The Power of Logos: Assessing the Impact of Organizational Branding on Email Survey Response Rates

Young Hoon Kim, Raymond Fang, Morgan Yung, Forrest Kim

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Abstract

This paper examines the impact of including organizational logos, specifically Berkeley and MIDS logos, in email surveys on response rates among students, alumni, and faculty in the MIDS program. We hypothesize that the presence of these logos will significantly increase the response rate to the survey compared to an email without the logos. Utilizing a randomized controlled trial (RCT) design, we randomly assign 2,000 participants to either a treatment group, receiving an email with the survey link and the logos, or a control group, receiving an email with just the survey link. The emails are sent out in two separate batches, two days apart, to account for potential confounding factors. We analyze the data using causal inference estimators, such as Average Treatment Effect (ATE), Intent-to-Treat (ITT), and Complier Average Causal Effect (CACE), to determine the causal impact of the logos on the response rate. Our findings contribute to the understanding of the effectiveness of organizational logos in email communications and provide insights into strategies for enhancing survey participation.

1. Introduction

In today's digital age, online surveys have become a popular approach for collecting data due to its ability to easily reach a large sample size at a low cost. However, response rates for online surveys have declined in recent years (Saleh, A., & Bista, K. (2021)). To increase response rates, various strategies have been employed, including the use of incentives, catchy headlines, and the inclusion of logos or symbols in email invitations to participate in the survey.

The purpose of this study is to investigate whether the inclusion of a school's [UC Berkeley's] logo in an email invitation to participate in a survey will increase response rates compared to a standard email invitation without a logo. Previous research has suggested that the inclusion of logos or symbols in email invitations may increase response rates. For example, Schaefer and Dillman (1998) found that the use of a company logo in a mailed survey increased response rates compared to a survey without a logo. Similarly, Salisbury and Karrh (2009) found that the use of a company logo in email invitations increased response rates compared to email invitations without a logo. While these findings suggest that the use of logos can potentially increase response rates in surveys, it is still unclear if this effect extends to email invitations for online surveys.

We hypothesize that the inclusion of a school logo in an email invitation to complete a survey will result in a higher response rate compared to a standard email invitation without a logo. One potential reason for this is that a school logo can serve as a visual cue that reminds potential respondents of their affiliation with the school, which may increase their motivation to participate in the survey. In addition, the school logo may enhance the perception of authority or legitimacy of the survey and the email invitation, which may potentially increase response rates (Schaefer and Dillman, 1998). We believe that the addition of a school logo in an email invitation to participate in a survey has the potential to increase response rates.

2. Preliminary Knowledge

In this section, we review the key causal inference theories that underpin our experimental design. Understanding these concepts is essential for interpreting the results of our study and assessing the causal impact of organizational logos on email survey response rates.

2.1. Randomized Controlled Trials (RCTs)

Randomized controlled trials (RCTs) are a gold standard experimental design for establishing causal relationships between variables. In an RCT, participants are randomly assigned to either a treatment or a control group, ensuring that any differences in outcomes between the groups can be attributed to the treatment. By eliminating potential confounding factors and selection biases, RCTs provide robust evidence for causal inference.

2.2. Average Treatment Effect (ATE)

The Average Treatment Effect (ATE) is a key causal inference parameter that quantifies the expected difference in outcomes between the treatment and control groups. It measures the average effect of the treatment on the entire population under study. ATE is useful for understanding the overall impact of an intervention, such as the inclusion of organizational logos in email surveys. Mathematically, ATE is defined as:

$$ATE = E[Y(1) - Y(0)] \tag{1}$$

where E denotes the expectation, Y(1) represents the potential outcome for the treated group, and Y(0) represents the potential outcome for the control group.

2.3. Intent-to-treat (ITT)

The Intent-to-Treat (ITT) analysis is an approach that includes all participants in the study, regardless of whether they received the intended treatment or not. It is defined as:

$$ITT = E[Y|Z = 1] - E[Y|Z = 0] \tag{2}$$

where Z denotes the *intention to treat* on the outcome variable . ITT is important for maintaining the benefits of randomization and minimizing biases due to noncompliance or attrition. In our experimental context, the ITT analysis allows us to include all participants in the analysis, ensuring that our results are less biased and more generalizable.

