Biannual Conference – Economic Society of South Africa

Grahamstown, 30 August – 1 September 2017

Framing, Loss Aversion, and Student Achievement

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Abstract

Are learning incentives more effective when framed as losses instead of gains? Although extensively discussed in the fields of economics and public policy, findings from behavioral economics have neither been integrated into educational theory nor have they reached the educational practice in a broader sense. Instead, the view on students' decision-making in educational settings is still dominated by the idea of "rational choices by autonomous individuals" (Spencer, Rowson, & Bamfield, 2014, p. 5) - an assumption that has been continuously challenged by research findings over the past 50 years. With framing and loss aversion, we applied two central phenomena of behavioral economics to an educational setting to observe their practical suitability for facilitating learning behavior in a real class situation. We designed a bonus system with two logically equivalent conditions for 75 undergraduate students in an introductory statistics course. Under both conditions, students were able to earn bonus points for their final exam. Students were randomly assigned to one of two groups. While the first group gained bonus points for completing optional course assignments, the second group started with the maximum amount of bonus points and lost points for not taking the optional assignments. Students in the second group gained 68% (0.58 standard deviations) more bonus points for their final exam. Although we did not find statistically significant effects on the final exam score, the results substantiate the idea of integrating behavioral insights into educational theory and practice. Furthermore, the study exemplifies that popular motivation concepts like awarding bonus points can be more effective – and at no additional costs – when designed from a behavioral economist's point of view.

1. Introduction and Theory

It is a common expression that optimists tend to see a glass half full while pessimists perceive it as half empty. What is generally less known is that two differently worded but logically equivalent versions of the same decision problem can lead to different decision tendencies. This so-called framing effect is considered an anomaly which clearly contradicts the rational choice theory by violating its assumption of invariance. A prominent example is the so-called *Asian Disease Problem*. Tversky and Kahneman (1981) asked participants to choose between two treatments for a deadly disease that 600 people were about to be affected by. While treatment A would result in the certain death of 400 people, treatment B offered a 1/3 chance that no one would die and a 2/3 chance that everyone would die. Depending on whether the choice was presented framed positively or negatively (200 people will survive instead of 400 people will die) participants responded very differently. In the positive condition, 72% preferred treatment A over treatment B, dropping to 22% in the negative condition. Numerous studies have observed framing dependency in laboratory and real-world decision-making, from stock market forecasts (Glaser, Langer, Reynders, & Weber, 2007) and pension planning (Brown, Kling, Mullainathan, & Wrobel, 2008) to health-related behavior (Block & Keller, 1995) and even conference registrations (Gächter, Orzen, Renner, & Starmer, 2009), proving framing to be a universal concept and explanation for decisions under various conditions. Since framing effects lead to relatively stable decision tendencies, framing can be used to stimulate beneficial decisions (Thaler & Sunstein, 2003). However, the question of how framing can help to promote students' engagement in learning activities or raise academic motivation remains widely unaddressed.

Motivation defined as "the process whereby goal-directed activity is instigated and sustained" (Schunk, Pintrich, & Meece, 2008, p. 4) is considered a central concept for the explanation of learning and academic performance. While certain types of motivation foster student achievement independently from cognitive abilities, others tend to impede it (Schiefele & Schaffner, 2015). The source of motivation is not necessarily the outcome of an action but may also be located inside the activity itself. Regarding this, the differentiation of intrinsic from extrinsic motivation is widely accepted (Ryan & Deci, 2000). When someone studies just to get good grades or to prevent bad grades, her motivation to learn is considered extrinsic. If she studies because she is interested in a certain topic, her motivation is intrinsic. Determining the nature of someone's motivation is not always easy. In fact, learners can be both intrinsically and extrinsically motivated. A lack of clarity in definitions makes a characterization even more difficult. Educational psychologists keep emphasizing the primacy of intrinsic motivation, which is undeniably the better predictor for successful learning (Murayama, Pekrun, Lichtenfeld, & vom Hofe, 2013; Schiefele & Schaffner, 2015). Although it has been a major concern in educational psychology that external rewards could undermine a learner's intrinsic motivation (Deci, Koestner, & Ryan, 1999), empirical findings do not substantiate the hypothesis that negative effects on motivation can consistently be shown under valid everyday conditions (Cameron, Banko, & Pierce, 2001; Rheinberg, 2010).

