Does use of survey incentives degrade data quality?

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Introduction

Student surveys are a widely used tool for collecting information about educational quality. However, many institutional and educational researchers are well aware that response rates for assessment surveys have been declining over the past few decades (Dey, 1997; Laguilles, Williams, & Saunders, 2011). As a result, many researchers have noted that our ability to adequately assess student academic experiences, satisfaction, engagement, use of campus resources, and other important topics in higher education are at risk (Pike, 2008). Consequently, use of incentives are one tool that many institutional researchers have come to rely on to boost or hold steady their response rates for various campus student surveys. For example, more than 50% of the institutions participating in the National Survey of Student Engagement now use incentives to boost response rates, a dramatic increase from only a few years ago (Sarraf & Cole, 2014). Though research regarding the efficacy of incentives to boost survey response rates in higher education is scant, the research that does exist suggests that incentives are an effective way to boost response rates (Heerwegh, 2006; Laguilles, Williams, & Saunders, 2011; Sarraf, & Cole, 2014).

With the increased reliance on incentives though, some wonder if some students are completing the survey merely to qualify for the incentive (Keusch, Batinic, & Mayerhofer, 2014). If so, one concern of educational survey researchers is the extent to which students complete each survey item with sincerity and thoughtfulness. This study investigates the association between use of incentives and survey data quality.

Use of Incentives for Web-Based Surveys

As with most higher education surveys, the data for this study comes from an online survey instrument. Compared to traditional paper surveys, web surveys provide researchers with an easy platform to administer surveys and quickly access respondent data (Umbach, 2004). However, along with this survey administration mode, researchers face increasing difficulty convincing students to respond. Many researchers have noted decreasing response rates are a threat to the validity and generalizability of survey data (Pike, 2008), though other higher education research suggests low response rates provide reliable population estimates (Hutchison, Tollefson, & Wigington, 1987; Fosnacht, Sarraf, Howe, & Peck, 2013). To counter these decreasing response rates, many survey researchers employ incentives. These incentives take many forms. Some examples include: incentive paid prior to completion (pre-paid); eligibility for the incentive only upon completion of the survey (post-paid); lottery-based where the respondent has a chance to win the incentive; participation based where every respondent receives the incentive; one high-dollar, lottery-based incentive; many low dollar value incentives with greater odds of winning, and many others. The primary purpose for using incentives is to increase student motivation to respond, especially for those students that would otherwise refuse (Singer & Ye, 2013). Many researchers have found incentives effective at increasing responses rates for general population surveys using random digit dialing, mailed paper surveys, and face-to-face interviews (Cobanoglu, & Cobanoglu, 203. 2003; Deutskens, De Ruyter, Wetzels, & Oosterveld, 2004; Heerwegh, 2006). For example, in a study of motives for participating in a survey panel participation, Keusch, Batinic, & Mayerhofer found that "reward seekers. . . . participated in web surveys primarily because of the incentives they received" (2014, p 175). They found that reward seekers were more likely to respond to the survey than respondents not motivated by the incentive. In 2013, Sarraf and Cole reported that cash, gift cards and technology prizes were all associated with increased response rates. In addition, these researchers found that increased financial investment by the institution also resulted in higher responses rates.

Leverage-Salience Theory

As noted by Groves, Singer, and Corning (2000), there have been "scores" of studies investigating influences of survey cooperation in a variety of fields. However, many of these studies provided idiosyncratic results with interventions for one study proving effective, but the same intervention in another study proving ineffective. So many inconsistent results led Groves, Singer, and Corning (2000) to claim that "such a status is common in science when the hypotheses may be true, but only for a limited set of circumstances" (p. 299). To counter the prevalence of the abundance of atheoretical research in the area, they proposed the Leverage-Salience Theory.

Leverage-Salience Theory (LST) is a decision-making theory that considers the "subjective weight" of various factors to participate or not participate in relation to the salience of the survey invitation to the individual (Groves, Singer, & Corning, 2000). The salience of the survey topic and attributes of the survey request contribute to the individual's decision to respond and to the bias introduced by nonresponse. Thus, LST predicts that individuals interested in the survey topic will be more likely to respond. For example, those that are more involved in the community (volunteerism, politics, community groups, etc.) are significantly more likely to complete a survey about their community (Groves, Singer, & Corning, 2000). Leverage-Salience Theory (LST) is also particularly relevant for studies investigating the use of survey incentives where the survey incentives are the "leverage." The leverage varies depending on the size of the incentive. A $5 pre-paid gift card provides some leverage, but a $20 pre-paid gift card provides even stronger leverage. LST is an attempt to move beyond the atheoretical research that is common in nonresponse studies and that have resulted in idiosyncratic, non-generalizable results.

Social Exchange Theory

Social Exchange Theory (SET) is another theory that explains why respondents choose to participate in a survey (Dillman, 1978). The theory claims there are three important factors individuals consider when presented with an opportunity to complete a survey. One factor is the perceived reward of the individual. In other words, what does the respondent expect to gain by participating in the survey? An individual also considers the "cost" of participation. How much does it "cost" to obtain the reward. Costs can include time, effort, providing personal information, or other things. The third factor is whether or not the individual "trusts" the reward will outweigh the costs. If the costs are too great or the potential respondent does not believe he or she will receive the reward, then their participation in the survey is not likely.

