying yields the optimal choices of studying and course load:

$$s^* = \frac{a(\delta + \alpha) - \gamma}{\delta + \gamma + \alpha} \tag{1}$$

$$c^* = \frac{\alpha(1 + a)}{\delta + \gamma + \alpha} \tag{2}$$

We can then substitute these optimized choices back into the GPA function

$$G^*(a, s^*, c^*) = \frac{\delta(1 + a)}{\delta + \gamma + \alpha} \tag{3}$$

As expected, when we allow students to choose their course load and studying, their GPA is determined by their ability a, how much they value a better GPA δ, leisure time γ, and earlier graduation α.

Negative Correlation between Course Load and GPA: The model allows for a negative correlation between course load and GPA in a few ways. Decreasing the importance of GPA δ will increase course load while decreasing studying. This is evident from Equation 1, which has a derivative that is always positive in δ:

$$\frac{\partial s^*}{\partial \delta} = \frac{(a+1)\gamma}{a(\delta+\gamma+\alpha)^2} > 0$$

and from Equation 2, which has a derivative that is always negative in δ:

$$\frac{\partial c^*}{\partial \delta} = -\frac{\alpha(a+1)}{(\delta+\gamma+\alpha)^2} < 0$$

In other words, students who are less concerned with GPA but equally concerned with timely graduation will take more courses without increasing their studying.

It is also possible for students that value timely graduation (α) more to explain a negative relationship between course load and GPA. Increasing the importance of timely graduation clearly decreases equilibrium GPA (Equation 3) while increasing course load. To see this, the partial derivative of c^* with respect to the marginal value of additional courses α is

$$\frac{\partial c^*}{\partial \alpha} = \frac{(a+1)(\gamma+\delta)}{(\delta+\gamma+\alpha)^2} > 0$$

which is always positive.

This is a good place to note that policies aimed at increasing the normal semester course load among college students could be represented as an increase in α. The model, then, predicts that increasing the importance of timely graduation would increase course loads and studying, but the net effect would be a decrease in GPA.

Positive Correlation between Course Load and GPA: On the other hand, it is also possible to observe a positive relationship between course load and GPA. First – and probably most expected – is students with higher ability a will take more courses (Equation 2) and study more (Equation 1), earning a higher GPA.

While ability may be relatively observable, how students value leisure time – or what constitutes leisure time – is both difficult to observe and may change over time. It is important to remember that leisure time captures all non-study time, which could mean work, family obligations, clubs and sports, or health-related time commitments. These non-academic commitments can change in ways unobservable to a researcher that would also generate a positive correlation between course load and GPA. An increase in the value of leisure time γ will reduce equilibrium GPA (Equation 3) while also decreasing equilibrium course load (Equation 2). As a result, any changes to the value of non-academic commitments will generate co-movements between GPA and course load. In other words, a high-performing student may experience an increase in the value of her leisure time, causing her to reduce her study time and her course load. But her course load reduction will not completely compensate for her decreased study time, and on net her GPA will decrease.

3.2 Case 2: Choosing Study Time Only

What is of interest empirically is how well students can absorb forced increases in course load. To observe this, students must have exogenous changes to their course load *without being able to adjust their existing course load.* Exogenous changes to c will induce marginal changes in study time, but those changes must occur after a student has effectively locked in her semester course load.

Modifying the model illustrates why it would then become possible to understand how students substitute between study time and leisure. We modify the utility function by removing the Timely Graduation component and allow the student to only choose study time:

$$U(G(s;a,c),L(1-s)) = \delta \ln(1+as-c) + \gamma \ln(1-s)$$

Now the first-order condition and optimal choice of s is

$$s^* = \frac{a\delta - \gamma}{a(\delta+\gamma)} + \frac{\gamma}{a(\delta+\gamma)}c \tag{4}$$

First, increasing course load should also increase study time as $\frac{\gamma}{a(\delta+\gamma)} > 0$. Next, increasing the value of leisure γ always decreases study time. Consider the partial derivative:

$$\frac{\partial s^*}{\partial \gamma} = \frac{\delta a\,(c - (1+a))}{(\delta a + \gamma a)^2} < 0$$

Because $c \in [0,1]$, the term $c - (1+a)$ is always negative in the numerator.

We can also derive the resulting GPA when there are exogenous changes in student course load:

$$G^*(s^*; a, c) = \frac{\delta(1+a)}{\delta+\gamma} - c\left[1 - \frac{\gamma}{\delta+\gamma}\right] \tag{5}$$

The final term, $\left[1 - \frac{\gamma}{\delta+\gamma}\right]$ is always positive, which means unplanned increases in course load c will decrease GPA.

