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A Meta-Analysis of the Effects of Incentives on Response Rate in Online Survey Studies

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A META-ANALYSIS OF THE EFFECTS OF INCENTIVES ON RESPONSE RATE IN ONLINE SURVEY STUDIES

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Abstract

Meta-analysis was used to investigate the effect of incentives on response rates of web-based survey studies. Whereas numerous meta-analyses that address the effect of incentives on increasing response rates in survey studies are available in the literature, these analyses are based on mail surveys, so there is a need for an applied meta-analysis to examine the effect of incentives on response rates in online survey studies. A meta-analysis of an online method of survey administration was used because the use of online surveys has greatly increased, making web-based survey administration an important form of data collection in multiple fields of research. Out of 12 located experimental published studies, nine studies met the selection criteria. Log-odds ratio (OR) was chosen as the main effect size estimator. The result of the heterogeneity Q test showed a statistically significant heterogeneity among these studies around the mean effect size Odds Ratio = 1.72, Q (18) =70.16, p < .0001. Sample size, participants' description, number of reminders, and type and amount of incentives were investigated as potential moderators. The results indicate significant differences between groups, based on amount of incentives, which means that it was a significant predictor of effect size, $p < 0.05$. No evidence was found for relationship between response rate and sample size, participants' description, number of reminders, or type of incentives. Finally, sensitivity analysis related to dependence in the sample is discussed.

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Table of Contents

A Meta-analysis of the Effects of Incentives on Response Rate in Online Survey Studies

Introduction

In survey methodology, three common methods are used to collect data: face-to-face interviews, phone interviews, and mail surveys. However, during the last two decades the methods have clearly changed with breakthroughs of new computer-based administration methods. These methods include audio computer-assisted self-interviewing (ACASI), which became a popular replacement for face-to-face interviews; interactive voice response (IVR), which is an electronic way to collect data using phones; and Web surveys, which look like conventional mail surveys (Fricker, Galesic, Tourangeau, & Yan, 2005). Further, Dillman (2002) states that there are five methods of survey administration that are widely used: "face-to-face procedures, telephone interviews, mail surveys, internet surveys, and touchtone entry (or IVR) surveys" (p.476). He also believes that prospective survey studies are more likely to use different methods of survey administration for different studies than to replace traditional methods with recent ones. Therefore, the choice of survey method depends on the study that a researcher is conducting. According to Fowler (2012),

> The choice of data collection mode, mail, telephone, the Internet, personal interview, or group administration, is related directly to the sample frame, research topic, characteristics of the sample, and available staff and facilities; It has implications for response rates, question form, and survey costs (p.68).

Web-based surveys have become a very common tool of scientific research recently. In 1999 Sheehan and Hoy (as cited in Cook, Heath, & Thompson 2000) estimated that the number of Internet users would double every 100 days and by 2005 one billion of the Earth's population would be web- intelligent. On the other hand, some researchers do not recommend online survey administration to conduct survey research due to problems of using the Internet alone. The main concern is about the response rates of web-based surveys due to unequal opportunities to access the Internet for some populations. Thus, Web survey research differs from mail surveys in the fact that it usually targets specific populations who have Internet access such as university students and company employees (Shih & Fan, 2008). Yet, with improvements in technology, the online survey provides numerous advantages over other types of survey administration. These advantages include: low cost, easy to administer and manage, and a faster and more secure way to collect data (Cook, Heath, & Thompson 2000; Eysenbach & Wyatt, 2002).

Literature Review

Response Rates

Response rate is an essential parameter to evaluate the effort of data collection in research studies. It can be calculated by dividing the number of respondents by the number of people sampled. The denominator includes all people in the target population including people who did not complete the survey for some reason such as noncompliance, language barrier, sickness, or lack of availability (Fowler, 2012). In the literature, consistent studies indicating low response rates of web-based surveys compared to other survey modes can be found. For example, a meta-analysis comparing the response rates of web-based surveys to other modes found that web surveys yield an 11% lower response rate than the other modes (Manfreda, Bosnjak, Berzelak, Haas, & Vehovar, 2008). Moreover, multiple studies comparing the response rates of online surveys to mail, or face-to-face questionnaires, indicated that response rate in Internet surveys is often lower than the response rate in other data collection methods (Couper, 2001; Dillman & Bowker, 2001; Petchenik &Watermolen, 2011; Shin & Fan 2008).