Both theories help explain the potential effectiveness of survey incentives and related survey promotions. The leverage of LST and the reward of SET both help to understand the impact of incentive types and value. The salience of LST explains why promotional efforts can arouse interest in a survey. The cost of SET helps us to understand the effort and time commitment that respondents perceive. The attributes (SET) of the promotional material and survey help to explain the importance of survey design and effective promotion. Finally, the trust from SET helps survey designers to consider the total value a respondent feels they are gaining from their participation.

Both of these theories help to explain why incentives are effective at increasing response rates. However, this increase in response rates may come at a cost. Some researchers have expressed concern regarding the potential deleterious effects incentives may have on survey data quality via the process of satisficing (Barge & Gehlbach, 2012).

Satisficing

Schaeffer and Presser (2003) describe satisficing as the process of “conserving time and energy and yet producing an answer that seems good enough for the purposes at hand” (p. 68). Krosnick, Narayan, and Smith (1996) identify three regulators of satisficing: task difficulty, performance ability, and motivation. *Task difficulty* has to do with how familiar the language is to the respondent. *Performance ability* generally refers to the cognitive task required to recall the information needed to provide an accurate or best-estimate answer. *Motivation* is how willing the respondent is to provide an accurate or best-estimate answer. Depending on the weight of these factors, some individuals use satisficing as a response strategy (Blair & Burton, 1987). Indications of satisficing includes the clumping of numerical estimates around common multiples, such as 5 or 10, straight-lining sets of items, item skipping, speeding through the survey, early break-off, and other respondent behaviors (Huttenlocher, Hedges, & Bradburn, 1990; Kaminska, Goeminne, & Swyngedouw, 2006; Krosnick, Narayan, & Smith, 1996)

It is important to note that the mere presence of straight-lining on a given set of survey items does not in itself signify either a data quality problem or an instance of satisficing. That is, a respondent may have thoughtfully considered and responded to each item, but the result is a set of identical responses. Without additional information, it is difficult to distinguish this form of straight-lining from that of a satisficing respondent who strategically elects identical answers in order to complete the survey more quickly.

Incentives and satisficing

As described above, research has demonstrated the efficacy of using incentives to increase survey response. The concern though, is that with increased reliance on incentives, there will be increased satisficing behaviors and thus lower data quality. In a review of several studies, Toepoel (2012) found no evidence that survey incentives effects data quality. In fact, Toepoel concludes that, “there seems to be no relationship between incentives and data quality” (p. 216). However, very few studies focused on the deleterious effect incentives may have on survey data quality in higher education assessment and evaluation. A recent study by Barge and Gehlbach (2012) did focus on higher education research and reported results contrary to the results reported by Toepeol (2012). Barge & Gehlbach (2012) reported that respondents receiving a $15 incentive were much more likely to satisfice as indicated by increased item skipping, rushing (shorter duration), and straight-lining compared to those that received no incentive. The authors also reported that this increase in satisficing was also associated with a decrease in data quality and, more specifically, scale reliability. The authors stated, “If it turns out that incentives can degrade item-level data quality under certain situations, many institutions may need to rethink their data collection plans (Barge & Gehlbach 2012, p 197). However, this study did not parse out the effects due to incentives. Thus, the direct impact of incentives on scale properties and parameter estimates is still not well understood. Though the research on surveys incentives and measurement error is sparse, there is some indication that survey incentives do not contribute to measurement invariance or increased measurement error (Medway & Fulton, 2012).

As prior research has shown, incentives can be effective at increasing survey response rates. Though most research has shown that there is little evidence that incentives undermine data quality, one of the few studies in the higher education research field did report deleterious effects. This study investigates the use of incentives in higher education research and effects on data quality.

Specifically, this set out to investigate the following research questions:

1. Are survey respondents at incentive institutions more likely to use the same response option for a set of questions (straight-lining), skip individual questions, have shorter duration times (rushing), and leave the survey incomplete?
2. Is incentive usage by institutions associated with changes in NSSE scale scores (aka, Engagement Indicators) and factor structure?

Method

Data Source

Data for this study comes from 152,818 first-year students and 203,071 seniors that completed the 2014 *National Survey of Student Engagement* (NSSE). These students represented 622 US higher education institutions. Using information collected from institutions, it was determined that 316 (51%) offered an incentive to complete NSSE, while 306 (49%) did not. Private or Special Focus institutions were slightly more likely to offer incentives, whereas differences for other institution types were small (Table 1). The most common type of incentive institutions offered was a lottery (95%), followed by offering a guaranteed prize (2%), an incentive to the first 'x' number of respondents (2%), and donations to causes or other intangible incentives (1%).

As is typical for higher education surveys, females responded more often than males (Table 2). Females appear to be slightly over-represented at incentive institutions compared to their peers at non-incentive institutions. Likewise, White respondents were slightly over-represented at incentive institutions, whereas Black respondents were more likely at institutions not offering an incentive. These gender and race/ethnicity differences provide a rationale for using these characteristics as statistical controls for analyses.

Table 1. Institutional Characteristics.

	Incentive: No Incentive	Incentive: Yes Incentive	Count
Control			
Public	52%	48%	263
Private	47%	53%	359
Carnegie Level			
Baccalaureate	50%	50%	217
Masters	49%	51%	280
Doctoral	50%	50%	96
Special Focus/Other	38%	62%	29
		Total Count	622

Table 2. Respondent Characteristics.