2.3.1 ITT_D

The ITT_D is the effect of being assigned to treatment, on *receiving a dose of treatment*. In other words, it is an estimate of the causal effect of the treatment for a specific subgroup of compliers, i.e., individuals who comply with their assigned treatment only under certain conditions. ITT_D is defined as:

$$ITT_D = E[d_i|z_i = 1] - E[d_i|z_i = 0] \tag{3}$$

The ITT_D can be viewed as a weighted average of the individual treatment effects for the compliers in the population. ITT_D is important in the context of our experimental design because it allows us to estimate the treatment effect for a specific subgroup of participants who actually comply with the treatment under certain conditions, such as when receiving the email with the logo. By incorporating the ITT_D into our analysis, we can gain a more nuanced understanding of the causal relationship between the treatment and the outcome for this particular subgroup of interest.

2.4. Complier Average Causal Effect (CACE)

The Complier Average Causal Effect (CACE) is an estimate of the causal effect of the treatment on the population of compliers, i.e., individuals who comply with their assigned treatment. It is defined as:

$$CACE = \frac{ITT}{ITT_D} = \frac{E[Y|Z = 1] - E[Y|Z = 0]}{E[d_i|z_i = 1] - E[d_i|z_i = 0]} \tag{4}$$

CACE is important because it allows us to estimate the treatment effect for a specific subgroup of participants who actually comply with the treatment. In our experimental context, the CACE represents the difference in survey response rates between the treatment and control groups for those who opened the email. This allows us to better understand the effect of the treatment on the subpopulation of interest, providing more specific insights into the effectiveness of the treatment.

Understanding these causal inference concepts and their importance is essential for designing robust experiments and interpreting the results accurately. By incorporating these concepts into our experimental design, we can make more informed conclusions about the causal relationship between the treatment and the outcome.

3. Experimental Design

3.1. Hypothesis

The main hypothesis of this study is that the presence of an organization logo, such as the Berkeley and MIDS logos, in an email significantly increases the response rate to the survey compared to an email without the logos.

3.2. Variables

In an experimental design, the independent variable is the factor that is manipulated or controlled by the researcher, while the dependent variable is the outcome that is measured. Identifying these variables is crucial for understanding the cause-and-effect relationship between them and establishing the validity of the hypothesis.

3.2.1 Independent Variable

The independent variable in this study is the presence of Berkeley and MIDS logos in the email. These logos represent the organizational affiliation and are hypothesized to have an impact on the participants' engagement with the survey.

3.2.2 Dependent Variable

The dependent variable in this study is the response rate to the survey. This metric is used to measure the effectiveness of the intervention, which is the presence or absence of the logos in the email.

3.3. Data Collection

Data for this experiment are collected from students (including alumni) and faculty in the MIDS program. To track email engagement, we utilize MixMax (a sales-engagement platform) to distribute and track email open rates. For the survey, we use Qualtrics (a survey platform) to track participation. The data collected include open rate and response rate to the survey for both the treatment and control groups.

3.4. Randomized Sampling

To ensure a 95% confidence interval, participants are randomly assigned and evenly split between the treatment group and the control group. The sample size is determined based on the total number of participants available and the desired level of precision for the results. Participants are defined as any email recipient that has opened the email.

3.5. Experimental Design

We have structured our experimental design into five comprehensive phases to ensure a systematic approach, enabling a valid and reliable evaluation of the hypothesis. Our design also allows for robust causal inference, as it takes into account potential biases and confounding factors. Each phase is described in greater detail below:

3.5.1 Recruitment and Randomization

During the recruitment process, we draw participants from a diverse pool within the MIDS program, including current students, alumni, and faculty members. This varied group helps increase the generalizability of the findings. We systematically gather contact information from the program's Slack channels to maintain an up-to-date list of potential participants.

Upon compiling the list of participants, we employ a random number generator to randomly assign each individual to either the treatment or control group. This randomization process helps minimize selection bias and ensures that both groups have similar baseline characteristics, thus increasing the internal validity of the study.

3.5.2 Intervention

In the intervention phase, we craft distinct emails for both the treatment and control groups. For the treatment group, we include the survey link, Berkeley and MIDS logos in the email, while the control group receives an email with just the survey link. By keeping the emails as similar as possible, except for the presence of the logos, we can isolate the effect of the independent variable on the response rate.

