Research Article

Who Fills the Seats? Offering Extra Credit and Instructor Perceptions of Who Will Attend

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JEL Codes: A20, D01, Q81, I21
Keywords: Decision-making, extra credit, perceptions, student effort model

Abstract
Past research on the effectiveness and fairness of offering extra credit opportunities to students has been mixed. This paper contributes to this ongoing literature in two ways. First, we develop a student effort model that investigates how student utility, study time, productivity, and knowledge change when faculty offer extra credit opportunities. Second, we employ a survey of 251 college instructors from across the United States to examine instructor perceptions of which students attend extra credit events and at what point in the semester students are more likely to attend.

1 Introduction

Many economics instructors use a variety of strategies to enhance their courses, such as inviting distinguished economics speakers to campus. To encourage participation, these instructors sometimes offer extra credit to encourage students to attend these opportunities. The present paper examines instructor perceptions about which students will take advantage of extra credit or similar opportunities. A student effort model is used to investigate how a student's study time, knowledge, and leisure change when extra credit events are offered. The model suggests a positive correlation between knowledge, grade, and the incremental utility from an extra credit opportunity.

A panel of 251 college instructors from across the United States completed a Qualtrics survey to investigate instructor perceptions, including which students will attend extra credit events and when during the semester they will be more likely to attend. We use the results of this survey to investigate the educational factors that influence instructor beliefs about student behavior regarding extra credit activities. These empirical results align with our effort model, suggesting that differences in student behavior are based on student motivations.

This paper proceeds with a literature review, presents a simple model of student effort, examines instructor perceptions of students who will likely attend extra credit events, and ends with instructor perceptions of when during the semester students are more likely to attend such events. This analysis could apply equally well to extra credit opportunities besides speakers, and we briefly look at an additional extra credit example, but for purposes of efficient exposition we stick with the speaker example through most of the paper.

2 Literature Review

The pedagogical practice of offering extra credit in higher education appears to be a somewhat controversial and an unsettled issue in the academic literature. Several authors across academic disciplines have found theoretical and empirical justification for both dismissing and supporting the practice of offering extra credit. For example, Faud and Jones (2012) found that extra credit in upper-level computer science courses motivated student effort, improved grades and learning, and potentially lowered mental pressures. This positive viewpoint suggests that extra credit can motivate students to work harder, can allow students to explore course topics in greater detail, and can be used if the student has a serious illness or problem. Felker and Chen (2020) examined extra credit to encourage the effort and work distribution by students to reduce procrastination and found that it was effective. On the other hand, Norcross, Horrocks, and Stevenson (1989) and Weimer (2011) discussed several factors as to why professors do not provide extra credit opportunities to their students including the belief that it discourages responsible student attitudes, the unfairness associated of offering it to select students (e.g., those students with poor performance), and the impracticality of giving additional work to those students who have trouble with basic course material. Wilson (2002) suggested extra credit promotes moral hazard stating, "The existence, or the hope of extra credit may induce students to prepare less carefully for exams and papers with the expectation that additional points can be earned on future assignments" (p. 97).

It is not surprising that without academic consensus on exactly how the use of extra credit assignments (ECAs) and different ECA types translate into student knowledge, participation, and utility, many instructors find themselves spending a great deal of time on constructing exercises that have uncertain outcomes (Hill, Palladino, and Eison 1993). Haber and Sarkar (2017) suggest that instructors "spend significant amount of time designing, administering, and grading ECAs without sufficient and precise knowledge of how this effort justifies the learning outcome or if it does so at all. Faculty today predominately rely on their intuitive knowledge and scant scientific evidence for designing and administering ECAs for their courses" (p. 291). Key characteristics for instructors employing extra credit include the desire to see students succeed and improve their work ethic. The present paper might be thought of as a contribution to this literature as flexibility in grading via extra credit allows more degrees of freedom for students trying to turn effort into a grade.

Extra credit offers one type of flexibility in grading. Other forms include allowing retakes of exams or rewriting of papers. Michaelis and Schwanebeck (2016) developed an expected utility model that allows variation in testing arrangements and rules. While the authors failed to conclude that offering retakes improve utility, they do find that student effort can be affected by second exam policies. Paredes (2017) examined the effect of relative and absolute grading systems on student effort. The author applied a model where students maximized their utility by choosing effort. Brustin and Chavkin (1997) ran an experiment on grading systems and law school student effort. The authors found evidence that student participation and preparedness increased for a majority of students in clinical courses when grades were assigned to those classes. In a limited sample, Mays and Bower (2005) provided extra credit opportunities to 40 engineering students over the course of a semester. Interesting findings included the fact that more ECAs were attempted after midterm grades were posted (e.g., second half of the semester), and students thought the extra credit was fair and helped their final grades. In addition, other activities that students were involved in such as work and leisure deterred from their participation in the ECAs. Dalakas and Stewart (2020) determined that instructors should frame extra credit opportunities as a loss of an opportunity as opposed to gaining one in order to motivate students in participating in the extra credit opportunity.

As far as we are aware, the treatment of how uncertainty affects student effort on extra credit events is unique to the present paper, but our model below otherwise has similarities to that of Allgood, Walstad, and Siegfried (2015) and Lewer, Corbett, Marcum, and Highfill (2021). These studies found that standard student effort models of expected utility are often based on knowledge, grades, and leisure, but relatively few studies allowed for uncertainty. Oettinger (2002) has a model of student effort where the relationship between study effort and course grade was subject to a random shock. He found empirical evidence that students cluster around the bottom boundaries of letter grades and that students near bottom grade boundaries had stronger performances on final exam scores. Foltz, Clements, Fallon, and Stinson (2021) surveyed undergraduate students and found that most students are motivated to attend academic related speaker events based on receiving extra credit. Finally, Gneezy et al. (2019) used an experimental approach to test international differences in student effort in response to certain incentive programs. They found that U.S. students improved their scores on standardized tests in response to incentives, while Chinese students did not.