	FY students		SR student	
	No Incentive	Yes Incentive	No Incentive	Yes Incentive
Sex				
Female	63%	66%	62%	65%
Male	37%	34%	38%	35%
Race/Ethnicity				
Am Indian	<1%	<1%	<1%	<1%
Asian	5%	5%	4%	5%
Black or Afr Am	12%	9%	11%	8%
Hispanic/Latino	13%	11%	11%	9%
Native HI or PI	<1%	<1%	<1%	<1%
White	58%	61%	63%	66%
Other	<1%	<1%	<1%	<1%
Foreign	4%	4%	3%	3%
Two or more races	3%	4%	2%	3%
Unknown	5%	5%	5%	5%

Variables

Straight-lining is defined as selecting the same response option for a set of items using the same scale. There were potentially six, five and three sets of items to be straight-lined on the first three survey screens for a total of 14 items sets.

Skipped items are defined as items presented on a survey screen where the respondent did not provide a response. Missing items are those items on survey screens that were never presented to the respondent, typically because the respondent broke off prior to reaching that screen. Total missing data is the sum of skipped and missed items.

A completed survey is defined as those respondents that completed 95% or more of the total number of items on the survey (total missing data <5%). For this study, we used 103 items for this calculation. We excluded some items from this total if they were conditioned on a previous response or not included in the core survey for all students. The minimum number of items needed to be considered a complete survey is 98.

Survey duration is defined as the length of time in minutes it took the respondent to complete the core survey. Given the extreme upper ranges of duration (presumably due to the respondent leaving their browser open on the final screen), 2.5% of the top duration times were excluded resulting in a maximum duration time of 70 minutes.

NSSE Engagement Indicators represent the multi-dimensional nature of student engagement. Each Engagement Indicator provides valuable information about a distinct aspect of student engagement by summarizing students' responses to a set of related survey questions. In all, there are ten Engagement Indicators that encompass 47 items. Detailed information about each Engagement Indicator can be found here: nsse.indiana.edu/html/engagement_indicators.cfm

Analysis

We calculated adjusted means for total number of straight-lined item sets, total items missing, and duration for incentive and non-incentive groups using ANOVA. The means were adjusted by including student level factors gender and race/ethnicity and institutional factors Carnegie level reclassified as baccalaureate, masters, doctoral, or special focus, and control (public or private).

A columns proportion z-test with a Bonferroni adjustment determined significant differences between groups for those that submitted each screen with no skipped items. A chi-square test was used to determine differences between the two groups and the proportion that completed the survey.

Factor invariance analyses assessed the stability of scale structures across groups. Specifically, we used a multi-group confirmatory factor analysis (MGCFA) for each NSSE scale (aka, Engagement Indicators or EIs) to test measurement invariance across the two groups by class level. Confirming measurement invariance ensures that "psychometric test scores can be attributed to differences in the properties that such tests measure" and that a score relates "to the same set of observations in the same way in each group" (Borsboom, 2006). The ten EIs analyzed included: Higher-Order Learning (HO); Reflective & Integrative Learning (RI); Quantitative Reasoning (QR); Learning Strategies (LS); Collaborative Learning (CL); Discussions with Diverse Others (DD); Student-Faculty Interaction (SF); Effective Teaching Practices (ET); Quality of Interactions (QI); and Supportive Environment (SE).

The MG-CFA for each EI followed several steps. First, a CFA was run separately for each group until the same model fit all groups well. If no model fit groups, measurement invariance was rejected and we pursued no additional testing. Second, assuming a model fit groups well, we then ran tests for configural, metric, and scalar invariance sequentially. Once a lower level of invariance was tested and rejected, we did not proceed with running tests for higher levels of invariance. Scalar invariance signifies the highest level of invariance, while configural is the lowest. Criteria used for determining acceptable model fit was RMSEA <.06, Chi-square p-value >.05, and CFI/TLI >.90. An even higher level of scalar invariance could be achieved when the Chi-square difference test p-values were greater than .05 and ΔCFI was less than .01.

To determine any effect incentives may have had on Engagement Indicator scores, we calculated adjusted means for the incentive and non-incentive groups using MANOVA. The means were adjusted by including student level factors gender and race/ethnicity and institutional factors Carnegie level (reclassified as baccalaureate, masters, doctoral, or special focus) and control (public or private).

Results

Out of the 14 item sets that were eligible for straight-lining, first-year and senior students, regardless of incentive group, straight-lined just over 3 item sets. The presence of incentives did not result in significantly higher occurrences of straight-lining (Table 3). In fact, for both first year and senior students, those in the incentive group straight-lined significantly less than their peers in the non-incentive group. It is important to note that even though both differences are statistically significant, the effect size is near zero, indicating no meaningful effect. Unsurprisingly, the percentage of students straight-lining more than half of the item sets (7+ category) was significantly higher for the no incentive group for both first year and senior students (Figures 1 and 2).

Table 3. Mean number of item sets straight-lined (maximum=14).