One final result is noteworthy. Students who already dedicate more time to studying either have a relatively low value for leisure – low γ – or value GPA more, high δ. While course load always decreases GPA in the model, we can look at the cross-partials to see potential heterogeneous effects relative to a student's current course load:

$$\frac{\partial^2 G^*}{\partial c\,\partial \gamma} = \frac{\delta}{(\delta+\gamma)^2} > 0$$

$$\frac{\partial^2 G^*}{\partial c\,\partial \delta} = -\frac{\gamma}{(\delta+\gamma)^2} < 0$$

The first equation means the value of leisure and the marginal effect of course load move in the same direction. Decreasing the value of leisure – lower γ – decreases (makes more negative) the effect of course load. The second equation means students who value higher GPA – higher δ – will also make the negative effect of increasing course load more negative. In other words, students who are already shouldering high course loads are more likely to experience losses in GPA as their course load is increased.

4 Setting and Empirical Approach

Students at West Point are required to take two additional training (AT) courses per year. These AT courses are designed to require as much time as a 1.5 credit course. They are mostly physical courses but also include coursework and extra practice time outside of the classroom. Some examples are nutrition, workout design, survival swimming, and military movement (See Appendix for a full list). AT courses occur during regular school hours as any other course would. They have 19 hour-long classes, which is exactly half of a regular three credit course. When combined with the additional out-of-class work and final evaluations, the courses require roughly half of the same time required of a three-credit course. Grades in AT courses have real consequences on what summer activities and career options are available to cadets, which is why cadets are often practicing outside of class.

Because they must complete two AT courses a year, students can be assigned zero, one, or two AT courses in a single semester. How their AT courses are distributed across the school year is random. Importantly, students arrange their course schedule before knowing which (and how many) AT courses they will be assigned in a semester, making the change in their schedule exogenous. Furthermore, rearranging their schedule is difficult, not normally allowed, and extremely rare.

The baseline specification we estimate is

$$G_{isy} = \theta + \beta_1 \mathrm{AT1}_{isy} + \beta_2 \mathrm{AT2}_{isy} + \phi_{\bar{y}} + \varepsilon_{isy} \tag{6}$$

where i represents an individual student, s represents the semester (fall or winter), and y represents the academic year. AT1 and AT2 are indicator variables for having one AT course (AT1) or two (AT2). We account for systematic differences in course difficulty with the four-year fixed-effect, $\phi_{\bar{y}}$.[5] In later specifications, we also control for gender, race, and ACT

[5]As Denning et al. (2022) show, there is well-documented grade inflation. The specification is robust to other controls, such as a linear time trend.

score. We can also include individual fixed-effects, ρ_i, given we have repeated observations of students, even within the same year. The outcome G_{isy} is a student's academic GPA earned in semester s where we've only counted the core classes required of all students. The coefficients of interest, β_1 and β_2, will be interpreted as the increase or decrease in the GPA if student i has any AT classes in semester s in year y.

The identification strategy relies on the assumption that the timing of AT classes is randomly assigned to students and is not impacted by anything students can control, including their academic and physical performance throughout their time at West Point and before West Point. The one exception is when a cadet is injured. If the injury and length of recovery make passing their AT course unreasonable, cadets will make up the course in a later semester. Even in this case, however, when the cadet makes up the course is not deterministic.

5 Data and Results

We use academic performance data for students from 2001 through 2019. We only look at students in their freshman, sophomore, and junior years because students pick their AT course in their senior year. We only include the cohorts for whom all three years are visible, which means the cohorts are those that started from 2001 through 2017. Each observation is a cadet $\times$ semester. We remove any observations in which a cadet has fewer than 15 credits since these are exceptional cases that require special permission and circumstances.[6] We only look at fall and spring semesters.

Table 1 provides basic summary statistics for the entire sample as well as broken out by treatment status. We have 106,814 Cadet $\times$ Semester observations representing 19,192 cadets. In the table, we have included the GPA for mandatory classes and for all academic courses (see the Appendix for a list of mandatory classes). Overall, semesters with increased

[6] Such cases occur only when a cadet is seriously injured or a Division I athlete. Classes missed in these cases are made up in the summer semesters, which we do not include.

AT courses do have slight decreases in both GPA measures. For mandatory classes, mandatory GPA falls from 2.908 to 2.843 and 2.772 for one and two AT courses. However, there is no apparent selection based on ACT score, age, number of classes or academic credits. Similarly, the distribution of USMA prep school students and prior-service cadets is constant across treatment groups. Rows three and four also preview our results regarding course failures: 2.8% of students fail at least one course when they have no AT course, but that increases to 3.5% for students with one AT course and 4.1% when they have two.

We can check more rigorously for potential selection on unobservable characteristics. In Table 2, we provide basic balance checks by regressing the observable characteristics such as race, USMA prep school, prior service, ACT score, and an indicator for the number of classes on each treatment. Because the number of AT classes in the spring is determined by the number of AT classes in the fall, the sample in Table 2 only includes the fall semester. None of the estimated coefficients is statistically significant at the 5% level, and the F-test for joint hypothesis testing is not significant.