3 Student Effort Model

Suppose student effort is not subject to diminishing returns and produces knowledge K, an abstract or latent measure of the level of learning that indirectly translates to grades:

$$K = \alpha X + \beta S + \gamma XS \tag{1}$$

where $\alpha > 0$, $\beta > 0$, and $\gamma \geq 0$ with $\alpha > \beta$ when $\gamma = 0$. Regular study effort S produces knowledge at a rate measured by β; X, the time spent on extra credit, produces knowledge at a rate of α. There may also be an interaction term so that time spent on extra credit activities actually makes regular study time more productive, at a rate measured by γ. The student can choose to not participate in the extra credit activity in which case $X = 0$; if they choose to participate, the value of X is set by the instructor and the student takes it as a parameter. In this model, we assume the instructor creates specific extra credit opportunities that take a certain amount of time, such as attending events, and students have the discrete choice whether to complete the opportunity or not. Note that students will only spend time on extra credit if it is more productive than regular studying, thus the assumption that $\alpha > \beta$; otherwise, they would just stay home and study instead of attending the event.

Study effort produces knowledge with certainty, but there is uncertainty about how knowledge is reflected in the total points earned in the course, λ. To keep things as simple as possible, the instructor decides between the "default" grade and a "higher" grade based on the point total at the end of the semester. Suppose that a given knowledge level K can result in a range of possible point totals, with the number of points being uniformly distributed on the exogenous range $2R$ centered on K, that is on the range $(K - R, K + R)$ with a pdf of ½R. The "probability of the higher grade" is:

$$PHG = \Pr(K \geq C) = \int_C^{K+R} \frac{1}{2R}\, d\lambda = \frac{K + R - C}{2R} = \frac{1}{2R}(\alpha X + \beta S + \gamma XS + R - C) \tag{2}$$

where C is the grade cutoff. For a very simple example, suppose study effort S is 100 and $\beta = 1.2$ (and no extra credit), so that knowledge K is 120. If $R = 30$ and the cutoff for the higher grade is $C = 145$, then $PHG = \frac{120+30-145}{60} = .0833$ so there is an 8.33 percent probability of the student getting the higher grade.

The student has a time endowment N and time not spent on studying is "leisure" (L), so that:

$$L = N - X - S\,. \tag{3}$$

Assume $\beta N - C \geq 0$, that is, a student who spends all their time endowment studying will at least achieve the cutoff for the higher grade.

The student chooses S to maximize utility, which is a function of the probability of the higher grade, knowledge, and leisure:

$$U = g\log(1 + PHG) + h\log(K) + j\log(L) \tag{4}$$

subject to equations (1)–(3), and noticing that one is added to the probability because a log utility function is assumed. Without loss of generality, assume $g \geq 1$, $h \geq 1$, and $j \geq 1$.

Conceptually, the student chooses study effort, S, but it will be algebraically convenient to change variables and rewrite the optimization problem in terms of knowledge K. From equation (2):

$$1 + PHG = \frac{2R + K + R - C}{2R} = \frac{K - Z}{2R}, \tag{5}$$

where the composite parameter $Z = C - 3R$ for algebraic convenience, captures the grading parameters. From equation (1):

$$S = \frac{(K - \alpha X)}{(\beta + \gamma X)}. \tag{6}$$

Plugging equation (6) into equation (3):

$$L = \frac{(\beta + \gamma X)(N - X) + \alpha X - K}{(\beta + \gamma X)} = \frac{M(X) - K}{(\beta + \gamma X)} \tag{7}$$

where

$$M(X) = (\beta + \gamma X)(N - X) + \alpha X = \beta N + (\alpha - \beta)X + \gamma XN - \gamma X^2. \tag{8}$$

Looking at the right-hand side of the composite parameter $M(X)$, the first term of the right-hand side is the knowledge output if the entire time endowment were spent on regular study; the next term captures the positive increment for time spent on extra credit. The final two terms capture the interaction effect, which will be discussed later, but notice that X has both a positive effect and negative effect on $M(X)$ when $\gamma > 0$. Intuitively, $M(X)$ represents total knowledge available to the student from their time endowment if they do nothing but study.

The first order condition (assuming an interior solution) of equation (4) with respect to knowledge is thus:

$$\frac{g}{K - Z} + \frac{h}{K} - \frac{j}{M(X) - K} = 0. \tag{9}$$

The full model will be examined shortly, but a couple of special cases may aid intuition. Suppose a student is motivated by the probability of a higher grade rather than by knowledge. That is, suppose $h = 0$ in equations (4) and (9). The optimal knowledge is:

$$K = \frac{jZ + gM(X)}{g + j} = \frac{j(C - 3R) + g(\beta N + (\alpha - \beta)X + \gamma XN - \gamma X^2)}{g + j} \tag{10}$$

and the optimal study time is:

$$S = \frac{jZ + gM(X) - \alpha(g + j)X}{(g + j)(\beta + \gamma X)} = \frac{j(C - 3R) + g(\beta N + (\alpha - \beta)X + \gamma XN - \gamma X^2) - \alpha(g + j)X}{(g + j)(\beta + \gamma X)}.$$

For a second special case, suppose a student is motivated by knowledge rather than grades. That is, suppose $g = 0$ in equations (4) and (9). Knowledge is:

$$K = \frac{h\,M(X)}{h + j} = \frac{h\,(\beta N + (\alpha - \beta)X + \gamma XN - \gamma X^2)}{h + j} \tag{11}$$

and study effort is:

$$S = \frac{hM(X) - \alpha(h+j)X}{(h+j)(h(\beta+\gamma X)} = \frac{h(\beta N + (\alpha-\beta)X + \gamma XN - \gamma X^2) - \alpha(h+j)X}{(h+j)(h(\beta+\gamma X)}.$$

The first special case for a grade-motivated student illuminates the instructor choices with regard to the grading variables. Notice first from equation (10) that an increase in the grade cutoff increases knowledge. From equation (2), holding knowledge constant, an increase in the grade cutoff reduces the probability of the higher grade, and the question arises of whether a student will study less if you raise the grade cutoff for an A from, say, 89 to 90. These results suggest that in fact a grade-motivated student will respond by studying more. There is an argument here that instructors should think quite hard about grade cutoffs, and perhaps raise them, while keeping in mind their specific situation, and the mores and standard practices of their department and institution.