	FY students		Seniors	
	No Incentive	Yes Incentive	No Incentive	Yes Incentive
M_{adj}	3.42	3.25	3.55	3.37
SE	.055	.055	.053	.053
F(Sig)	98.66(.001)		187.42(.001)	
ES	.001		.001	

Note: Means were adjusted using the following factors: sex, race/ethnicity, Carnegie level, and control

Figure 1. Percent of respondents straight-lining items sets (First-year students)

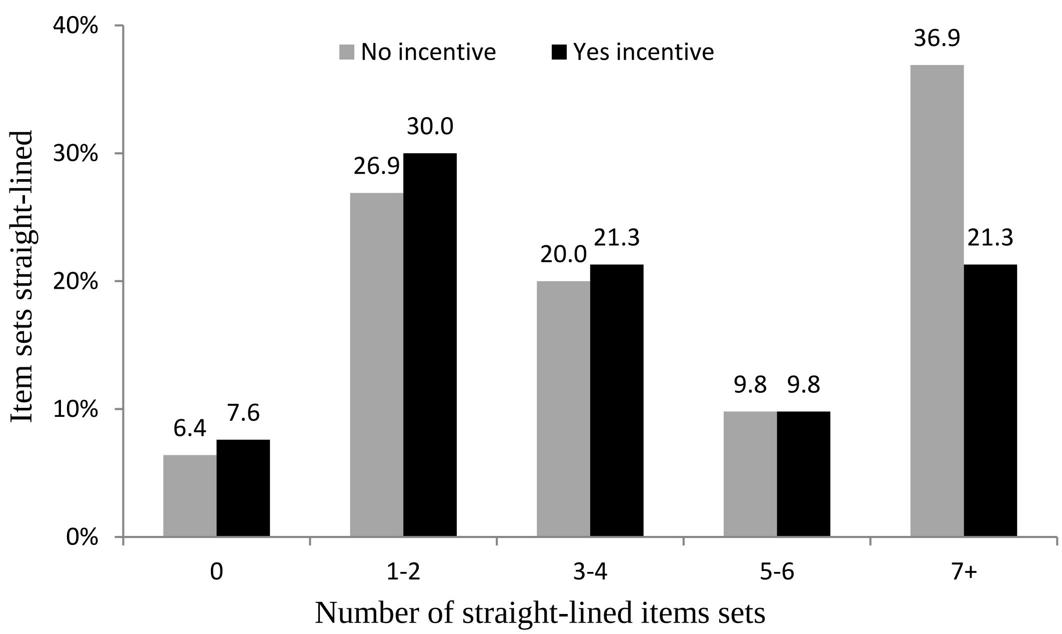
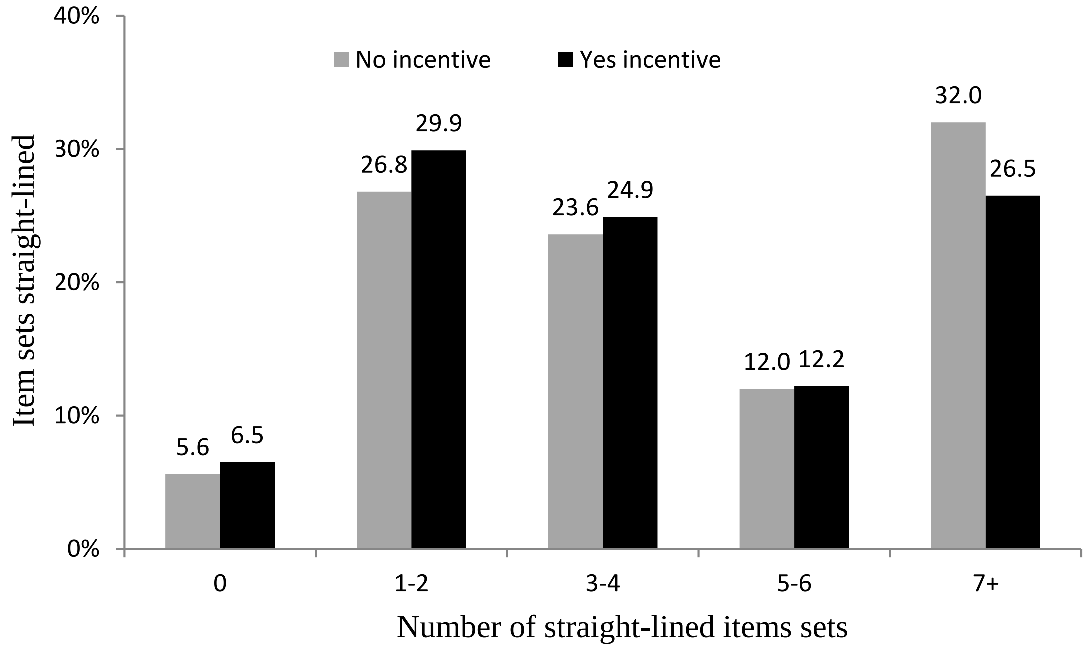


Figure 2. Percent of respondents straight-lining items sets (Senior students)



For both first year and senior students, each screen submitted by respondents in the incentives group was significantly more likely to have no skipped items ($p<.05$) (Figures 3 and 4). For example, first-year students offered an incentive were significantly more likely to submit Screen 4 with no skipped items compared to their peers at institutions that did not offer an incentive (73.6% vs 68.4%, $p<.05$).