3.5.3 Data Collection

In the data collection phase, we send out the survey emails in two separate batches, with a 2-day interval between them. This staggered approach allows us to monitor any unexpected issues that may arise during the process and make necessary adjustments for the second batch, ensuring the quality of the data collected. Additionally, the time gap between batches helps to mitigate the risk of potential confounding factors, such as external events or changes in participants' attitudes, which could influence their responses.

By carefully tracking email open rates and survey responses, we can identify and filter out unread emails, focusing our analysis on the participants who opened the emails. We give participants up to two weeks to participate in the survey, providing ample time for them to respond at their convenience.

The data collection process contributes to causal inference in our experiment by maintaining the integrity of the random assignment of participants to the treatment and control groups. Through diligent monitoring and the staggered approach in sending the surveys, we ensure that the data collected accurately reflects the impact of the independent variable on the response rate, allowing us to draw robust causal conclusions.

3.5.4 Data Analysis

During the data analysis phase, we focus on two primary metrics: the open rate and the survey response rate for both the treatment and control groups. Analyzing both of these metrics enables us to gain a deeper understanding of the impact of the independent variable on participants' behavior.

To establish causal inference in our analysis, we consider the Average Treatment Effect (ATE), which represents the average difference in outcomes between the treatment and control groups. Calculating the ATE allows us to quantify the effect of the presence of logos on the response rate.

Complementary to the ATE analysis, we also examine the Complier Average Causal Effect (CACE), which estimates the causal effect of the treatment for the subpopulation of participants who complied with their assigned treatment. This analysis helps refine the causal inferences by accounting for any potential non-compliance with the assigned treatment.

By conducting these analyses, we can establish the causal relationship between the presence of logos in the email and the response rate to the survey. Our use of rigorous statistical methods, such as the paired t-test, ensures the reliability and validity of our findings and strengthens our causal inferences.

3.5.5 Results

In the final phase, we display the response rates for both the treatment and control groups, considering the open rates and the survey response rates separately. By doing so, we can provide a more comprehensive understanding of the impact of the presence of Berkeley and MIDS logos in the email.

We also present the causal estimators, such as Average Treatment Effect (ATE) and Complier Average Causal Effect (CACE), which highlight the causal relationships in our experiment. These estimators allow us to assess the effectiveness of the logos in increasing survey participation while accounting for potential confounding factors and non-compliance.

We interpret the results and discuss the strength of the causal inference drawn from our experiment, ultimately determining if our hypothesis - that the presence of Berkeley and MIDS logos in the email significantly increases the response rate to the survey - is supported or not. The results will be displayed using tables and graphs, making it easy for the audience to visualize and understand the findings.

In summary, our experimental design is comprehensive and robust, allowing us to make valid causal inferences regarding the impact of the presence of organization logos (i.e. Berkeley and MIDS) in an email on the response rate to the survey. By addressing potential biases and confounding factors, we ensure the reliability and validity of our findings.

4. Analysis

In this section, we present a detailed analysis of the experimental data. Our goal is to determine whether the presence of organizational logos significantly affects the email survey response rates. We use several statistical tests to ensure the robustness of our findings and employ different causal inference techniques to estimate the treatment effect.

4.1. Exploratory Data Analysis

Before delving into our main analysis, we conducted an exploratory data analysis (EDA) to better understand the data and identify any patterns or trends. This process allowed us to gain insights into the data and informed our subsequent analysis.

4.1.1 Open Rate Analysis

Our initial exploration focused on the open rate of emails in the control and treatment groups, as shown in Figure 1. We observed a slightly higher open rate in the treatment group compared to the control group. However, this difference was likely due to chance, as no intervention was applied to the email recipients concerning opening the email we sent out.