The grading parameter R, which measures the range of grades a given level of effort might result in, is perhaps less in the control of the instructor. But they might be able to influence it, including for example by changing their system for assigning partial credit, or how they treat missed questions. From equation (2), with study effort held constant, a reduction in R increases the probability of a higher grade when $K > C$ and decreases it when $K < C$, and therefore from equation (10), reducing R increases the student's optimal study effort and knowledge.

Comparing the two special cases, notice that if the weights in the utility functions are all equal to one, knowledge for the grade-motivated student is greater than for the knowledge-motivated student (subtract equation (11) from equation (10)). More plausibly, if the weights differ between the two special cases, comparing knowledge depends on those weights.

Turning to the full model now, the first order condition (9), after multiplying by denominators and rearranging, is equivalent to the quadratic equation:

$$(g+h+j)K^2 - \big((j+h)Z + (g+h)M(X)\big)K + hZM(X) = 0$$

and therefore, using the quadratic formula:

$$K = \frac{(j+h)Z + (g+h)M(X) + \sqrt{T}}{2(g+h+j)}, \tag{12}$$

where the constant T (for algebraic convenience) is:

$$T = \big((j+h)Z + (g+h)M(X)\big)^2 - 4(g+h+j)hZM \tag{13}$$

and noting that the larger root is required for an interior solution.

Our goal is to look at the comparative statics with respect to X, the extra credit variable. To that end it will be algebraically convenient to first find the effect of a change in $M(X)$ on knowledge. Although the calculations will be omitted for brevity, it can be shown that

$$\frac{d\sqrt{T}}{dM(X)} = \frac{(g+h)\sqrt{T - 4ghj\,(g+h+j)Z^2}}{\sqrt{T}} > 0 \tag{14}$$

which implies $\frac{dK}{dM(X)} > 0$ from equations (12) to (14). Notice that from condition (5), the probability of a higher grade is a linear function of knowledge, so this implies that $\frac{dPHG}{dM(X)} > 0$ as well.

The optimal leisure is found by substituting equation (12) into equation (7). To investigate how $M(X)$ affects leisure it will be convenient to first look at $(\beta + \gamma X)L$, which we will call the knowledge cost of leisure, denoted by KCL. That is, it is the amount of knowledge that the time spent on leisure could have created. Looking at equation (7) again, $K + KCL = M(X)$ (that is, actual knowledge plus knowledge cost of leisure equals total available knowledge). We use equation (7) and equation (12) to write:

$$KCL = (\beta + \gamma X)L = \frac{(g+h+2j)M(X) - (g+h)Z - \sqrt{T}}{2(g+h+j)} \ . \tag{15}$$

As above, the ultimate goal is to do comparative statics with respect to X, the extra credit parameter, but the strategy is again to first look at the comparative statics of $M(X)$. Differentiating equation (15), we find:

$$\frac{dKCL}{dM(X)} = \frac{(g+h+2j) - \frac{d\sqrt{T}}{dM}}{2(g+h+j)}. \tag{16}$$

To prove that $\frac{dKCL}{dM(X)} > 0$ in equation (16), we assume that the numerator is positive, and show that that assumption leads to a necessarily true inequality. That assumption is the equivalent of:

$$(g+h+2j) > \frac{d\sqrt{T}}{dM}.$$

We then substitute equation (14) into the numerator of equation (16):

$$(g+h+2j) > \frac{(g+h)\sqrt{T - 4ghj\,(g+h+j)Z^2}}{\sqrt{T}}.$$

Squaring both sides:

$$(g+h+2j)^2 > \frac{(g+h)^2(\,T - 4ghj\,(g+h+j)Z^2)}{T}.$$

Solving for T:

$$\left(\frac{(g+h+2j)^2}{(g+h)^2} - 1\right)T > -4ghj\,(g+h+j)Z^2.$$

This inequality is necessarily true because the left-hand side is positive while the right-hand side is negative. And because all of our previous steps were reversible, it necessarily implies that our original assumption of $\frac{dKCL}{dM(X)} > 0$ is true.

The arguments of the student utility are now characterized in terms of Z, the parameter capturing the grading parameters, and $M(X)$, the parameter derived from the time constraint. We can now explore the effects of the instructor's choices about the type and scale of the extra credit opportunity on student knowledge, leisure, and utility. We will focus on the differences between students in the next section. Formally, this will be done by looking at:

$$\frac{dK}{dX} = \frac{dK}{dM(X)}\frac{dM(X)}{dX} \quad \text{and} \quad \frac{dKCL}{dX} = \frac{dKCL}{dM(X)}\frac{dM(X)}{dX}$$

and the implications of these relationships. It has been shown that both $\frac{dK}{dM(X)} > 0$ and $\frac{dKCL}{dM(X)} > 0$. Therefore, the sign of $\frac{dK}{dX}$ and $\frac{dKCL}{dX}$ depends on the sign of $\frac{dM(X)}{dX}$. From equation (8):

$$\frac{dM(X)}{dX} = (\alpha - \beta) + \gamma N - 2\gamma X \ . \tag{17}$$

The implications for the instructor's choice of the size of X depend on the interaction effect in the knowledge production function (1). Suppose first that $\gamma = 0$. In this case $\frac{dM(X)}{dX} > 0$ and so a larger X always increases knowledge and the probability of a higher grade. Noting that $L = \frac{KCL}{\beta}$ in this case, $\frac{dM(X)}{dX} > 0$ also implies $\frac{dKCL}{dX} > 0$ and $\frac{dL}{dX} > 0$. The increases in knowledge, the probability of a higher grade, and leisure ensure that utility is increasing. Total study time, the sum of $S + X$, is decreasing because leisure is increasing. When it comes to extra credit, from the student's point of view, the more the better. Table 1 gives a numerical example.