Figure 3. Screen submits (first-year students)

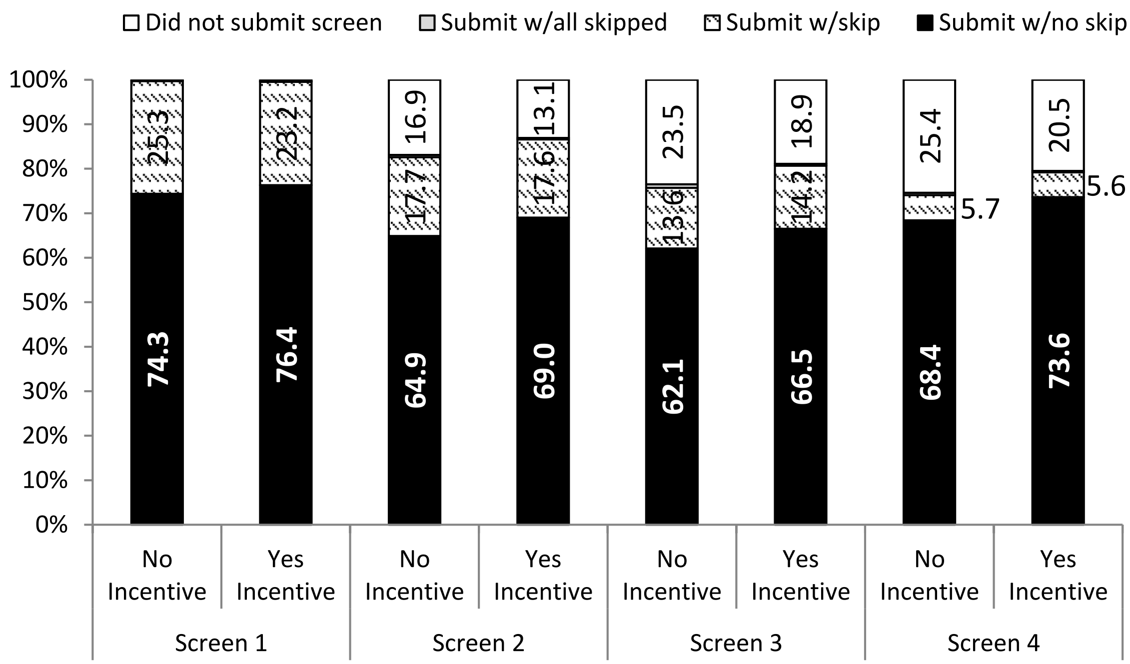
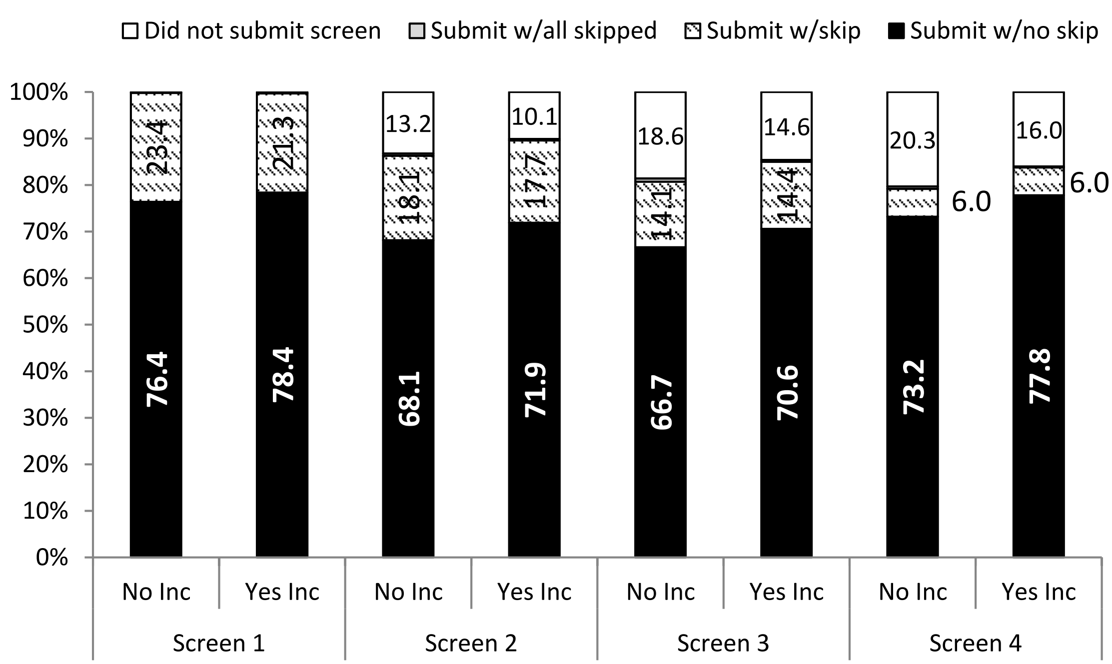


Figure 4. Screen submits (senior students)



First year and senior incentive students had significantly less total missing data than their no-incentive peers (Table 4). Though the effect size is small for both mean differences, incentive students had on average about 3 fewer items missing compared to no-incentive students.