Although the number of web users has increased with a growing use of online surveys administered, response rates declined especially in web-based surveys, which raised concerns about multiple problems such as less accuracy, less statistical power, potential bias of the results, and less reliable studies (Van Horn, Green & Martinussen, 2009). Response rates in online surveys can differ depending on the targeted population.

For instance, professionals who work for a particular organization usually have work-related email addresses and can be more easily reached to participate in Internet surveys. On the other hand, it is difficult in web-based surveys to have a representative sample of the general public because not everyone has an email address or is able to constantly access the Internet (Carrozzino-Lyon, McMullin, & Parkhurst, 2013). Low response rates raised the problem of nonresponse error in survey administrated studies. According to Pedersen and Nielsen (2014), "Survey nonresponses reduce the effective sample size and may easily involve that an obtained survey sample is unrepresentative of a larger population" (p.229). Further, Hox and deLeeuw (1994) explain potential bias of surveys' results due to nonresponse issues as follows:

> Research results can be biased if the nonresponse is nonrandom, and if it is in some way correlated with the variables measured in the survey. Since the process leading to nonresponse is usually unknown, it is often optimistically assumed that when the response is high, there is no serious nonresponse bias. Thus, a high response rate is viewed not only as desirable, but also as an important criterion by which the quality of a survey is judged (p.330).

The reasons for lower response rates in a web-based method than in telephone mode, for example, are related to the nature of self-administered online surveys (Vehovar, Manfreda, & Batagelj, 2001). Fricker (2005) believes that the reason for low response rates in web-based surveys is that individuals find it harder to refuse or ignore phone survey requests than mail or internet invitations. Further, taking online questionnaires requires more effort than answering questions on the phone (as cited in Manfreda et al., 2008). Obtaining a high rate of response from participants is very important to increase the validity of the findings and to be able to generalize the outcomes of the study (Erwin & Wheelright, 2002). Therefore, researchers have been trying to provide optimal response-facilitation methods to increase response rates. One popular method that has encountered significant consideration in the literature is the use of incentives (Church, 1993; Van Horn, Green & Martinussen, 2009).

Incentives

According to Laguilles, Williams, and Saunders (2011), “Within the survey research literature, the term “incentive” has been used in reference to both material (and often tangible) and non-material (and non-tangible) rewards associated with survey participation” (p.541). The literature on mail surveys confirms that the most influential factors to improve response rate and quality are follow-ups and incentives (Deutskens, De Ruyter, Wetzels, & Oosterveld, 2004). Moreover, a recent systematic review conducted by Singer and Ye (2013) about the use and effect of incentives in surveys concluded that “incentives increase response rates to surveys in all modes” (p.134). Meanwhile, some researchers argue that the use of incentives generate some potential issues related to the survey validity. For example, providing incentives may motivate particular types of participants to complete the survey, which yields a biased sample. Another concern is that some individuals may become entirely motivated by the incentive and give multiple responses which yield more than one response from the same individual. Finally, the use of incentives may cause fast responses without respondents paying attention to the questions being asked (Göritz, 2006b). Nevertheless, Helgeson, Voss, and Terpening (2002) conducted a study about mail survey respondents’ decision process as well as the variables that affect this process using a hierarchy-of-effects model. The decision to complete a mail survey was modeled as a process moving through many steps. Several variables that influence the survey-completion decision process were examined and the result showed that incentive is an element in each level of the model.

The use of incentives in survey studies depends on a huge range of circumstances that is related to the incentive condition, the probability and time of receiving incentive, their type, method of delivery, amount, type of target population, etc. The most common categories are pre-incentives (unconditional) and post-incentives (conditional) (Sánchez-Fernández, Muñoz-Leiva, Montoro-Ríos, & Ibáñez-Zapata, 2010). In the literature, multiple studies indicated that pre-paid or provided incentives more strongly influence the response rate to mail surveys. For instance, Green and Hutchinson (1996) conducted a meta-analysis reviewing the research on mail survey response rates. In their review of the impact of incentives on response rate of mail surveys, they examined two meta-analyses conducted by Hopkins and Gullickson (1992) and Church (1993). They stated,

> Hopkins and Gullickson found an average increase of 19% (95% CI: 17%, 22%) with enclosed incentives and an average 7% (95% CI: 3%, 12%) with promised incentives. Church found a 24% average increase for enclosed incentives. Both studies found a significant relationship between amount of the enclosed monetary gratuity and response rate (p.2).