We can preview our core results by looking at the relationship between course load and GPA. Starting with Figure 1, we observe the well-documented positive relationship where an increase of one credit correlates with an increase in GPA of 0.02 points. When we include the individual fixed-effects in Figure 2, we find a meaningful negative correlation where each additional credit reduces GPA by 0.02. This turns out to be roughly equivalent to our core results from using the natural experiment. While other studies find either zero or positive effects from increased course load – even after including individual fixed-effects (Huntington-Klein and Gill, 2020) – our setting allows us to mostly circumvent these self-selection issues with individual fixed-effects. Because students at West Point must graduate within four years, there is much less flexibility in which courses they take in which years. Students choose their major in the Spring of their first year, and they rarely switch. Students have a limited ability to redistribute their courses, change their major, or have heterogeneous changes in their non-academic time commitments. As a result, the fixed-effects should account for the unobservable characteristics driving the original, positive relationship in Figure 1.

Our core results are in Table 3. The outcome for each column is the GPA for mandatory classes. We start with the base regression as in Equation 6. In Column 2 we add controls for ACT score, gender, and race. In Column 3 we add indicator variables for each course credit. Lastly, in Column 4 we remove the demographic characteristics and add individual fixed-effects. Across all the specifications, the effect of an AT course is negative and statistically significant, ranging from -0.03 to -0.05 grade points per semester for a single AT course. The effect of two AT courses ranges from -0.06 to -0.11 grade points. For mandatory classes, a standard deviation in GPA is 0.68, which means adding two AT courses decreases GPA by 9 to 16% of a standard deviation. For a student with five courses, this is the equivalent of dropping two course grades from A to A- or one course by two "half" letters (e.g. A to B+).

Beyond average decreases in GPA, we can look at how additional courses affect student pass rates. Table 4 shows the results of the specification in Equation 6 but with the outcome variable changed to an indicator for having failed one or more courses in that semester. Because only 3% of students fail in a semester, we have foregone the specification with individual fixed-effects. A single AT course increase the probability of failing at least one course between 0.3 and 0.5 percentage points, which is a 10-15% increase. Two AT courses increases it by 0.5 to 1 percentage points (15-30%). While significant, these odds are small relative to the potential value of having completed an additional course.

The results in Table 3 suggest there may be heterogeneous effects based on the number of courses students are currently taking. Because 98% of students in our sample are taking either five or six courses per semester, we can break the sample by these two groups. Figure 3 shows average GPA by number of AT courses, broken out by the number of academic courses (five or six). Both groups have a decreased GPA as AT courses are added. The effects of additional courses are nearly double when students are already taking a full course load. These results are also shown in Table 5. For students with six courses, one additional AT course decreases GPA by 0.085 points and 0.186 points for two AT courses. This is roughly 25% of a standard deviation. For a student enrolled in six courses, this represents a drop from an A to an A- in four of her six courses. In other words, for a student taking a standard maximum course load of six classes (18-20 credits), an additional three-credit course substantially reduces her performance in other classes.

As with GPA, course failures appear to increase substantially more for students who already have a maximum course load. Figure 4 breaks out the average fraction of Cadet × Semester observations that have at least one course failure by course load. These results are quantified in Table 6. While adding two AT courses to students already enrolled in five courses has only moderate effects on course failures (increasing by about 0.5 percentage points or a 15% increase), the effects are dramatic for students with six courses: these students increase their probability of failing a course that semester by 3.4 percentage points, which is more than double their counterparts with no AT courses. Doubling the fraction of students with at least one course failure suggests students with six courses are already severely time constrained.

6 Conclusion

Our results demonstrate modest performance costs from increasing a 15- or 18-credit course load. Admittedly, students at West Point are unique. West Point cadets are selected in part based on their time management and discipline, which would suggest these results are positively biased. However, these selection criteria are not substantively different from selective universities in the nation. The 25th and 75th percentile of ACT scores at West Point are 25 and 31, which is comparable to North Carolina State University and Purdue University. On the other hand cadets also have significant time commitments outside of the classroom for military training and required extracurricular activities. This would suggest cadets may be more time constrained than other students, meaning our results are negatively biased. However, average GPA and GPA trends at West Point track similarly to those nationally

(Denning et al., 2022). In the end, students at West Point must still allocate their time and leisure as students elsewhere would. Certainly these results illustrate real limits on student time and the eventual costs of increasing student course loads.

Because of the inherent self-selection into courses, it has proven difficult for economists to fully measure the effects of additional time commitments on college performance. Students may elect higher course loads because they are high performers, because they value on-time graduation more, or because they value leisure less. This inherent self-selection is why a straight comparison between course load and GPA may have non-intuitive results, even after controlling for student ability. Other research looking to understand how work or athletic commitments may affect college performance suffer from similar self-selection concerns.