Table 1. Example Outcomes when $\gamma = 0$

X	K	PHG	L	S	$S + X$	U
0	150	0.21	52.75	147.25	147.25	9.17
100	170	0.5	63.24	36.76	136.76	9.69

C = 170, R = 34.5795, N = 200, α =1.3256, β = 1.0187, $g = h = j = 1$, and $\gamma = 0$

The considerations for the instructor's choice of X when $\gamma > 0$ are more complicated but still essentially driven by $M(X)$. From equation (17), this function is maximized when the value of the extra credit variable is:

$$X_{KMax} = \frac{(\alpha - \beta) - \gamma N}{2\gamma} \ . \tag{18}$$

The notation reflects the observation that maximizing $M(X)$ is equivalent to maximizing knowledge, and thus the probability of a higher grade (i.e., $\frac{dK}{dX} = 0$ if and only if $\frac{dM(X)}{dX} = 0$). Below this value, increasing X increases knowledge, the probability of a higher grade, and the knowledge cost of leisure. Whether this change increases leisure (or utility) depends on the relative size of the parameters in $M(X)$. But in the neighborhood of X_{Kmax}, the effect on leisure can be signed; it is negative. To see this, recall $\frac{dM(X)}{dX} = 0$ implies $\frac{dKCL}{dM} = 0$ so that from the definition of KCL

$$\frac{dL}{dX} = -\frac{\gamma L}{(\beta + \gamma X)} < 0 \,.$$

This implies that for values of X that are close to the one that maximizes knowledge X_{Kmax}, an increase in extra credit decreases leisure. The extra credit level that maximizes knowledge most definitely does not maximize student utility, and since leisure is falling in that neighborhood, the level of extra credit that maximizes utility is less than the one that maximizes knowledge.

In some cases, the type and scale of an extra credit project are not completely within the control of the instructor. Some projects are "chunky" and may require a time commitment above X_{Kmax}. The question might be whether the knowledge a student gets from the project is greater than that of no extra credit at all (i.e., $X = 0$) even though it is less than the maximum knowledge attainable. Looking at the definition of $M(X)$ in equation (8) again

$$X_{K0} = \frac{(\alpha - \beta) - \gamma N}{\gamma} \,. \tag{19}$$

The notation here reflects the fact that when X reaches X_{K0}, knowledge has declined back to the level of no extra credit whatsoever. Notice $X_{K0} = 2X_{Kmax}$. An example is given in Table 2.

Table 2. Example Outcomes when $\gamma > 0$

X	K	PHG	L	S	$S + X$	U
0	150	0.21	52.75	147.25	147.25	9.17
56	169.23	0.49	49.29	94.71	150.71	9.43
X_{Kmax} = 80.68	171.22	0.52	45.76	73.56	154.24	9.38
100	170	0.50	42.42	57.58	157.58	9.29
116	167.14	0.46	39.35	44.65	160.65	9.17
X_{K0} = 161.36	150	0.21	29.44	9.20	170.56	8.58

C = 170, R = 34.5795, N = 200, α =0.8255, β = 1.0187, $g = h = j = 1$, and $\gamma = 0.005$

Notice that the α in Table 2 is calibrated to give the same values for K between Table 1 and Table 2 both when $X = 0$ and $X = 100$ (where $K = 150$ and $K = 170$, respectively). Without an interaction term, α must be greater than β for anyone to attend an extra credit event. With the interaction term though, the direct effect of the extra credit event on knowledge α can be less than that for regular study time measured by β as long as the indirect effect γ is large enough. (Because of scale issues, γ is very small compared to α or β.)

An instructor thinking about the best or optimal X to choose from options in Table 2 might pick X_{Kmax} = 80.68 because it maximizes knowledge. The student would do the extra credit because utility is greater than that of $X = 0$, and for the student it is a binary decision—they either do the extra credit or not. But they would prefer a smaller project; here student utility is maximized when $X = 56$. For simplicity, integer values of X are used except for the solutions to equations (18) and (19). An instructor with complete control of X would never choose a project larger than 80.68 and might well choose a smaller one to be sensitive to student concerns. But if projects are "chunky" in their time requirements they might assign a project up to $X = 116$, where students are indifferent between doing the assignment and not completing it.

One implicit assumption that has been made is that the variable X captures all the cost considerations of the extra credit. But some types of extra credit may have higher opportunity costs than others, and the cost may differ between students. For a simple example, consider an extra credit event not during class time for a student with a child. Suppose the student needs to trade childcare with a neighbor to be able to attend the extra credit event. In that case the time constraint would be:

$$L = N - \theta X - S \tag{20}$$

where $\theta \geq 1$. For example, if the student had to spend the same amount of time watching the neighbor's child as the neighbor spent watching the student's child, then $\theta = 2$, so the extra credit event costs this student more time than a student without a conflict. A similar argument could be made for a student with a class conflict for the extra credit event; they might have to devote time to make up the missed class.

From equations (20) and (7), leisure is now:

$$L = \frac{(\beta + \gamma X)(N - \theta X) + \alpha X - K}{(\beta + \gamma X)} = \frac{M(X) - K}{(\beta + \gamma X)} \tag{21}$$

where

$$M(X) = \beta N + (\alpha - \theta\beta)X + \gamma XN - \theta\gamma X^2 \tag{22}$$

abusing the notation slightly or thinking of the definition of M in equation (8) as the special case of equation (22) when $\theta = 1$.

The formal results above hold for this extension of the model, because $\frac{dM(X)}{d\theta} < 0$, and all of the results that depend on $M(X)$ are qualitatively similar but smaller. An increase in θ decreases knowledge, the probability of a higher grade, leisure, and utility. Note as well that equations (18) and (19) are now:

$$X_{KMax} = \frac{(\alpha - \beta) - \gamma\theta N}{2\gamma\theta} \text{ , and}$$

$$X_{K0} = \frac{(\alpha - \beta) - \gamma\theta N}{\gamma\theta} \text{ .}$$

Clearly an increase in θ makes the extra credit project more costly in terms of time and reduces both the knowledge maximizing level of X, and what we might think of as the hard upper bound on X.