Most pertinent to this study, Jia-ming and Pei-ji (2010) stated that in Web surveys there are many kinds of incentives that can be used and they can be classified into two categories: material incentives and nonmaterial incentives. Furthermore, in their three meta-analyses to examine the effects of material incentives, promised material incentives, and contingent material incentives on Web survey completion, the result indicated that all three types of incentives motivated participants to complete Web-based surveys with average increase of 16%, 14%, and 12% respectively.

There is extensive evidence in the literature that response rates to mail questionnaires are increased by the use of material incentives, especially when they were provided to participants in advance and in large amounts (Church, 1993; Collins et al., 2000; Shank et al., 1990). On the other hand, the effect of pre-paid incentives on response rates for web-surveys is unclear. In fact, some studies found that pre-paid incentives have no influence on response rates for web-surveys (Downes-Le Guin et al., 2002; Heerwegh et al., 2006; Kypros and Gallagher, 2003) while a meta-analysis conducted by (Cook et al., 2000) indicated lower response rates associated with the use of incentives. Yet, they explained that this paradox might occurred because participants involved in very long or uninteresting surveys perceived the necessity of receiving big prizes for survey completions.

In institutional researchers, lottery-based incentives were used as an effort to reduce non-response in student surveys even though there is an absence in the survey research literature of theoretical or empirical evidence of their effectiveness. Likely motivated by the difficulty of using per-paid incentives in web-based surveys comparing to mail surveys, the use of lotteries as incentives in Web surveys seems a quite common practice in higher education and marketing research (Porter, & Whitcomb, 2003). Laguilles et al. (2011) conducted four experiments to investigate the effectiveness of lottery incentives on Web survey response rate. Their results suggested that lottery incentives increased Web survey response rate with differences in response rates between their treatment and control groups ranging from 5% to 10%. They explained that these differences are not negligible differences in the language of response rates saying:

> For example, the 6.6 percentage point difference in response rates for the IT survey translates into a gain of nearly one hundred respondents. Secondly, across all four surveys, respondents in the treatment groups were less likely to drop out of the survey than respondents in the control groups. Thus, it appears that lottery incentives can positively impact both survey response and survey completion rates (p.549).

Purpose of the Study

The effect of incentives in mail surveys is extensively covered in the literature. There are some experimental studies of the effect of incentives in online surveys. Yet they are limited by being specific to a certain target population, survey topic, or the implementation procedure applied. Therefore, the global effect of incentives on Web based surveys response rates is not clear. A need thus exists for a meta-analytic approach, quantitatively synthesizing the available studies of the effects of incentives on response rate in the online method of data collection. Such an approach would show on an aggregate level whether incentives in web surveys actually influence response rate. The focus of this paper is on two types of online surveys email and Web- based surveys. Therefore, the present meta-analysis provides a recent estimate of the effect of using incentives on response rates in web-based survey studies. Additionally, it examines the impact of multiple moderators on response rates.

Problem Statement

The problem for this study was: What relationship, if any, exists between response rates of web-based survey design and incentives?

Research Questions

The research questions were:

1. Is there a significant difference in response rates between surveys that used incentives and that did not use incentives?
2. What are the relationships, if any, between response rate and sample size, participants' description, number of reminders, and type and amount of incentives?

Method

Sample of Published Studies

The review of the literature included an electronic search of two databases, PsycInfo; and ABI/INFORM Collection, that were anticipated to contain experimental studies of the effects of incentives on response rate in web-based surveys. The Google Web search engine was also employed to prevent potential publication bias and find as many studies as possible. The initial key word combinations that were used were "survey," "questionnaires," "web-based survey," "online questionnaires," "email survey," "survey and response rates," and "incentives." To collect more studies, a second-level backward reference search was conducted by looking at the reference list to find other sources that had been cited in the initial study. Mendeley software was used to manage the reference list and to easily access each study.