Our results are novel in that they are the first to use a true natural experiment on student time constraints. Not only are students at West Point randomly assigned to AT courses, they cannot adjust their course load in response to an additional time commitment. While the effects we observe are meaningful, it is difficult to comment on whether the additional course is "worth it" in the long run, especially given our setting. We can conclude, however, that course load and performance are substitutes, all else equal. Therefore, policy makers looking to increase average course loads should focus on ways to decrease other non-academic commitments.

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Tables

Table 1: Summary Statistics on Student Characteristics by Treatment

	Total	0 AT	1 AT	2 AT
GPA (Mandatory Classes Only)	2.848	2.908	2.843	2.772
	(0.679)	(0.680)	(0.675)	(0.679)
GPA (All Academic Courses)	2.974	3.016	2.975	2.902
	(0.644)	(0.662)	(0.632)	(0.644)
1+ Course Failure	0.0341	0.0279	0.0350	0.0409
	(0.181)	(0.165)	(0.184)	(0.198)
Number of Classes Failed	0.0420	0.0351	0.0424	0.0512
	(0.246)	(0.232)	(0.244)	(0.272)
ACT Score	27.95	27.95	28.00	27.79
	(3.482)	(3.503)	(3.472)	(3.472)
Age	20.79	20.81	20.79	20.76
	(1.329)	(1.337)	(1.326)	(1.323)
Number of Classes	5.296	5.375	5.280	5.222
	(0.487)	(0.533)	(0.475)	(0.430)
USMA Prep School	0.143	0.141	0.140	0.151
	(0.350)	(0.348)	(0.347)	(0.358)
Prior Service	0.160	0.158	0.159	0.165
	(0.367)	(0.365)	(0.366)	(0.371)
Cadet $\times$ Semester	106814	30373	56789	19652
Cadets	19192	17536	18748	16033

This table provides summary statistics for the complete sample and by treatment status. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet $\times$ Semester. Only freshmen, sophomores, and juniors are included in the sample because there is no clear treatment in the senior year. GPA is recorded for each semester, and a list of mandatory classes is provided in the Appendix.

Table 2: Balance Checks

	(1) 0 AT Courses	(2) 1 AT Course	(3) 2 AT Courses
Black	0.0186	-0.00191	-0.0167
	(0.0149)	(0.0160)	(0.0107)
Hispanic	-0.00211	0.000794	0.00132
	(0.0110)	(0.0104)	(0.00802)
White	-0.00191	-0.0154	0.0173^{+}
	(0.0110)	(0.0116)	(0.00908)
USMA Prep School	0.0204	-0.0208	0.000379
	(0.0177)	(0.0156)	(0.0106)
Prior Service	-0.0141	0.0186	-0.00456
	(0.0177)	(0.0157)	(0.0140)
ACT Score	-0.000403	0.00159	-0.00119
	(0.00177)	(0.00185)	(0.00135)
Number of Classes=6	0.0169	-0.0400	0.0231
	(0.0346)	(0.0274)	(0.0177)
Outcome Mean	0.268	0.546	0.186
Cadet × Semester	53717	53717	53717
Cadets	19152	19152	19152
F-Statistic	0.724	0.874	1.189
p-value	0.632	0.517	0.320

This table shows the results from three separate regressions testing whether observable characteristics correlate with or predict assignment to treatment. Because students must complete 2 AT courses a year, their assignment in the fall determines how many AT classes they will take in the spring, so the sample is limited to only observations from the fall semester. The F-statistic is a test of joint significance with the p-value reported below. Standard errors are clustered by Year × Grade, as are all the results. However, the results are robust to this clustering decision. None of the coefficients are statistically significant at the 5% level, and only one is significant at the 10% level.

$+$ $p < 0.1$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$

Table 3: Effect of an Additional Training Course on Student GPA

	(1) Mand. GPA	(2) Mand. GPA	(3) Mand. GPA	(4) Mand. GPA
1 AT Course	-0.0350*	-0.0492***	-0.0283*	-0.0270*
	(0.0150)	(0.0135)	(0.0118)	(0.0104)
2 AT Courses	-0.103***	-0.105***	-0.0614**	-0.0657***
	(0.0241)	(0.0232)	(0.0193)	(0.0181)
4-year Group	X	X	X	X
Characteristics		X	X	
Credit Indicators			X	X
Individual FE				X
Outcome Mean	2.848	2.848	2.848	2.848
Cadet × Semester	106814	106814	106814	106814
Cadets	19192	19192	19192	19192