Table 3 extends the example of Table 2 to the case where θ is greater than one. The knowledge maximizing value of X here has fallen to 64.08 from 80.68 in Table 2. The utility maximizing X here has fallen to 42 from 56 in Table 2. And for a given value of X, set at 100 in the examples, the utility here is 9.04, which is less than that for $X = 0$, so the student would not do this project. In Table 2 where $\theta = 1$ when $X = 100$ the utility is 9.29, which is greater than that for no extra credit at all, so the student would choose to do it.

How much control an instructor has over extra credit opportunities depends on many factors of course. If an instructor could create an extra credit project without the extra time requirement implied by $\theta > 1$ that met the same pedagogical goals, they might strongly consider doing so to help students with childcare issues or long commutes. If that is not possible, then the smaller the scale of the project, the more likely it is that it would benefit all students.

Table 3. Example Outcomes when $\gamma > 0$ and $\theta > 1$

X	K	PHG	L	S	$S + X$	U
0	150	0.21	52.75	147.25	147.25	9.17
42	162.96	0.40	49.39	104.41	146.41	9.33
X_{Kmax} = 64.08	164.71	0.42	46.01	83.49	147.58	9.29
85	163.14	0.40	42.10	64.40	149.40	9.17
100	160.08	0.36	38.95	51.05	151.05	9.04
X_{K0} = 128.17	150	0.21	32.38	26.63	154.05	8.68

C = 170, R = 34.5795, N = 200, α =1.3256, β = 0.8255, $g = h = j = 1$, $\gamma = 0.005$, and θ = 1.1

4 Survey

We commissioned a Qualtrics panel of 251 college instructors from across the United States. The panel had no restrictions on age for adults, gender, academic field, or other demographics; participants were only required to teach in higher education and use exams for grading. Participants were compensated for completing the survey, which took about 15 minutes to finish. The survey asked about demographics and academic background, instructor policies, beliefs about students, and whether those beliefs shape teaching policies such as offering extra credit opportunities and instructor perceptions on who would complete extra credit opportunities. Table 4 shows the demographics and relevant background of survey respondents that will be used for future regressions.

Instructors were asked about their perceptions of student motivations, given three possible motivations and “other.” They were asked to rank those motivations in order of importance to students and give percentages of students with that as their primary motivation (Table 5).

A simple model such as the one developed obviously misses many important aspects of student motivations and behavior. Allowing for the considerable simplification of theory, we have modeled grade-motivated students and knowledge-motivated students. Career-motivated students are perhaps best described by the full model. Instructors in the sample clearly saw students as being motivated by earning a grade, while learning for future career goals or job skills was also an important student motivation. Knowledge and understanding for personal satisfaction get a respectable showing, but not quite as much as the collective category of other motivations. Of course, professor perceptions of student motivations may be incomplete or incorrect, but professors do not have complete information about their students and must design their course on their best estimate of student motivations and responses.

Student behavior is sometimes complex. But as long as student behavior is informed by time decisions such as trading off leisure and course effort, we would argue that students with all three motivations will react in qualitatively similar ways to an extra credit opportunity. Perhaps not surprisingly given that consistency, the primary empirical results to be discussed below do not vary much with differences in instructor perceptions of students’ motivations, with one exception for when during the semester students are more likely to attend an event. We will return to the latter below.

Table 4. Demographics and Background (n = 251)

Variable	Level	Frequency
Gender	Female	65.74%
	Male	33.86%
	Other	0.40%
Age	18–30	9.16%
	31–40	29.88%
	41–50	22.31%
	51–60	21.12%
	61–70	13.94%
	71+	3.59%
Teaching Experience	1–3 years	7.17%
	4–7 years	22.71%
	7–12 years	25.10%
	13–20 years	19.52%
	21–30 years	16.73%
	30+ years	8.76%
Course Format	Face to Face	79.28%
	Hybrid	9.56%
	Online	11.16%
Position	Ranked Professor	39.44%
	Full-Time Instructor	30.68%
	Part-Time Instructor	29.88%
Academic Field	Business/Agri. Business	9.96%
	Engineer	3.19%
	Humanities	27.09%
	Natural Science	23.51%
	Social Science	25.10%
	Pre-Professional	9.16%
	Tech	1.99%
Grade Flexibility:	Helps Overall	79.68%
	Hurts Overall	20.32%
Same-credit Makeups for Sleeping in	Yes	35.86%
	No	64.14%

Offering extra credit events requires considerable effort on the part of the instructor to arrange as well as the effort of students to attend. Instructors presumably invite speakers or create events that are complementary to the other learning goals or strategies of the course. But the theory suggests that for students, time spent on the extra credit is a substitute for time spent on regular course activities. In fact, the theory suggests that even knowledge-motivated students will more than substitute time-on-extra-credit for time-on-regular study.

Table 5. Survey Question

What percentage of your students do you think have the following motivation? (n = 251)		
Student Primary Motivations	**Mean Percent of Students in Each Category**	**Percent of Respondents Ranking #1**
Earning a grade	50.6%	58.6%
Learning for future career goals or job skills	30.2%	29.5%
Knowledge and understanding for personal satisfaction	13.5%	5.2%
Other	5.7%	6.8%
Total	100%	100%

5 Who Attends Extra Credit Opportunities?

In the theory section we argued that when there is no interaction effect between extra credit and regular study time and there are no significant secondary costs to the extra credit, like extra commuting time or trading child care with a neighbor, then all students benefit from extra credit. If either of these conditions are not met, then the instructor must be more sensitive to the scale of the extra credit for everyone to potentially benefit. But notice that for X values sufficiently small, all students will benefit. In this section we suppose that the instructor designs a project that does benefit all students. But the amount of benefit a specific student gets will certainly vary. To investigate these differences, we will use the "increment" in utility from the extra credit opportunity denoted $U_{XC} - U_R$. We will begin with the special cases. For grade-motivated students, substitute from equations (10) and (7) (setting $h = 0$) and using the log properties of the utility function to write the increment in utility as:

$$U_{XC} - U_R = (g + j)(\log(M(X) - Z) - \log(M(0) - Z))$$

noting that $PHG + 1 = \frac{g(M(X)-Z)}{2(g+j)}$. In a comparative statics sense, as the weight on the grade in the utility function g increases, knowledge, the probability of higher grade, and the increment in utility from extra credit also increase.