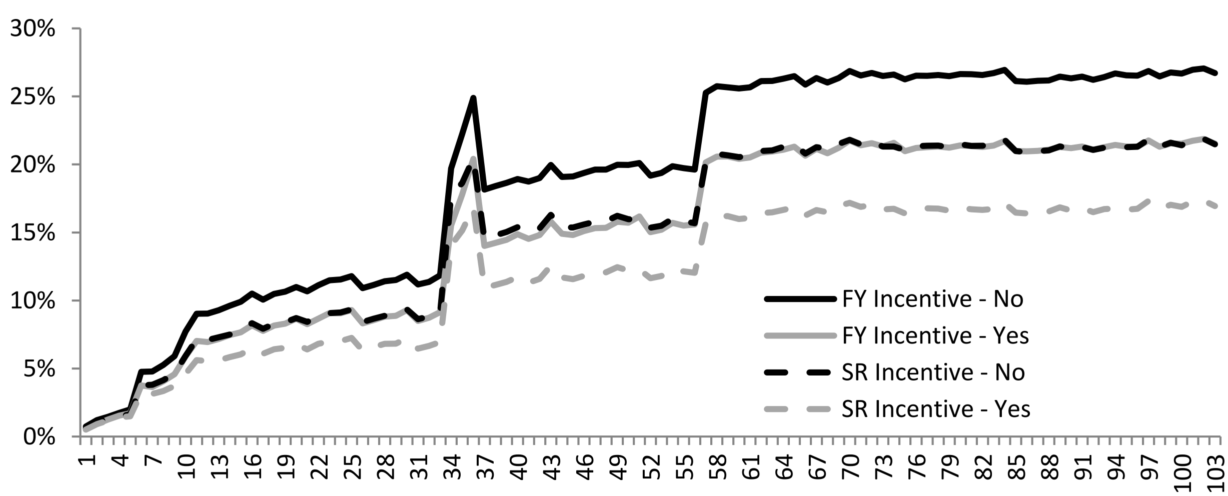
Table 4. Adjusted mean differences in total item missing.

		FY Students		SR Students	
		No incentive	Yes incentive	No incentive	Yes incentive
Missing items	M_{adj}	19.50	15.88	14.83	11.82
	SE	.588	.588	.583	.583
	F(Sig)	440.11(.001)		491.30(.001)	
	ES	.001		.003	

Note: Means were adjusted using the following factors: sex, race/ethnicity, Carnegie level, and control

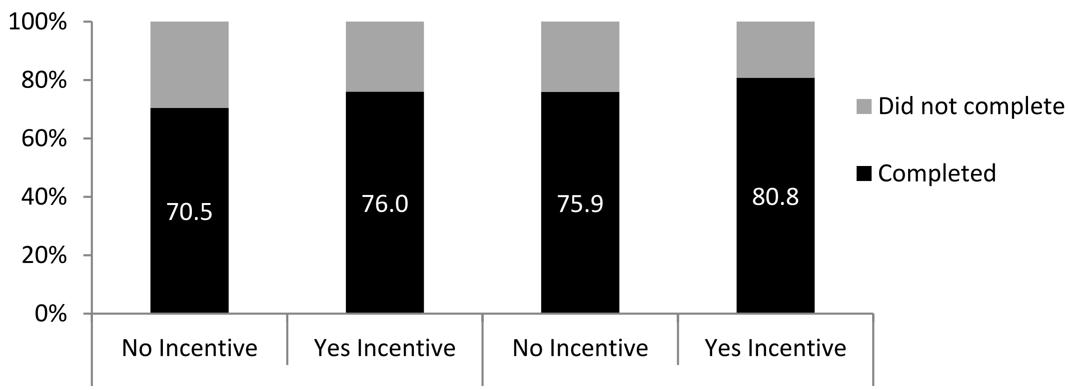
Figure 5 shows total missing items across the survey in order of item appearance on the survey. Across the survey, first-year and senior students at incentive institutions were missing fewer data than those at non-incentive institutions.

Figure 5. Total missing items from break offs and skipping.



Not surprising given the results above, incentive students were more likely to complete at least 95% of survey items (Figure 6). More than three-quarters (76%) of first year students and almost 81% of seniors at incentive institutions completed the survey, about 5% higher than their respective peers.

Figures 6. Percent completing NSSE.



Durations times for incentive students were significantly higher than for non-incentive students. However, effect sizes were near zero indicating no meaningful difference for duration. It is not surprising that duration time is slightly higher for students in the incentive group given that, on average, they completed more items.

Table 5. Adjusted mean duration

		FY Students		SR Students	
		No incentive	Yes incentive	No incentive	Yes incentive
Duration	M_{adj}	13.02	13.13	13.12	13.32
	SE	.175	.175	.192	.190
	F(Sig)	4.41 (.040)		18.79(.000)	
	ES	.000		.000	

Note: Means were adjusted using the following factors: sex, race/ethnicity, Carnegie level, and control

Of particular import for this study was determining whether the NSSE Engagement Indicators are invariant across the two groups (incentive and non-incentive). A multi-group confirmatory factor analysis (MGCFA) was used to calculate fit indices and measurement invariance. As indicated in Tables 3 and 4, the fit indices for 5 of the 10 engagement indicators (other 5 are 3-item scales and thus not available for CFA), were generally all acceptable with the one possible exception of QI for first year students. For that scale, CFI and TLA indices are adequate, however the RMSEA and chi-square are not. Measurement invariance (scalar invariance) was achieved for all EI's with the exception of QI for first year students (Table 5).

Table 3. CFA results for FY students.