Whenever learning behavior is predominantly motivated by external circumstances, the decision to study or not to study can be considered as a decision under uncertainty. Students normally do not know for sure whether their learning activity will bring them closer to their goal, e.g. passing their next exam. As for framing, experimental results also reveal stable deviations from a rational agent model when decisions are made under uncertainty (Tversky & Kahneman, 1992).

A well-studied phenomenon is 'loss aversion', which means that the "disutility of giving up an object is greater that (sic!) the utility associated with acquiring it" (Kahneman, Knetsch, & Thaler, 1991, p. 194). Loss aversion does not just offer an explanation for stock market anomalies like the equity premium puzzle (Benartzi & Thaler, 1995) or for why investors tend to hold on to losing investments for too long (Odean, 1998). It can also be utilized to stimulate beneficial decisions and behavior. In their idea of a "libertarian paternalism" Thaler and Sunstein (2003) argue that public and private institutions should design decision situations in such a way that allows people to make better decisions for themselves while retaining their freedom of choice. Although educational institutions constantly force students into decision-making, findings from behavioral economics have not yet had a substantial impact on educational theory or practice. However, initial empirical studies indicate promising potentials in this field (Apostolova-Mihaylova, Cooper, Hoyt, & Marshall, 2015; Levitt, List, Neckermann, & Sadoff, 2016; McEvoy, 2016; Wüst & Beck, 2012).

In the present paper, we test and discuss whether decisions in a learning context can be influenced by framing incentives as losses instead of gains. With the awarding of bonus points for a final exam, we choose a widely used incentive concept that can be considered an extrinsic motivator to test the idea under ecologically valid conditions.

2. Procedure and experimental set-up

75 undergraduate students (35 females) that enrolled in the seven semester Bachelor's degree program *Management of Medium-sized Companies* at Kaiserslautern University of Applied Sciences, attended an introductory course in statistics.[1] For organizational reasons, students were randomly

[1] *Statistics* is one of the toughest courses in the management program as the average failure rate often lies between 60%-70% of the students.

assigned to one of two groups. Both groups were offered optional assignments to earn bonus points for the final exam. The maximum score of the assignments was 20 points, representing 15% of the final exam score. While the first group (control condition) gained bonus points for completing the optional course assignments, the second group (experimental condition) started with the maximum amount of bonus points and lost points for not completing the optional assignments.

2.1. Measurements

We measured mathematical skills at the beginning of the course, the number of bonus points earned, the final exam score, semester, and gender. Furthermore, we registered whether it was a student's final re-examination. In this situation, students should presumably be more motivated to learn.

2.2. Hypotheses

H1: The share of students taking optional assignments is larger in the experimental condition than in the control condition.

H2: On average, students in the experimental condition earn more bonus points than students in the control condition.

H3: Students in the experimental condition score higher in the final exam.

3. Results

Before observing group differences, we tested for structural differences between the two groups. They did not differ regarding gender (χ^2 (1, N = 75) = .475, p = .491), share of final re-examination candidates (p = .391, Fisher's exact test), mathematical skills (U(44,31) = 595.5, p = .351), or semester (U(44,31) = 561, p = .176). Bonus points and exam score were highly correlated in the experimental (r_S(31) = .571, p < .001, 95% CI [.397, .807]) and the control group (r_S(44) = .636, p < .001, 95% CI [.238, .789]). With reference to the calculated confidence intervals, the strength of the relationship did not differ significantly between the two groups.

Table 1: Means and standard deviations by group

	N	Bonus Points		Exam Score		Semester		Math Test		FRC	m
		M	SD	M	SD	M	SD	M	SD		
CG	44	3.82	4.49	45.88	20.52	4.84	2.35	8.25	5.86	5	22
EG	31	6.42	5.79	47.85	23.64	4.13	1.54	7.23	6.08	1	18

Note: CG = control group, EG = experimental group, FRC = final re-examination candidates, m = number of male students. Students can acquire up to 20 points in Math Test.