Studies taken into account in this meta-analysis met the following criteria: (1) experimental studies with treatment and control groups; (2) written in English; (3) authors reported response rates or other data from which completion numbers of control group and treated group could be calculated. The search resulted in 12 published studies ranging from 2003-2016. The researcher imposed a limiter to identify experimental studies that contained treatment and control groups. Therefore, three studies were excluded from the sample because either they lacked control groups or enough information to obtain an effect size was not provided. Response rates of 19 surveys were used as multiple studies reported more than one experiment. In this case, dependency was taken into consideration since some studies conducted more than one experiment with the same control group. The effect of dependency on the results of this meta- analysis was assessed through a sensitivity analysis procedure.

Coding Procedure

From each study, the following variables were extracted: author, publication year and type, and quality of the study. In addition, sample size, response rates, total number of participants in control groups, number of completion in control groups, total number of participants in treated groups, and number of completion in treated groups were coded. In order to perform moderator analyses, it was necessary to obtain some related characteristics that may explain variation in the effect size across studies. These characteristics include participants' description, number of reminders, and type and amount of incentives. These characteristics were coded as categorical moderators. Type of incentives was coded as 1: Lottery, 2: Pre-paid, 3: Post-paid, 4: Promised, 5: Mixed, and 6: Extra credits while incentives amounts were coded into two categories 1: $50 and less, and 2: more than $50. These amounts were chosen because the sample studies contained multiple types and amounts of incentives ranging from $2-$250. Most of the high amounts of incentives were lotteries type. Table 1 shows incentives' types and amounts for studies included in this meta-analysis.

Table:1

Incentives' Type and Amount by Study

Study	Type of incentive	Amount of incentive
Laguilles et al. (2011)	Lottery	T1 iPod Nano ($150)
		T2 Dining gift cards ($50)
		T3 iPod Touch ($230)
		T4 iPod Touch ($230)
Parsons and Manierre (2014)	Pre-paid	$2
Cobanoglu and Cobanoglu (2003)	T1 Pre-paid	Luggage Tag (LT) NA
	T2 Lottery	Personal digital assistant (PDA) NA
	T3 Pre-paid + Lottery	(LT+PDA) NA
Brown et al. (2016)	Post-paid	$5
Bosnjak and Tuten (2003)	T1 Pre-paid	$2
	T2 Promised	$2
	T3 Lottery	$25 and $50
DeCamp and Manierre (2016)	Promised	T1 $2
		T2 $5
Gajic et al. (2011)	T1 Pre-paid	$2
	T2 Lottery	$25
	T3 Lottery	$250
Magro et al. (2015)	Extra credit	NA

Wilson et al. (2010)	Promised	12 $

Note. NA= not applicable or no value was provided

For the purpose of examining coding reliability, another qualified coder coded four random studies of the studies used in this meta-analysis (44%of the sample). The initial codebook and coding form are found as Appendix A and Appendix B. The inter-rater reliability was calculated using the agreement rate method (AR). This method is the most common way to assess the reliability of the coding process. It can be simply calculated by dividing the number of studies in which the coders (two coders or more) agreed with the same coding characteristics by the number of assigned studies for coding (Orwin & Vevea, 2009 as cited in Card 2012). The initial agreement rates were 75% and after issues were resolved, raters reached 100% agreement.

Analysis

In experimental psychology, there are three families of effect size estimators: differences, correlations, and ratios (Rosnow & Rosenthal, 2003). The focus of this meta-analysis is the effect of incentives compared to no incentives on response rate. Therefore, odd ratio (OR) was chosen as the main effect size estimator. If OR ≤1, incentives show no advantages over no incentives, and the effect of incentives is not significant. On the other hand, if OR > 1 and is statistically significant, it shows incentives can motive potential participants to complete surveys. The odds ratio was calculated using Equation 1 with A, B, C, D cells defined in Table 1.

$$OR = \frac{A/B}{C\ /D} \tag{1}$$

Table:2

Odds Ratio Calculation

	Not-completed	Completed	OR
Control	A	B	Equation 1
Treatment	C	D	

The Q test, which computes the amount of heterogeneity in effect sizes among studies, was calculated using a random-effects model. The transformed effect size was the dependent variable and coded characteristics of the sample studies were independent variables. A moderator analysis was also performed using meta-ANOVA (Card, 2012). Finally a sensitivity analysis was conducted by running the model with studies that had one effect size and excluded studies that provided more than one outcomes to find out whether dependency effected the overall result.