EI's	CFI	TLI	RMSEA	Chi-Square	p-value (Chi-Square)	df
HO	--	--	--	--	--	--
RI	0.999	0.996	0.039	48.624	.000	6
LS	--	--	--	--	--	--
QR	--	--	--	--	--	--
CL	--	--	--	--	--	--
DD	--	--	--	--	--	--
SF	1.000	1.000	0.009	1.336	.248	1
ET	1.000	1.000	0.013	5.398	.145	3
QI	0.988	0.970	0.076	100.629	.000	4
SE	0.996	0.993	0.053	180.197	.000	15

Cut-off criteria for acceptable fit: TLI/CFI > .90; RMSEA < .06; Chi-square p-value >.05

Table 4. CFA results for senior students.

EI's	CFI	TLI	RMSEA	Chi-Square	p-value (Chi-Square)	df
HO	--	--	--	--	--	--
RI	0.999	0.997	0.034	32.143	.000	5
LS	--	--	--	--	--	--
QR	--	--	--	--	--	--
CL	--	--	--	--	--	--
DD	--	--	--	--	--	--
SF	1.000	0.999	0.026	4.097	.043	1
ET	1.000	0.999	0.031	10.938	.031	2
QI	0.997	0.989	0.039	22.628	.000	3
SE	0.997	0.993	0.054	170.714	.000	13

Cut-off criteria for acceptable fit: TLI/CFI > .90; RMSEA < .06; Chi-square p-value >.05

Table 5. Measurement invariance (scalar) results.

	Invariance achieved?	
EI's	First year students	Senior students
HO	Yes	Yes
RI	Yes	Yes
LS	Yes	Yes
QR	Yes	Yes
CL	Yes	Yes
DD	Yes	Yes
SF	Yes	Yes
ET	Yes	Yes
QI	No	Yes
SE	Yes	Yes

MANOVA results indicate very minimal differences in scale scores by incentive group for both first year and senior students (Table 6 and 7). Though adjusted mean differences were sometimes significant, the effect sizes (partial eta squared) were near zero indicating that even the largest mean difference (first year DD scores of 41.6 compared to 42.4) were trivial.

Table 6. Adjusted mean Engagement Indicator scores (first-year students).

EI's	Incentive	M_{adj}	SE	Sig	ES
HO	No	39.7	.29	.095	.000
	Yes	39.9	.29		
RI	No	36.4	.27	.000	.000
	Yes	36.9	.26		
QR	No	26.2	.35	.796	.000
	Yes	26.2	.34		
LS	No	38.7	.30	.856	.000
	Yes	38.7	.30		
CL	No	32.2	.30	.000	.000
	Yes	32.9	.29		
DD	No	41.6	.34	.000	.000
	Yes	42.4	.33		
SF	No	21.4	.31	.774	.000
	Yes	21.4	.31		
ET	No	41.4	.28	.073	.000
	Yes	41.2	.27		
QI	No	41.8	.26	.010	.000
	Yes	41.6	.26		
SE	No	37.4	.29	.079	.000
	Yes	37.2	.29		

Table 6. Adjusted mean Engagement Indicator scores (seniors).

EI's		M_{adj}	SE	Sig	ES
HO	No	42.2	.35	.017	.000
	Yes	42.0	.34		
RI	No	40.3	.32	.886	.000
	Yes	40.3	.32		
QR	No	30.3	.43	.010	.000
	Yes	30.0	.43		
LS	No	40.7	.37	.000	.000
	Yes	40.2	.36		
CL	No	33.0	.36	.000	.000
	Yes	33.7	.36		
DD	No	43.6	.40	.004	.000
	Yes	43.9	.39		
SF	No	26.0	.41	.000	.000
	Yes	26.4	.41		
ET	No	41.8	.34	.000	.000
	Yes	41.4	.34		
QI	No	42.5	.29	.032	.000
	Yes	42.3	.29		
SE	No	33.7	.36	.971	.000
	Yes	33.7	.35		

Discussion

This study set out to investigate potential deleterious effects survey incentives may have on survey data quality. In particular, we wanted to know if the concern raised by Barge and Gehlbach (2012) that incentives may "degrade item-level data quality under certain situations" (p. 197) is a valid one. Theories such as Leverage-Salience Theory and Social Exchange Theory provide causal explanations as to why survey incentives might be effective at increasing response rates, however little empirical information exists about the impact these incentives have on data quality. With so many colleges and universities employing survey incentives these days, addressing this issue becomes critically important, especially for large survey projects such as

NSSE that encourage its participating institutions to use them (NSSE, 2015). Though response rates are generally recognized as *the* data quality indicator, it may be imprudent to use incentives for bolstering response at the expense of other data quality indicators. At the very least, incentive users should be fully aware of any potential tradeoffs, if they do exist.

Overall, this study, using hundreds of thousands of student respondents from over 600 colleges and universities, found little evidence that survey incentives negatively affect data quality. Our analyses showed minimal differences between incentive and non-incentive groups with regard to straight-lining, item skipping, total missing items, and completion. Contradicting Barge and Gehlbach's finding, we found, in fact, that incentive respondents actually had better data quality than non-incentive respondents. Though the effects were small, they consistently favored the incentive student group. Not surprisingly, incentive students were significantly more likely to complete the survey and take slightly more time doing so. The measurement invariance analysis demonstrated that the presence of an incentive does not compromise the validity of Engagement Indicator scores and the underlying factor structures. The one exception was QI for first-year students where we detected variance between the two groups. However, for the 19 other Engagement Indicator comparisons (9 for first year students and 10 for seniors), all scales proved invariant. In addition, we found all mean differences for Engagement Indicators between groups to be trivial. These findings are especially good news for institutions tracking engagement results overtime where they may use incentives inconsistently from one administration to the next.