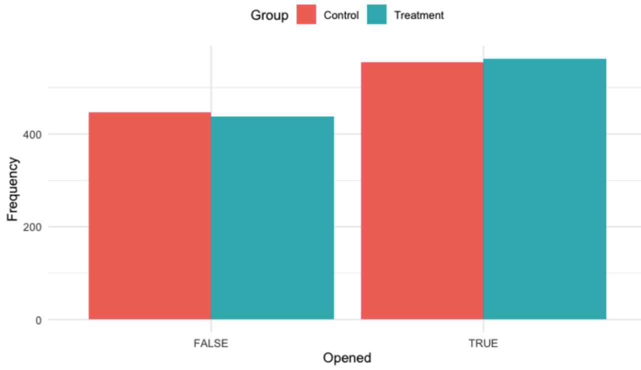

Figure 1: Opened Emails in Control and Treatment Groups

4.1.2 Survey Response Analysis

We then examined the number of survey responses in both the treatment and control groups. As depicted in Figure 2, the treatment group had a higher number of responses than the control group, although the difference was less than 10. This finding provided a preliminary indication of the potential effect of our treatment on survey response rates.

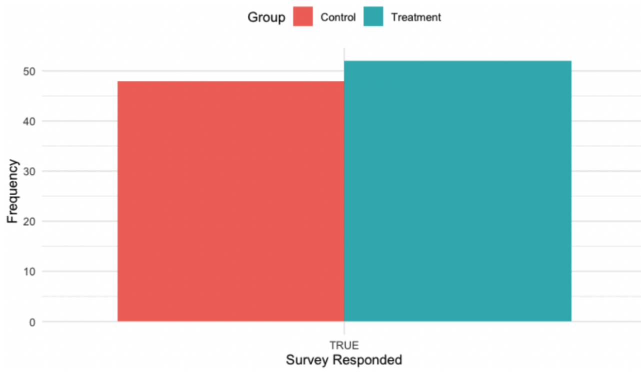

Figure 2: Survey Responses in Control and Treatment Groups

4.1.3 Survey Duration Distribution Analysis

Lastly, we analyzed the distribution of survey durations in both groups. We employed the Kullback-Leibler (KL) divergence metric to assess any meaningful differences between the two groups.

The KL divergence result was 2.5366 with a p-value of 0.6815, suggesting that although the treatment group's duration distribution demonstrated a higher concentration of durations less than 1000 seconds, there was no statistically significant difference between the two groups (Figure 3).

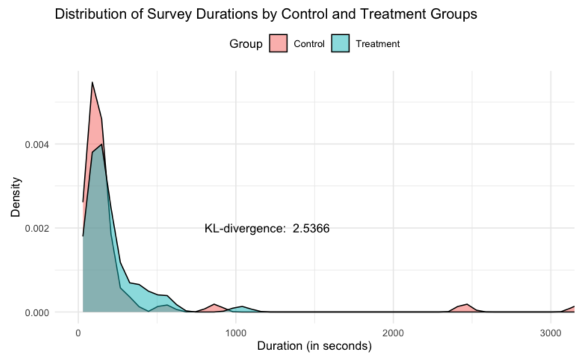

Figure 3: Distribution of Survey Durations by Control and Treatment Groups

In summary, our exploratory data analysis provided an initial understanding of the data, revealing some interesting trends that warranted further investigation. Although the differences observed in open rates, survey responses, and survey durations were not statistically significant, they informed our subsequent analyses and helped shape the direction of our study.

4.2. Preliminary Checks for Unobserved Heterogeneity

Before analyzing the treatment effect, we first examine if there is any unobserved heterogeneity between the treatment and control groups in terms of email open rates. Using a t-test, we obtain an open rate of 55.4% for the control group and 56.2% for the treatment group, resulting in a p-value of 0.719. Since the p-value is greater than our designated threshold of 0.05, we conclude that there is no significant unobserved heterogeneity between the two groups.

4.3. Complier Average Causal Effect (CACE)

We filter out participants who did not open the email to determine the CACE on the survey response rate. The control group has a response rate of 8.66%, while the treatment group has a response rate of 9.25%, resulting in a CACE of 0.61%. Using a t-test, we obtain a p-value of 0.731. As the p-value is greater than 0.05, we fail to reject the null hypothesis, indicating no significant difference between the control and treatment groups in terms of survey response rates.

4.4. Average Treatment Effect (ATE) and Regression Analysis

We perform an Ordinary Least Squares (OLS) regression to verify our t-test results and estimate the ATE. The regression analysis shows a 0.4% increase in survey response rate when comparing the entire treatment group to the control group. The p-value associated with the ATE is 0.682, indicating that the ATE is not statistically significant.