For *table 1* it is interestingly to note that the passing bar on the final exam is 60 points – quite a bit more than average exam score due to a high rate of failure. Also, the students are taking the statistics course at a much later stage than expected by the faculty! Statistics is scheduled for the 2^{nd} semester, the majority of students delay the course to the 4^{th} and 6^{th} semester.

Hypothesis #1: To test whether the share of students taking optional assignments was larger in the experimental group, we determined the share of students that earned at least one bonus point at the end of the semester for each group and then tested for differences in the frequency distribution. 56.8% of the students in the control group and 67.7% in the experimental group earned at least one bonus point, revealing no significant difference between the two groups (χ^2 (1, N = 75) = .915, p = .246). A logistic regression was performed to control for semester, mathematical skills, gender, and re-examination candidates. The logistic regression model was statistically significant (χ^2 (8) = 21.656, p = .006). The model explained 34.0% (Nagelkerke R^2) but did not reveal a significant group effect (p = .143). In relative terms, students in the experimental group did not participate to a larger extent in the optional course assignments**.** Therefore, there is no empirical support for the 1^{st} hypothesis.

Hypothesis #2: Due to a large number of students with no bonus points at the end of the semester, the frequency distribution cannot be expected to be normally distributed. We, therefore, used the non-parametric Mann-Whitney U test to check for differences in central tendency. Students in the experimental condition (M = 6.42, SD = 5.79) earned, on average, 68% more bonus points than students in the control condition (M = 3.82, SD = 4.49), leading to a significant difference between the two groups (U(44,31) = 517,5, p = .034, one-tailed test). We calculated the effect size as described by Fritz, Morris, & Richler (2012) and found - according to Cohen (1988) - a small effect (r = .21). When we eliminated those students from the sample that did not earn bonus points in both groups, the result remained stable (U(25,21) = 172,5, p = .024) with a slightly increasing effect size **(**r = .29). By using a hierarchical multiple regression, we tested the group effect on bonus points while controlling for semester, final re-examinations, gender, and mathematical skills. The regression revealed that gender, mathematical skills, and semester contributed significantly to the regression model (F (5,69) = 5.040, p = .001) and accounted for 17.9% (adjusted R^2) of the variation in bonus points. Introducing the different starting conditions explained an additional 13.0% (adjusted R^2) of variation. This change was significant (F (4,70) = 14.247, p < .000). Together, the five independent variables accounted for 30.9% of the variance in bonus points – all of which exert a positive and significant influence on total bonus points. The group effect exceeds the effects of the two other dummy variables (final re-examination and female). The results give support to Hypothesis #2.

Table 2: Multiple regression on **bonus points**

n = 75	*coefficient*	Std. Error	*p*	*Adj. R^2*	*Prob (F-statistic)*
Model 1				17.9%	.0013
(constant)	-1.144	1.393	.414		
semester	.742***	.2423	.0031		
final re-examination	2.670	2.241	.2375		
gender (female = 1)	2.336*	1.274	.0709		
mathematical entrance test	.1739*	0.1026	.0945		
Model 2				30.9%	.0000
(constant)	-3.824	1.411	.0085		
semester	.873***	.228	.0003		
final re-examination	3.395*	1.851	.0710		
gender (female = 1)	2.584**	1.159	.0290		
mathematical entrance test	.217**	0.094	.0276		
group (experimental group = 1)	3.923***	1.069	.0005		

***, **, * - 1%, 5%, 10% significance level; White heteroscedasticity-consistent standard errors.

Hypothesis #3: As expected, the frequency distribution of the exam score in both groups showed a better approximation to a normal distribution. Due to differences in group size and inequality of variances, we also applied a non-parametric test on group differences, revealing no significant effect ($U(44,31) = 655.5$, $p = .776$) between students in the experimental ($M = 47.85$, $SD = 23.64$) and those in the control group ($M = 45.88$, $SD = 20.52$). In addition, we estimated a multiple regression to control for the omitted variable bias. Only mathematical skills and final re-examinations contributed strongly significantly – at the 5% and 1% level - to the regression model ($F\ (5,69) = 4.262$, $p = .002$) and accounted for 18.0% (adjusted R^2) of the observed exam score variance. The group effect became moderatly significant at the 10% level, while gender did not have an influencial effect on the exam scores. Our empirical results do support hypothesis #3.