This study is not without its limitations. For example, incentive institutions and their students may be different from others in ways that could influence the current results. Institutions using incentives may be doing other things to increase participation (using promotional posters, coordinating recruitment efforts across campus, etc.) which could affect satisficing behavior. These institutions may also be more committed to assessment and convince students in their recruitment messages that they will use the information they provide, which then in turn leads students to commit themselves more fully to the survey taking process. Though not explored in this study, we also know that considerable variation exists between institutions' average total missing items, regardless of incentive usage. It would be prudent to investigate why some institutions show more (sometimes much more) satisficing behaviors than others. For the institutions that use incentives, could these differences be explained by the types of incentives being offered? Different incentives appear to influence response rates in different ways (Sarraf & Cole, 2014). Given LST and SET theories, we hypothesize that incentive type could also influence satisficing behaviors in different ways as well. For this reason, we encourage others to conduct experiments whereby students are randomly assigned to groups with and without incentives, leaving all other administration aspects identical.

For now, the current study's findings with such a robust sample should allay any serious concerns NSSE users may have about incentives undermining data quality. Whether this finding and others are generalizable to other higher education assessment instruments is unknown at this time. These results suggest that the current literature generally indicating no effects when using incentives may not apply to all surveys.

References

Barge, S., & Gehlbach, H. (2012). Using the theory of satisficing to evaluate the quality of survey data. *Research in Higher Education, 53*, 182-200.

Blair, E. and Burton, S. (1987), Cognitive processes used by survey respondents to answer behavioral frequency questions, *Journal of Consumer Research, 14*, 280-288.

Cobanoglu, C., & Cobanoglu, N. (2003). The effect of incentives in web surveys: Application and ethical considerations. *International Journal of Market Research, 45*, 475-488.

Deutskens, E., Ruyter, K. D., Wetzels, M., & Oosterveld, P. (2004). Response rate and response quality of internet-based surveys: An experimental study. *Marketing Letters, 15*, 21-36.

Dey, E. (1997). Working with low survey response rates: The efficacy of weighting adjustments. *Research in Higher Education, 38*, 215-227.

Dillman, D.A. (1978). *Mail and telephone surveys: The total design method.* New York: Wiley.

Fosnacht, K., Sarraf, S., Howe, E., & Peck, L. (2013). *How important are high response rates for college surveys?* Paper presented at the Association for Institutional Research Annual Forum, Long Beach, CA.

Groves, R. M., Singer, E., & Corning, A. (2000). Leverage-salience theory of survey participation: Description and an illustration. *Public Opinion Quarterly*, *64*, 299–308.

Heerwegh, D. (2006). An investigation of the effects of lotteries on web survey response rates. *Field Methods, 18,* 205-220.

Hutchison, J., Tollefson, N., and Wigington, H. (1987). Response bias in college freshman's responses to mail surveys. *Research in Higher Education, 26*, 99–106.

Kaminska, Olena, Bart Goeminne and Marc Swyngedouw. *Satisficing in Early Versus Late Responses to a Mail Survey*. Midwest Association for Public Opinion Research (MAPOR). Chicago, Illinois, November, 2006.

Keusch, F., Batinic, B. and Mayerhofer, W. (2014) Motives for joining nonprobability online panels and their association with survey participation behavior, in *Online Panel Research: A Data Quality Perspective* (eds M. Callegaro, R. Baker, J. Bethlehem, A. S. Göritz, J. A. Krosnick and P. J. Lavrakas), John Wiley & Sons, Ltd, Chichester, UK.

Krosnick, J.A., Narayan, S. and Smith, W.R. (1996). Satisficing in surveys: initial evidence. *New Directions for Evaluation, Vol 70,* Issue 70, 29-44.

Laguilles, J. S., Williams, E. A., & Saunders, D. B. (2011). Can lottery incentives boost web survey response rates? Findings from four experiments. *Research in Higher Education, 52*, 537-553.

Medway, R. L., & Fulton, J. (2012). When More Gets You Less: A Meta-Analysis of the Effect of Concurrent Web Options on Mail Survey Response Rates. *Public Opinion Quarterly, 76*, 733-746.

NSSE—National Survey of Student Engagement. (2015, May). Survey Incentive FAQ. Retrieved from http://nsse.indiana.edu/html/survey_incentive_FAQ.cfm

Pike, G. (2008). Using weighting adjustments to compensate for survey nonresponse. *Research in Higher Education, 49,* 153-171.

Sarraf, S, & Cole, J. S. (2014). Survey lottery incentives and institutional response rates: An exploratory analysis. Paper presented at the annual conference of the Association for Institutional Research, Orlando, FL.

Schaeffer, N.C. and Presser, S. (2003). The science of asking questions. *Annual Review of Sociology, 29*, 65-88.

Singer, E., & Ye, C. (2013). The use and effects of incentives in surveys. In D. S. Massey, & R. Tourangeau (Eds.), *The ANNALS of the American Academy of Political and Social Science* (pp. 112–141). London, England: Sage.

Toepoel, V. (2012). Effects of incentives in surveys. In L. Gideon (Ed.), *Handbook of survey methodology for the social sciences* (pp. 209–223). New York, NY: Springer.