This table shows how Additional Training courses affect student performance in their mandatory academic courses (see Appendix for a list of courses). The 4-year group indicators control for systematic changes in student GPAs, though the results are robust to other methods of controlling for trends. Student characteristics are ACT score, gender, and race. Credit Indicators are a set of indicator variables, one for each credit-hour. All standard errors are clustered at the Year × Grade level. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet × Semester. Only freshmen, sophomores, and juniors are included.
+ $p < 0.1$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$

Table 4: Effect of an Additional Training Course on Course Failure

	(1) Course Failure	(2) Course Failure	(3) Course Failure
1 AT Course	0.00421*	0.00532**	0.00320
	(0.00206)	(0.00190)	(0.00194)
2 AT Courses	0.00990***	0.00971***	0.00531*
	(0.00268)	(0.00267)	(0.00259)
4-year Group	X	X	X
Characteristics		X	X
Credit Indicators			X
Outcome Mean	0.0341	0.0341	0.0341
Cadet $\times$ Semester	106814	106814	106814
Cadets	19192	19192	19192

This table shows how Additional Training courses affect the probability a student fails at least one course in that same semester. The 4-year group indicators control for systematic changes in student failure rates, though the results are robust to other methods of controlling for trends. Student characteristics are ACT score, gender, and race. Credit Indicators are a set of indicator variables, one for each credit-hour. All standard errors are clustered at the Year $\times$ Grade level. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet $\times$ Semester. Only freshmen, sophomores, and juniors are included.

$+$ $p < 0.1$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$

Table 5: Effect of Additional Training Course on GPA by Current Course Load

	(1) Mand. GPA (5 Classes)	(2) Mand. GPA (6 Classes)
1 AT Course	-0.0413*	-0.0848**
	(0.0168)	(0.0275)
2 AT Courses	-0.0982***	-0.186***
	(0.0235)	(0.0465)
Outcome Mean	2.820	2.901
Cadet × Semester	76566	28794
Cadets	19163	14713

This table replicates Table 3 where the sample has been split by whether students have five or six classes. The results here quantify the results in Figure 3, which is why the 4-year indicators, controls, and fixed-effects have not been included for parsimony. The outcome is GPA in mandatory academic courses (see Appendix for a list of courses). All standard errors are clustered at the Year × Grade level. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet × Semester. Only freshmen, sophomores, and juniors are included.
$+$ $p < 0.1$, $*$ $p < 0.05$, $**$ $p < 0.01$, $***$ $p < 0.001$

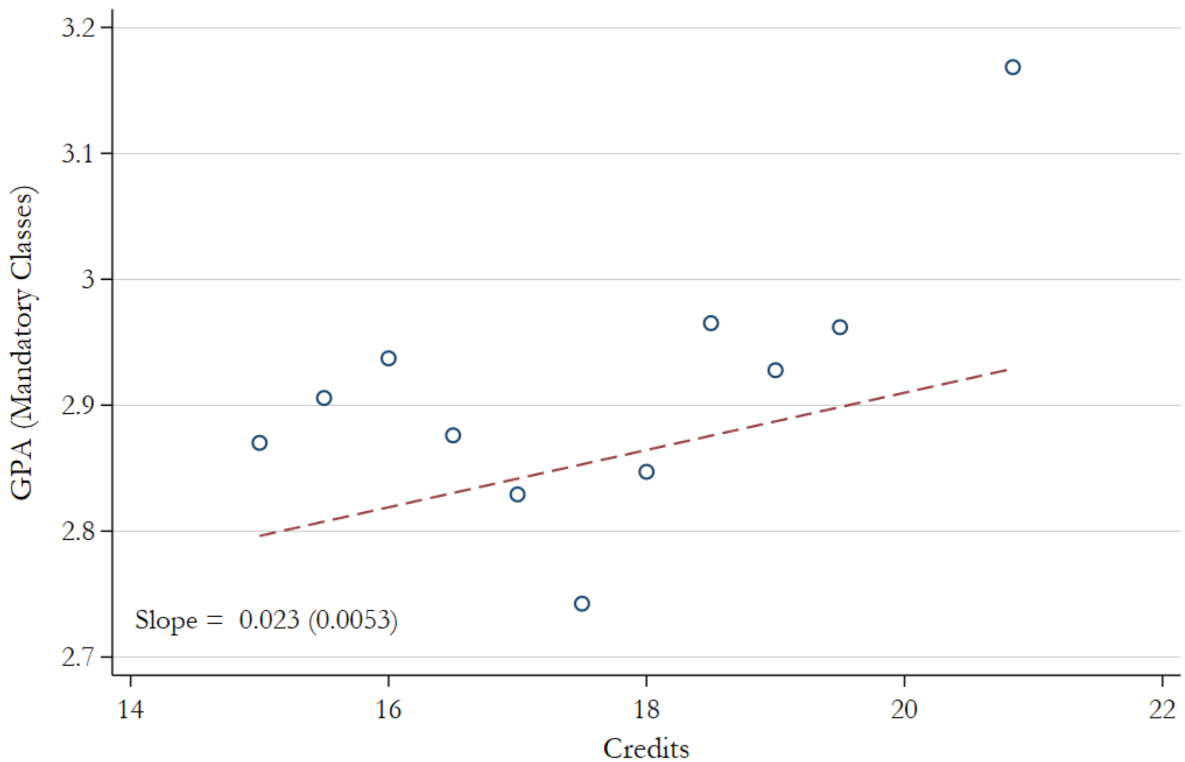
Table 6: Effect of Additional Training Course on Course Failure by Current Course Load