Results

Since the purpose of this meta-analysis was to find out whether there was a difference in response rate between incentive and no incentive groups, and then generalize the findings of this sample of studies to the population, a random- effects rather than a fixed-effects model was more appropriate for this study (Card, 2012). Therefore, a random-effects model was used to examine the effects of incentives. Figure 1 shows the individual and overall effect sizes (and 95% confidence interval = .24 to .53) of the impact of incentives (forest plot). The aggregate effect size was 0.39 representing an overall average increase in response rate of 8.6% between the incentive and control conditions. The result of the Q test showed statistically significant heterogeneity among these studies $Q_{(18)}$ =70.16, $p < .0001$. Therefore, analysis to explain part of that heterogeneity were performed.

Moderator analysis was conducted using meta-ANOVA to find out if sample size, participants' description, number of reminders, and type and amount of incentives were statistical significant moderators that contributed to the variation of the effect size across studies. Table 2 shows the results of ANOVA between group random-effects models that indicate significant, $p < 0.05$ differences between groups only for the amount of incentives, $Q(2)$ =7.29, p < .0001.

The results of sub-groups analysis for the amount of incentives as a statically significant moderator demonstrated that studies with an amount of incentives that was higher than $50 had higher response rates (OR = 1.65, 95% confidence limits: 1.50 and 1.81) than studies with incentives that were less than $50 (OR = 1.35, 95% confidence limits: 1.16 and 1.58). In other words, there was a 30% difference between response rates of the two groups. No evidence was found for differences between groups with sample size, participants' description, number of reminders, and type of incentives as moderators.

Table:3

Moderator Analysis Results

Moderator	Q test value	df	*p*
Sample size (N)	16.83	9	0.05
Participants' description	2.76	3	0.43
Number of reminders	3.85	4	0.42
Type of incentives	8.08	5	0.15
Amount of incentives	7.29	2	0.02