	Dependent variable:
	responded_to_survey
treatment	0.004
	(0.010)
	p = 0.682
Constant	0.048***
	(0.007)***
	p = 0.000
Observations	2,000
R^2	0.0001
Adjusted R^2	−0.0004
Residual Std. Error	0.218 (df = 1998)
F Statistic	0.168 (df = 1; 1998)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 4: OLS Survey Experiment - ATE

4.5. CACE Regression Analysis

Next, we filter the data to include only participants who opened the email and perform an OLS regression to estimate the CACE. The results show a 0.6% increase in response rate and a p-value of 0.732. Consistent with our previous findings, the CACE is not statistically significant, indicating no significant difference between the treatment and control groups.

	Dependent variable:
	responded_to_survey
treatment	0.006
	(0.017)
	p = 0.732
Constant	0.087***
	(0.012)***
	p = 0.000
Observations	1,116
R^2	0.0001
Adjusted R^2	−0.001
Residual Std. Error	0.286 (df = 1114)
F Statistic	0.118 (df = 1; 1114)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 5: OLS Survey Experiment - CACE

Table 1: T-test Results

Metric	Open Rate		Survey Response Rate	
	Control	Treatment	Control	Treatment
Mean	0.5540 (0.4973)	0.5620 (0.4964)	0.0866 (0.2816)	0.0925 (0.2900)
T-statistic	-0.3600		-0.3439	
Degrees of Freedom	1997.9929		1113.7408	
P-value	0.7189		0.7310	
Confidence Interval	(-0.0516, 0.0356)		(-0.0395 , 0.0277)	

4.6. Summary of Findings

Figure 4 presents the results of the OLS regression for ATE, figure 5 shows the results for the CACE, and Table 1 displays the t-test statistics for both email open rates and response rates. Across all tests, we find no significant difference between the treatment and control groups in terms of email survey response rates. Thus, we conclude that the presence of organizational logos does not have a significant impact on survey participation.

5. Suggestions for Further Research

5.1. Potential Bias Within This Study

The purpose of our experiment was to focus on creating a controlled study that measured a causal effect that can be reasonably supported. As a result, the scope and generalizability of our findings are limited to the specific constraints and assumptions of our study. Most importantly, our participants included those from the UC Berkeley School of Information slack. While the student population within our cohort is diverse, it is not an ideal sample of the general population. Furthermore, our experimental design has some bias assuming users are English speaking, with enough means to attend graduate education, and are not visually or otherwise impaired to restrict their ability to discern email and logos. As conscious data scientists, we do not want to perpetuate existing systemic bias, so we refrain from making more general claims about our findings that may be exclusionary towards groups other than those included in the study. While this limits the generalizability of our results, it serves to clarify the ways in which further research can improve upon our findings.

5.2. Potential Improvements to the Experimental Design

A larger and more diverse cohort of participants would be the first step to creating a more comprehensive study. Another potential way to increase the treatment effect might be to perform a follow-up designed study that would track survey responses over the course of an email campaign lasting multiple weeks or months. This approach could provide additional insights into the impact of logo presence on response rates and offer a more detailed understanding of user behavior in relation to logos in email communications. Furthermore, exploring variations in logo design, placement, or size may reveal different effects on survey response rates, allowing for a more nuanced understanding of the role of logos in email-based surveys.

6. Conclusion

In this study, we aimed to investigate the causal effect of including a logo in survey invitation emails on the response rate among students, alumni, and educators at UC Berkeley School of Information. Our experimental design, analysis, and results, however, showed no statistically significant difference between the treatment and control groups with respect to both open rates and survey response rates.

Although the treatment effect in our experiment was less than 1%, the findings provide valuable insights for future research. The study highlights the importance of understanding the context and audience when designing survey invitation emails, as well as the need to consider potential biases and limitations in the experimental design. Our results suggest that, at least for the population in our study, the presence of a logo does not have a substantial impact on survey response rates.

Future research should focus on expanding the sample size and diversity of the participants, as well as exploring the impact of other design factors, such as logo variations, placement, and size, on survey response rates. Additionally, conducting follow-up studies that track survey responses over a longer period, such as multiple weeks or months, could provide further insights into the relationship between logos and user behavior in email-based surveys. In conclusion, while our study did not find a significant effect of logo presence on survey response rates, it serves as a starting point for further exploration and investigation into the role of logos and other design elements in email communications.

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