	(1) Course Failure (5 Classes)	(2) Course Failure (6 Classes)
1 AT Course	0.00439*	0.0128***
	(0.00205)	(0.00374)
2 AT Courses	0.00569*	0.0357***
	(0.00281)	(0.00845)
Outcome Mean	0.0338	0.0363
Cadet × Semester	76566	28794
Cadets	19163	14713

This table shows the results of a basic regression of number of AT courses on GPA where the sample has been split by whether students have five or six classes. The 4-year indicators, controls, and fixed-effects have not been included for parsimony and to maintain comparability with Figure 4. The outcome is the fraction of students with at least one course failure that semester. All standard errors are clustered at the Year × Grade level. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet × Semester. Only freshmen, sophomores, and juniors are included.
$+$ $p< 0.1$, $*$ $p< 0.05$, $**$ $p< 0.01$, $***$ $p< 0.001$

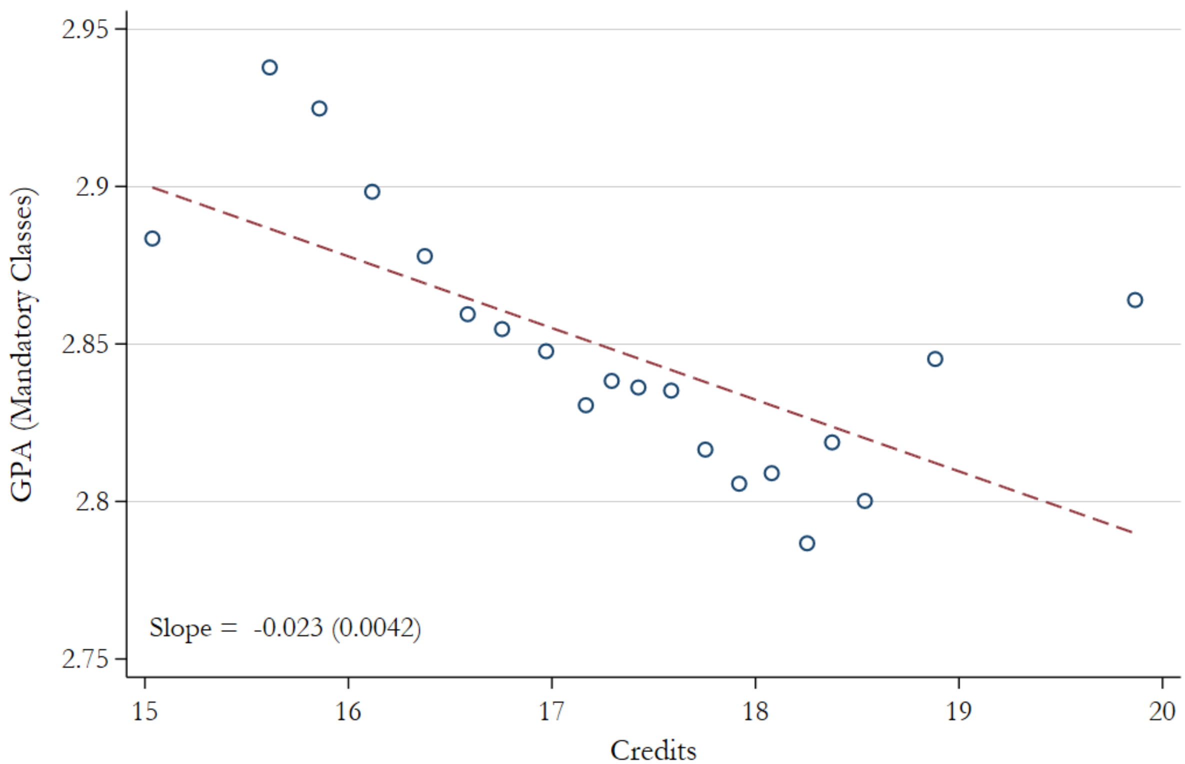
Figures

Figure 1: Correlation between Course Load and GPA



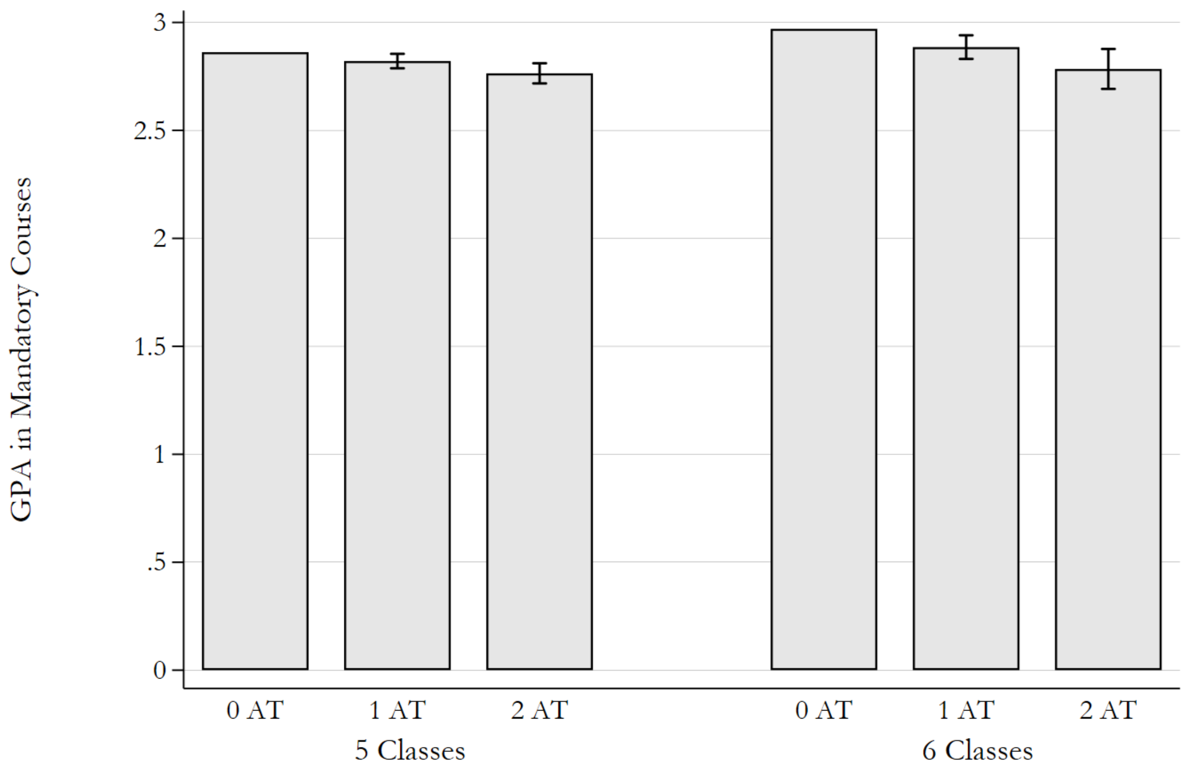
Note: This figure illustrates the basic correlation between student course load and their GPA in mandatory classes (see Appendix for a list of classes). Observations are binned based on their number of credits and points indicate the average GPA for that bin. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet $\times$ Semester. Only freshmen, sophomores, and juniors are included. This figure uses the Stata procedure `binscatter` (Stepner, 2013).