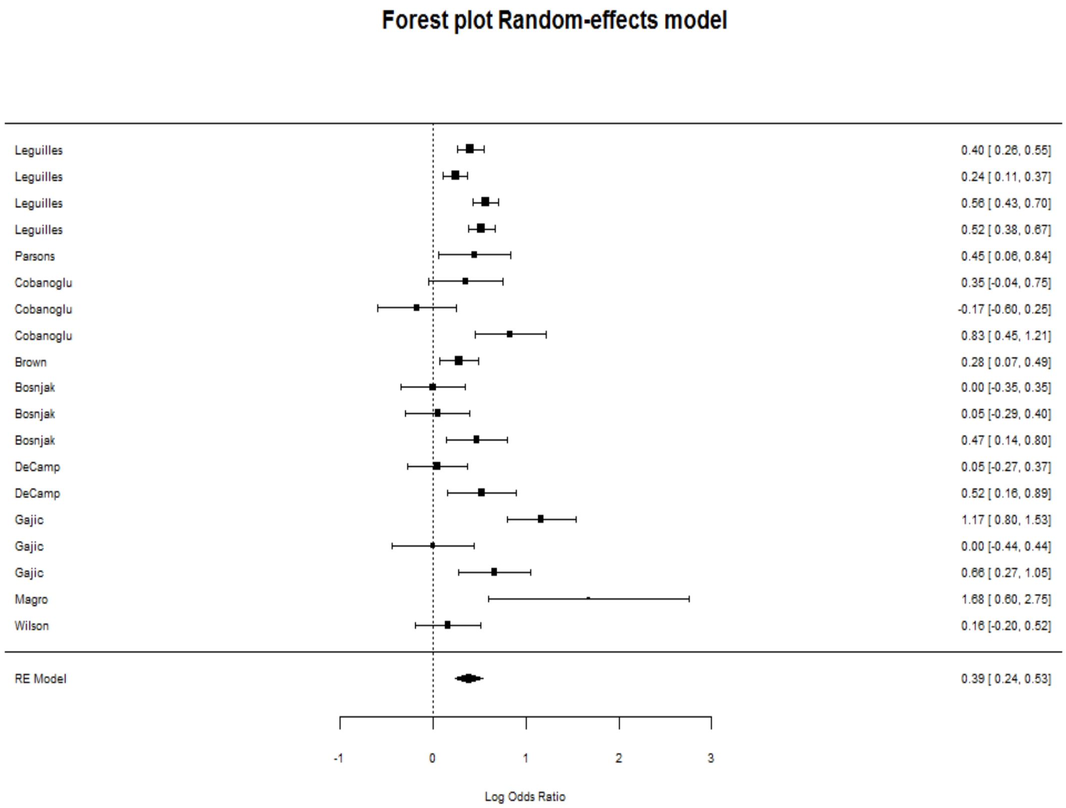

Figure 1. Forest Plot

Sensitivity Analyses

Dependency was an issue with the sample of studies included in this meta-analysis. It occurred because the included studies reported results for two and three treatment groups compared to the same control group. Because the same control group participants were included in each treatment/control comparison, the resulting effect sizes are statistically dependent. To address this issue a variable distinguishing studies that provided more than one effect size was added. This variable was coded as 1= yes, 2=no. A regression model was used to test for relationship between this variable and effect size. The result was not statically significant, $p = 0.88$.

Publication Bias

Meta-analysis is a quantitative analysis that aims to summarize and compare the results of different studies. It is threatened by publication bias, which is also called the file drawer problem. Publication bias is a wide spread issue that impacts the validity of meta-analysis studies. Using multiple techniques to deal with publication bias helps to improve the validity of the meta-analysis. Thornton and Lee (2000) explained the effect of publication bias as follows:

> The existence of publication bias is now widely accepted. Attempts to summarize evidence relating to a specific hypothesis, whether by narrative review or meta-analysis, can be seriously distorted by publication bias. For example, one recent analysis estimated that 45% of an observed association could be due to publication bias (p. 207).

Rosenthal (1979) stated an extreme view about the file drawer problem, saying; "journals are filled with the 5% of the studies that show Type I errors, while the file drawers are filled with the 95% of the studies that show nonsignificant results" (p.638). Therefore, steps were taken in order to test for publication bias.

According to Card (2012), "One of the best methods to evaluate the potential impact of publication bias is to include unpublished studies in the meta-analysis and empirically evaluate whether these studies yield smaller effect sizes than published studies" (p.262). Thus, the researcher conducted a wide search in Google and Google Scholar for unpublished articles such as unpublished dissertations, conference papers, books, etc. However, no experimental studies were located that could be included in this meta-analysis within the study criteria. Thus, bias was tested using the multiple approaches explained by Card (2012). First, the funnel plot method, which was initially introduced by Light and Pillemer (1984), was used to provide a visual evaluation of bias in the sample studies used in this meta-analysis. This method simply provides a scatter plot of the effect size of the studies related to their sample size. In this graphic, standard error is on the y-axis and effect size is on the x-axis. If the funnel plot shows asymmetry, that indicates the need for more studies with large samples to yield a symmetric plot. From Figure 2 it is obvious that there was publication bias in the sample studies' funnel plot because the two sides of the plot were not balanced. Card (2012) stated that using this approach with small size meta-analysis is challenging because it raises concerns of being a subjective judgment of publication bias.

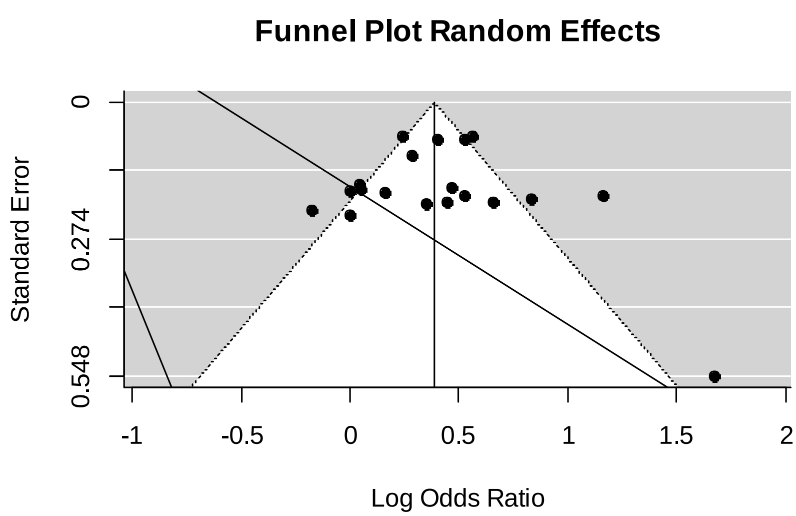

Figure 2. Funnel Plot

In addition, the formal statistical tests Egger's regression and rank correlation were used to test for asymmetry. In the Egger's linear regression test, the standard normal deviate is regressed on precision, defined as the inverse of the standard error. If the result of this linear regression indicates a significant intercept, publication bias is present. The results indicated the absence of publication bias because they were not statistically significant, $F(1,18) = 1.1031$, $p > 0.05$. The rank correlation test for the correlation between the effect size and the standard errors, in which a significant correlation indicates publication bias was not significant. The Kendall's tau value = 0.0409, $p > 0.05$, indicates absence of publication bias.