Interestingly, the model # 2 with the highest explanatory power (39.4% adjusted R^2) is limited to just three independent variables: bonus points, final re-examination and the test scores of the mathematical entrance test. Due to its strong positive correlation with the variable bonus points, the dummy variable experimental group does not exert a significant influence on the final exam score.

Table 3: Multiple regression on **exam score**

N = 75	*coefficient*	Std. Error	*p*	*Adj. R^2*	*Prob (F-statistic)*
Model 1				*18,0%*	*.0019*
(constant)	26.438	8.610	.0031		
semester	2.151*	1.222	.0829		
final re-examination	29.926***	9.307	.0020		
gender (female = 1)	.8673	5.840	.8824		
mathematical entrance test	1.093**	0.443	.0163		
group (experimental group = 1)	9.726*	5.434	.0779		
Model 2				*39,4%*	*.0000*
(constant)	32.779	4.531	.0000		
bonus points	2.416***	.454	.0000		
final re-examination	19.673***	5.888	.0013		
mathematical entrance test	.692*	.392	.0821		

***, **, * - 1%, 5%, 10% significance level; White heteroscedasticity-consistent standard errors.

4. Discussion and Perspectives

Framing learning incentives as losses instead of gains can stimulate students' participation in optional course assignments and - as a direct effect - foster learning behavior. Although the two compared modalities for acquiring bonus points in this study were both logically equivalent, losing points generally lead to a higher willingness to work on the given assignments. In our experiment, students in loss framed condition gained more than half a standard deviation (68%) more bonus points for their final exam than their classmates in the standard condition did. This confirms earlier findings under modified conditions (Levitt et al., 2016; McEvoy, 2016). Whenever using this or similar techniques to support learning behavior, it seems advisable to use framing to magnify the intended effect. Finding no significant effect on final exam scores in our data could be a result of the relatively low overall participation in the assignments offered or may be an indicator of an insufficient fit between assignments and exam tasks. It was the first time our students dealt with a framing modified bonus system. So, our findings could potentially be the result of a novelty effect. In this case, the positive effect of framing would vanish over time. This aspect should be addressed in future studies.

In general, the application of insights from behavioral economics to educational settings seems to be promising and needs further exploration. An obvious field of application is academic procrastination. Procrastination as a "tendency to delay initiation or completion of important tasks" (Howell, Watson, Powell, & Buro, 2006, p. 1519; Lay, 1986) is considered both a widespread self-regulation failure among students (Klingsieck, Fries, Horz, & Hofer, 2012) and a major contributor to academic performance (Howell et al., 2006). From an economic perspective, there is a solid base of empirical findings showing that people mentally discount the value they attribute to future gains. Since the discount factor increases, as the temporal distance decreases (Malhotra, Loewenstein, & O'Donoghue, 2002), people do not only show time-inconsistent behavior but they also tend to have trouble pursuing long-term goals. Going to the cinema with a friend two months before an exam instead of staying home to learn is no cause for a bad conscience: but what about the same situation two days before the exam? With reference to the motivation to learn, we can conclude that large temporal distances are unfavorable. But when we look at educational systems, large temporal distances are the rule rather than the exception. Institutional education in school or college is a long-term process. There is a good reason for that. However, there might still be room for improvement. When we think of how we organize study programs, a sequential structure of separate, blocked, short-term courses instead of multiple, parallel, one-semester courses could yield beneficial effects – not necessarily for straight A students, but probably for those students struggling with academic procrastination.

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