A similar argument can be made for knowledge-motivated students. Using equations (11) and (7) (setting $g = 0$), the increment in utility from the extra credit opportunity is:

$$U_{XC} - U_R = (h + j)(\log(M(X) - \log\big(M(0)\big).$$

In a comparative statics sense, as the weight on knowledge in the utility function h increases, knowledge, the probability of higher grade, and the increment in utility from extra credit also increase.

Since the same general results hold true for knowledge-motivated students and grade-motivated students, it seems likely they hold for students motivated by grades and knowledge. An increase in the weight in the utility function on either the probability of a higher grade or on knowledge will likely increase both knowledge and the extra credit increment in utility. However, because of the complexity of the general solution, we will rely on numerical evidence. Using the example from Table 1 (C = 170, R = 34.5795, N = 200, α =1.3256, β = 1.0187, $j = 1,\ \gamma = 0$), Table 6 shows the relationship between knowledge and utility as the preference for either the probability of a higher grade, measured by g, or the preference for knowledge, measured by h, changes, changing only one parameter at a time. Numerical evidence suggests that these qualitative results are representative for interior solutions.

Table 6. Knowledge and the Extra Credit Increment in Utility

g (h held constant at 1)	K_{XC}	U_{XC}	K_R	U_R	$U_{XC} - U_R$
1	170	9.69	150	9.17	0.52
2	188.33	10.19	165.55	9.46	0.73
3	198.38	10.8	173.98	9.86	0.94
h (g held constant at 1)	K_{XC}	U_{XC}	K_R	U_R	$U_{XC} - U_R$
1	170	9.69	150	9.17	0.52
2	183.1	14.86	160.42	14.21	0.65
3	192.01	20.1	167.7	19.32	0.78

In sum, theory suggests that the instructor can structure extra credit events or activities so that all students benefit. But it may be that students have something like adjustment costs in switching time from regular study to the extra credit opportunity. Students may have behavioral rules-of-thumb. It may be that the net increment from the extra credit opportunity must exceed some threshold before some students attend. In these cases, better students, whom we represent in the theory as those who place a higher weight on either grades or knowledge in a comparative statics sense, have a larger increment in utility from extra credit and would be more likely to attend an event.

The empirical survey asked instructors about their perceptions of who would attend extra credit events. Survey participants were told to suppose the existence of a hypothetical series of on-campus speakers, and asked about perceived student willingness to attend those events. We assume that participants based their responses to this hypothetical on their real-world experiences with offering extra credit through various channels. Using the question: "In your experience which students would be more likely to attend these extra credit opportunities?," we proxy the instructor's perceptions of student preference for grades or knowledge by whether a student was an A student, a B student, and so forth. See Table 7 for responses. We also construct a collapsed variable, with A students labeled as 1 and all other responses labeled as 0, which we will use for estimation.

A null hypothesis that the proportion of instructors saying A students are more likely to attend is 50 percent or smaller is rejected with a p value of 0.038. Indirect evidence of instructor estimates of the overall proportion of students that will attend extra credit events will be presented in the next section.

If we assume that A students have greater utility weights on grades and knowledge than other students, then one suggestion of our model is that they have a greater utility gain from the availability of extra credit, and thus are more likely to attend. So instructors who believe that A students are most likely to attend have a perception of students that aligns with our utility model and we can test what correlates with that perception. Table 8 reports Probit estimation of the probability of response that A students are most likely to attend, compared to all other responses, along with marginal means for each category (what the model predicts for probability if all data points were in that category).[1]

[1] We use this collapsed variable and a Probit estimation because we view A students as a different category, more motivated by grades and knowledge as opposed to leisure, compared to other students. Also, our categories are not fully ordered because

Table 7. Survey Question

Most Likely to Attend Extra Credit (*n* = 251)	
Type of Student	**Percent**
A Students	55.77%
B Students	20.31%
C Students	8.36%
D and F Students	1.99%
All Students Will Equally Attend	13.54%
Total	100%
Collapsed Variable	
A Students	55.77%
All other Responses	44.22%
Standard Deviation	0.498

Table 8. Probit Estimation Results

A Students Attend Extra Credit Events vs. All Else		
Variable	**Coefficient**	**Marginal Mean**
Constant	-0.757	
	(-1.58)	
1-3 years	-	0.401
		(0.114)
4-7 years	0.932*	0.724
	(2.47)	(0.056)
8-12 years	0.124	0.445
	(0.34)	(0.060)
13-20 years	0.275	0.499
	(0.72)	(0.069)
21-30 years	0.402	0.545
	(1.04)	(0.074)
30+ years	0.822	0.690
	(1.83)	(0.094)
Face to Face	-	0.569
		(0.033)
Hybrid	-0.145	0.422
	(-1.37)	(0.099)
Online	0.0292	0.579
	(0.11)	(0.088)

of the inclusion of the "All Students Will Equally Attend" response, making techniques such as an Ordered Logit model infeasible.

Table 8 continued.

Variable	Coefficient	Marginal Mean
Ranked Professor	-	0.509
		(0.049)
Full-Time Instructor	0.146	0.561
(Non-Tenure Track)	(0.68)	(0.056)
Part-Time Instructor	0.301	0.615
	(1.44)	(0.053)
Grade	-	0.574
		(0.039
Career	-0.123	0.530
	(-0.62)	(0.057)
Knowledge	-0.590	0.365
	(-1.45)	(0.132)
Other	0.251	0.660
	(0.70)	(0.113)
Belief that Flexibility Helps	-	0.526
		(0.033)
Belief that Flexibility Hurts	0.426*	0.672
	(1.97)	(0.061)
Business/Agri. Business	-	0.497
		(0.098)
Engineering	0.418	0.646
	(0.76)	(0.163)
Humanities	0.437	0.653
	(1.36)	(0.056)
Natural or Formal Sciences	-0.129	0.450
	(-0.40)	(0.065)
Pre-Professional	0.257	0.590
	(0.66)	(0.099)
Social Sciences	0.207	0.572
	(0.64)	(0.062)
Technical Education	-0.729	0.249
	(-1.06)	(0.186)
Instructors who do not give same credit makeups	-	0.492
		(0.039)
Instructors who do give same credits makeups	0.497**	0.667
	(2.63)	(0.048)
Pseudo R^2	0.100	
n	251	

Note: Figures in parentheses are *z* statistics where $^*p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$.