To find out whether the effect is entirely an artifact of bias, the Orwin Fail-Safe N technique that was introduced by Orwin (1983) was conducted. According to Borenstein (2005), this method will allow the researcher to “determine how many hidden studies would bring the overall effect to a specified level other than zero” and “specify the mean effect in the hidden studies as being some value other than nil” (p. 197). The result of this approach suggested that 19 additional studies would bring the effect size to a nonsignificant level.

Discussion

Sheehan and McMillan (1999) indicated that there are many reasons for survey methodologists to be concerned about improving response rates of electronic surveys:

> To date, response rates for e-mail surveys appear to be somewhat lower than those of traditional mail surveys. . . . Therefore, to begin to assess ways to increase this rate should be of key importance to researchers wishing to utilize this new mode of survey delivery (p.48).

A meta-analysis of nine experimental studies was conducted to examine the effectiveness of incentives in general on Web survey response rates. Since results showed significant heterogeneity among the effect size estimates, the use of incentives contributed to differences between studies. In addition, several moderator variables were coded to determine whether they could explain the variability among the effect size estimates. Of the variables coded, amount of incentives resulted in significant differences between group's effect sizes. The results of participants' description, number of reminders, and incentive type were particularly interesting because no statically significant differences were found between groups. Whereas in Church's (1993) meta-analysis on thirty-eight experimental and quasi-experimental studies concluded an average increase in mail response rates when using prepaid monetary incentives. In this meta-analysis no evidence were found for association between incentive type and response rate. This meta-analysis result indicated that the use of incentives increased response rates of web-based surveys by 8.6%. This increase is small comparing to the use of incentives in mail surveys that yield 19% and 24% increase with enclosed incentives.

Further analysis where the data was organized by type of incentive (see appendix D) show no clear indication of different trends, based on incentive type.

In addition, the result showed that studies that used incentive amounts higher than $50, which were lotteries type, had response rates of 30% more than studies that used incentives of less than $50. Compared to mail surveys, however, using the Internet to deliver pre-paid incentives is harder, and the impact of a pre-paid versus promised incentive in Web surveys may be different. According to Dykema et al. (2011), "more current research indicates that incentives of increasingly larger amounts (i.e., $50 or $100) may be needed to secure participation, even for mail surveys" (p.436).

Based on these results the researcher would recommend that in order to increase response rate for web-based surveys the use of incentives and higher amounts of incentives (more than $50) is encouraged. The result of this meta-analysis did not find evidence of relationship between response rate and type of incentive. Therefore, the use of lottery incentives with amounts that are higher than $50 should be more investigated considering that it is difficult to provide incentives for participants of online surveys in advance, and it is not cost effective to provide $50 for all participants.

Limitations

When planning a meta-analysis, the researcher developed a set of inclusion criteria that indicated the types of studies that would be included. Ideally, the researcher would be able to locate all studies that meet the criteria. Even with the advantage of electronic searching, it is likely that some studies that met the meta-analysis criteria escaped the search and were not included in the analysis. In addition, due to the limited number of experimental studies of the effect of incentives for online surveys, no unpublished studies were included in this meta-analysis. Although, the result of Egger's linear regression test and the rank correlation test were not significant, it is possible that the result was effected by not including unpublished studies and by the small sample size. The result of comparisons in this meta-analysis were made at the aggregate level.