Figure 2: Correlation between Course Load and GPA with Student Fixed-Effects



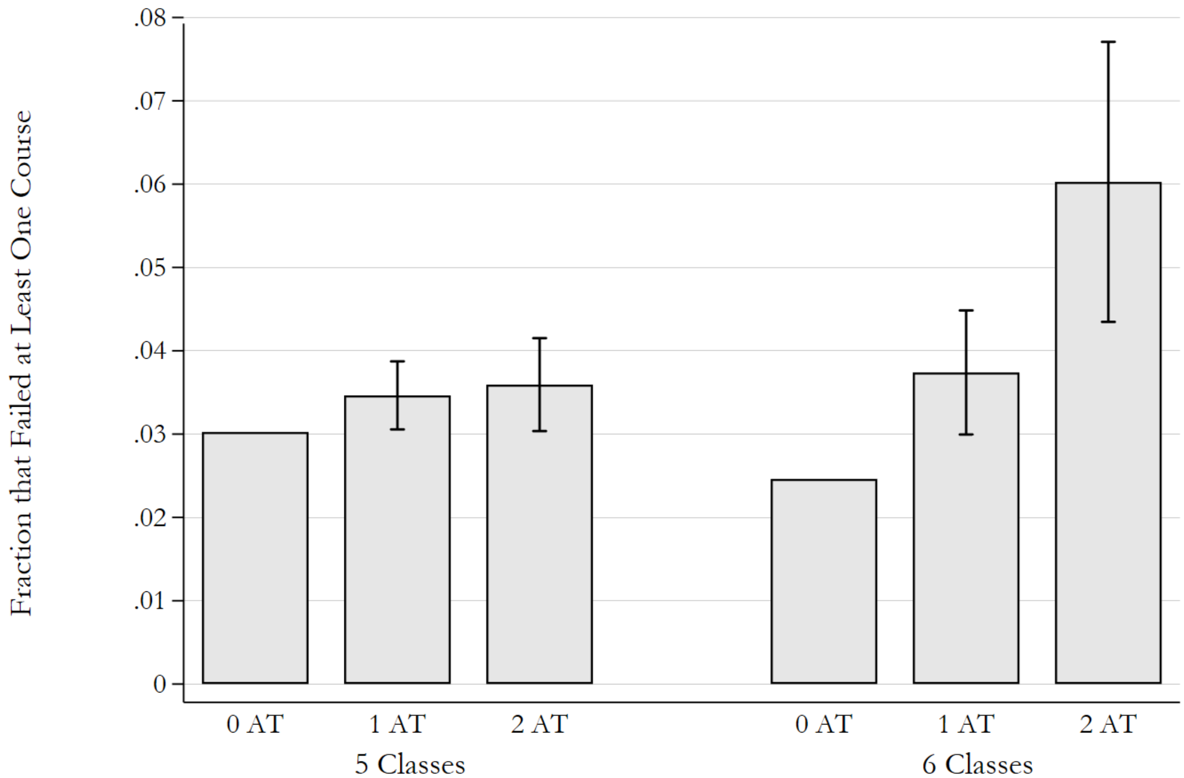
Note: This figure illustrates the correlation between student course load and their GPA after controlling for individual fixed-effects. GPA is for mandatory classes (see Appendix for a list of classes). GPA is residualized after adjusting for individual fixed-effects, and then binned based on their number of credits. The points points indicate the average (residualized) GPA for that bin. The sample contains students with 15 or more credit-hours of academic courses who appear in at least two semesters. Each observation is a Cadet $\times$ Semester. Only freshmen, sophomores, and juniors are included. This figure uses the Stata procedure `binscatter` (Stepner, 2013).

Figure 3: Average GPA by Number of Courses and Number of AT Classes



Note: This figure illustrates average student GPA in mandatory classes by the number of Additional Training courses. The sample is split between Cadet × Semester observations in which the student takes five or six classes. The results are quantified in Table 5. 95% confidence intervals are shown using standard errors clustered at the Year × Grade level.

Figure 4: Rate of Students Failing a Course by Number of Courses and AT Classes



Note: This figure illustrates the average fraction of students who fail at least one course in a semester. The bars are broken out by the number of Additional Training courses. The sample is split between Cadet × Semester observations in which the student takes five or six classes. The results are quantified in Table 6. 95% confidence intervals are shown using standard errors clustered at the Year × Grade level.

Appendix: List of Additional Training Courses

Course Name
Boxing
Military Movement
Fundamentals of Aquatics
Survival Swimming - Elementary
Survival Swimming - Low
Survival Swimming - High
Survival Swimming - Advanced
Fundamentals of Combatives
Close Quarters Combat
Combat Applications
Fundamentals of Personal Fitness
Wellness - Master Fitness Training Program
Strength Development
Personal Fitness - Master Fitness Training Program
Unit Fitness - Master Fitness Training
Army Fitness Development
Fitness Leader I
Fitness Leader II

Appendix: List of Mandatory Academic Courses

Course ID	Course Name
CH101	General Chemistry I
CH102	General Chemistry II
CH275	Biology
CY305	Cyber Foundations
EN100	Foundational Writing
EN101	Composition
EN102	Literature
EN302	Advanced Composition
EV203	Physical Geography
HI108	Regional Studies in World History
HI158	Advanced Regional Studies in World History
HI103/HI104/HI105	History of the United States
HI107	History of the World & Western Civilization
HI302	History of the Military Art 1900-Present
IT105	Computing Fundamentals
IT155	Advanced Intro to Computer and Information Technology
LW403	Constitutional/Military Law
MA103	Math Modeling / Intro to Calculus
MA104	Calculus I
MA153	Math Modeling / Intro to Differential Equations
MA206	Probability & Statistics
MA255	Advanced Multivariable Calculus
MX400	Officership
PH201/PH203/PH205	Physics I
PH202/PH204/PH206	Physics II
PH251/PH253/PH255	Advanced Physics I
PH252/PH254/PH256	Advanced Physics II
PL100	General Psychology for Leaders
PL150	Advanced General Psychology for Leaders
PL300	Military Leadership
PL350	Advanced Military Leadership
PY201	Philosophy & Ethical Reasoning
SS201	Economics – Principles/Problems
SS202	American Politics
SS307	International Relations
SS357	Advanced International Relations