Instructors are characterized by experience, appointment status, and fields; course delivery method is also included. As for experience, there is a positive coefficient on 4–7 years of experience. That is, instructors with 4–7 years of experience are more likely to pick the A student response than the comparison group of 1–3 years of experience. None of the other years of experience, nor any of the delivery methods, appointment status, or field variables were significant. Two pedagogical variables were included in the regression. The pedagogical practice variable is whether the instructor gives a full credit makeup if a final exam is missed. This coefficient is significant and positive. Instructors offering exam makeups are more likely to think that A students are more likely to attend the event. A pedagogical perceptions variable was also included. Instructors were asked whether they believe that grading flexibility helps or hurts students. Notice that the coefficient on the flexibility hurts variable is significant and positive. Instructors reporting that flexibility hurts students are more likely to choose the A students response.

With our model, we were able to show that different students receive different utility increments from the availability of extra credit, and we posit that those students who receive the largest increment are most likely to take advantage of extra credit opportunities. With this regression, we show that different instructors have different perceptions about which type of students fit that category.

6 When in the Semester Will Students Attend?

We turn now to the question of the timing of an extra credit event during the semester. The theory parameterizes an extra credit event by the time it takes the students, or equivalently, by the points earned. But it is possible to imagine other differences between extra credit events, in this case whether an event is scheduled earlier or later in the semester. The analysis above showed that an increase in $Y = (\alpha - \beta)X$ increases knowledge (and thus the probability of a higher grade), leisure, and utility. The assumption was that students know both α and β, the parameters that measure how time translates into semester points. Recall β is for time spent on regular study and α for time spent on the extra credit. But suppose there is something like a learning curve for the student in gaining knowledge about their own specific α and β, or for what really matters, about the size of the gap between them. In particular, suppose a student learns over the course of the semester that their own β is not as high as they had first thought (i.e., that semester points require more study time than they earlier imagined). In that case, the same theory that showed that extra credit opportunities are utility enhancing would suggest that more of them would be done later in the semester. The survey explored this issue by asking the questions shown in Table 9.

Table 9. Survey Question

When During the Semester Will Students Attend	
Suppose there are various on-campus speakers that students can attend for extra credit points, each all before the midpoint of the term. What percentage of students do you think would attend?	37.5% *SD* = 23.6%
What percentage of students do you think would attend if these speakers were at the end of the term rather than at midpoint?	53.1% *SD* = 26.9%
Paired *t*-test of equal means	*p* = 0.0000

Table 9 reports the average estimate of the percentage of students likely to attend an event based on when it is held in the semester. These results are supportive of Mays and Bower (2005) in that they suggest that instructors think students are more likely to attend events later in the semester as compared to before the midterm. Instructors were not asked for an overall estimate regardless of scheduling during the semester, but it seems reasonable to suppose that, on average, the estimate would have been between

37.5 percent and 53.1 percent. At a minimum, it seems that instructors predicted a considerable proportion of students would not attend an event.

Table 10 uses OLS to investigate the determinants of the responses to the questions in Table 9.[2] A fractional logit regression shows the same significance patterns.

Table 10. OLS Estimation of Regressions Examining Professor Expectation of Extra Credit Use

Variable	Percent Attending Before Midterm Event	Percent Attending Later in Term Event
Constant	65.24***	79.07***
	(8.10)	(8.19)
4-7 years	-19.30**	-16.13*
	(-3.10)	(-2.16)
8-12 years	-17.93**	-20.60**
	(-2.92)	(-2.79)
13-20 years	-16.76**	-12.83
	(-2.63)	(-1.68)
21-30 years	-15.73*	-19.14*
	(-2.42)	(-2.45)
30+ years	-12.05	-21.69*
	(-1.61)	(-2.41)
Hybrid	13.47**	5.812
	(2.71)	(0.98)
Online	-3.200	-1.746
	(-0.68)	(-0.31)
Full-Time Instructor	-7.889*	-5.223
(Non-Tenure Track)	(-2.23)	(-1.23)
Part-Time Instructor	-6.169	-4.612
	(-1.76)	(-1.10)
Career	1.452	-6.091
	(0.44)	(-1.52)
Knowledge	17.71**	-7.829
	(2.69)	(-0.99)
Other	-5.407	-6.992
	(-0.92)	(-0.99)

[2] We believe an OLS model is appropriate here: while our results are technically left and right censored at 0 and 100, there are only a small number of observations at each end, so a tobit model is unnecessary. And while our percentage responses could be treated as fractions and analyzed with a fractional logit, we believe the linear probability model (equivalent to our OLS regression) is preferred to logit in this circumstance, due to the interpretation and interpretability of coefficients: we believe moving from 90 percent to 80 percent is equivalent to moving from 40 percent to 30 percent (as in a linear model), compared to 40 percent to 23 percent (as a log-odds logistic model would suggest). And this change would be easily represented by a coefficient of -10 in our regression.

Table 10 continued.

Variable	Percent Attending Before Midterm Event	Percent Attending Later in Term Event
Belief that Flexibility Helps	2.234	4.428
	(0.62)	(1.03)
Engineering	10.33	-5.268
	(1.13)	(-0.48)
Humanities	-15.45**	1.424
	(-2.89)	(0.22)
Natural or Formal Sciences	-8.290	-1.343
	(-1.54)	(-0.28)
Pre-Professional	-11.80	-8.234
	(-1.81)	(-1.05)
Social Sciences	-14.32**	-12.06
	(-2.63)	(-1.85)
Technical Education	11.45	23.81
	(1.04)	(1.81)
Instructors Who Give Same Credit Makeups	0.765	2.774
	(0.24)	(0.73)
Adjusted R^2	0.125	0.03
n	251	251

Note: t statistics in parentheses; *p < 0.05, **p < 0.01, and ***p < 0.001.

Looking first at column 1, the percentage that will attend events before the midterm, notice that all levels of instructor experience (except for those with 30+ years of experience) gave a lower percentage than the comparison group of instructors with 1–3 years of experience. Turning to delivery method, instructors of a hybrid class have higher beliefs about attendance as compared to instructors of face-to-face courses. Full-time instructors (i.e., non-tenure track) have lower predictions compared to tenured or tenure-track faculty. Fields also matter in some cases, with instructors in the humanities and social sciences giving lower estimates than the comparison field of business. Pedagogical variables are not significant. There was one more interesting result; instructors who said that students were most motivated by knowledge (as compared to being motivated by grades or careers) gave a much higher estimate of the percentage of students that will attend an event before midterm. Column 2 provides the results for the question about events later in the semester. In this case, instructors of all levels of experience (except for those 13–20 years) again gave a lower percentage than the comparison group of instructors with 1–3 years of experience. The overall impression from Table 10 is that instructors with more experience will give lower estimates of student attendance, regardless of when the event is held during the semester.

Remember that in the model, students only complete extra credit if it increases their utility through its effects on knowledge, grades, and leisure, which have different effects based on students' motivations—specifically, values for g and h (our survey did not include questions about additional or more specific student motivations for behavior). One possible explanation of our results is that new instructors overestimate the effects of extra credit as perceived by their students (that is, they overestimate their students' values of g and h in the model—how motivated students are by grades and knowledge compared to leisure), and thus overestimate students' likelihood of completing that extra credit, compared to more experienced instructors with better-calibrated models. Other significant effects can also be interpreted as differences in student motivations between fields, course types, etc., and by differences in professor perceptions of those motivations.

7 Other Flexible Grading Options

The survey also asked about another hypothetical situation: students are only graded on their top six out of seven homework assignments, and may or may not submit the seventh assignment. Respondents were asked what percent of students would submit the seventh, out of those who had completed the first six assignments, and to rank categories of students by motivation on their likelihood of completing the assignment. While this scenario is technically not extra credit, it illustrates many similar concepts to extra credit. Overall, instructors expected an average of 48.8 percent of students to complete the assignment. The plurality of instructors thought that knowledge-motivated students were most likely to complete it, and grade-motivated students least likely to. This aligns with the idea that this assignment would contribute to knowledge creation, but only minimally improve course grades.

As a final comment, in the larger sense offering extra credit or dropping homework assignments are two ways of providing flexibility in grading for students, a more abstract issue touched on in the survey. Table 4 shows the percent of instructors who believe that grading flexibility overall helps or hurts students. Recall that in the Probit regression about which students will attend extra credit events, we saw that instructors who answered that grading flexibility hurts are more likely to choose the A student response. Instructors who answered that grading flexibility helps students were more likely to choose some other response to the questions, either another grade or all students will attend equally. It appears that those who think flexibility helps are more likely to think students besides A students will attend an extra credit event. On the other hand, instructors who offer same credit makeup exams, a different kind of grade flexibility, were more likely to choose the A student response rather than one of the others. Perhaps in at least some instructors' thinking offering extra credit with the options it provides for students is substantively different than offering a makeup for a required final exam. In any event, a strong majority of instructors believe grading flexibility helps students, even if they operationalize that flexibility somewhat differently. Instructor perceptions might be said to be nuanced.

8 Conclusion

Economics instructors may wonder if offering extra credit opportunities to students enhances student effort and takeaway knowledge. The theoretical results of the current paper suggest that it depends crucially on whether the extra credit makes regular study time more efficient or not. If it does not, then the model suggests that it is reasonable to suppose that students will ask their instructors for extra credit events as they increase knowledge and the probability of a higher grade but also leisure. Students, even knowledge-motivated ones, may reduce their regular study time by more than the time they devote to the extra credit.

When extra credit increases the productivity of regular study time, the results are a bit more complex. For small scale extra credit activities, the qualitative results are the same as above. But when the extra credit event requires a relatively large time commitment on the part of the student, it may be the case that the increase in productivity of study time prompts the student to do enough more of it that leisure is actually reduced. It is also possible to create an extra project so large no student would do it.

While many instructors care very much about student utility and perceptions, they may also have other goals. When there is feedback between the extra credit activity and regular study time—and more is not necessarily better—the instructor may try to scale the extra credit to maximize knowledge. Our results suggest that for projects of about that scale, leisure is decreasing as the size of the extra credit project increases. The implication is that student utility is maximized before knowledge is. Students would prefer a smaller project than the instructor, but they would still do the knowledge maximizing extra credit as it gives greater utility than not doing it. In some circumstances an instructor may be able to structure an extra credit project that actually increases the learning of regular study time. On the surface, the prospect seems quite appealing. These results suggest that considerable nuance is required.

Finally, the main empirical results from the instructor perceptions survey suggest that instructors think A students are more likely to attend, and that all students will be more likely to attend an event later in the semester. These results align with outcomes from our model. Findings also suggest that instructors with more experience give lower probabilities to student attendance at extra credit events. Last, the instructor perception survey found that instructors believe knowledge-motivated students are most likely to complete an additional assignment to replace a lower grade, while grade-motivated students least likely to, suggesting that extra class activities often contribute to knowledge enhancement while only marginally improving student grades.

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Acknowledgments: This work was supported by Bradley University's Foster College of Business Research Grant. No potential conflict of interest was reported by the authors. The research was approved and found exempt by the Bradley University Committee on the Use of Human Subjects in Research (CUHSR#: 37-19).

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4(4) doi: 10.22004/ag.econ.324804