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Appendix A

Coding Book

Note: 0 = N/A, Not Reported, or No for all coding categories

Research study identification

Author(s) (authors' names – last names)
Year of publication
Publication type:

1. Journal
2. Dissertation or Thesis
3. Conference paper
4. Report
5. Other

Study Quality:

1. Published
2. Unpublished

Sample characteristics:

Sample size N (values)
Sample description

1. Physicians
2. students
3. Employee
4. Mixed

Sample Method

1. Random
2. Not random

Incentives characteristics:

Incentives Type

1. Lottery
2. Pre-paid
3. Post-paid
4. Promised
5. Mixed

6. Extra credits

Multiple incentives in study

1. Yes
2. No

Incentives amount

1. 50$ and less
2. More than 50$

Number of reminders (values)

Response rates (values)

Number of participants in control groups (values)

Number of completion in control groups (values)

Number of participants in treated groups (values)

Number of completion in treated groups (values)

Appendix B
Coding Form

Note: 0 = N/A, Not Reported, or No for all coding categories

Study Identification

ID code #____

Research study identification

Author(s) ____
Year of publication__________________________________
Publication type____________________________________
Study Quality______________________________________

Sample characteristics

Sample size N (values) ______________________________
Sample description _________________________________
Sample Method ____________________________________

Incentives characteristics

Incentives Type_______________________________________

Multiple incentives in study_____________________________

Incentives amount _____________________________________

Number of reminders (values) ____________________________

Response rates (values) ____________________________________

Number of participants in control groups (values) ________________

Number of completion in control groups (values) ________________

Number of participants in treated groups (values) ________________

Number of completion in treated groups (values) _________________

Appendix C
Data Output

Random Effects Model

```
Random-Effects Model (k = 19; tau^2 estimator: REML)

  logLik  deviance       AIC       BIC      AICc
 -7.3807   14.7613   18.7613   20.5421   19.5613

tau^2 (estimated amount of total heterogeneity): 0.0725 (SE = 0.0333)
tau (square root of estimated tau^2 value):      0.2692
I^2 (total heterogeneity / total variability):   81.69%
H^2 (total variability / sampling variability):  5.46

Test for Heterogeneity:
Q(df = 18) = 70.1517, p-val < .0001

Model Results:

estimate       se     zval     pval    ci.lb    ci.ub
  0.3879   0.0734   5.2868   <.0001   0.2441   0.5317      ***

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> confint(proportion.random)

       estimate   ci.lb   ci.ub
tau^2    0.0725  0.0360  0.3060
tau      0.2692  0.1899  0.5532
I^2(%)  81.6851 68.9310 94.9588
H^2      5.4600  3.2186 19.8365
```

Run a meta-analysis for all the data

```
Number of studies combined: k = 19

                         OR            95%-CI     z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:
     Q d.f.  p-value
  70.16   18 < 0.0001
```

Moderators Analysis

Reminders

```
Number of studies combined: k = 19

                         OR            95%-CI     z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:
     Q d.f.  p-value
 70.16   18 < 0.0001

Results for subgroups (fixed effect model):
            k     OR            95%-CI     Q    tau^2   I^2
group = 3   6 1.5151 [1.4173; 1.6197] 18.77   0.0205 73.4%
group = 2   5 1.2896 [1.1269; 1.4759]  6.08   0.0133 34.2%
group = 0   4 1.5346 [1.2288; 1.9165] 17.31   0.274  82.7%
group = 1   3 2.0052 [1.6028; 2.5088] 15.86   0.2862 87.4%
group = 4   1 1.1739 [0.8218; 1.6768]  0.00       --    --

Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
Between groups   13.18    4   0.0104

Results for subgroups (random effects model):
            k     OR            95%-CI     Q    tau^2   I^2
group = 3   6 1.4894 [1.2948; 1.7133] 18.77   0.0205 73.4%
group = 2   5 1.2856 [1.0812; 1.5286]  6.08   0.0133 34.2%
group = 0   4 1.7299 [0.9641; 3.1039] 17.31   0.274  82.7%
group = 1   3 1.8556 [0.9706; 3.5473] 15.86   0.2862 87.4%
group = 4   1 1.1739 [0.8218; 1.6768]  0.00       --    --

Test for subgroup differences (random effects model):
                    Q d.f.  p-value
Between groups   3.85    4   0.4272

Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
```

Sample Size

```
Number of studies combined: k = 19

                         OR            95%-CI     z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]
```

```
Test of heterogeneity:
     Q d.f.  p-value
 70.16   18 < 0.0001

Results for subgroups (fixed effect model):
               k     OR             95%-CI     Q    tau^2   I^2
group = 3000   3 1.4635 [1.3495;  1.5871]  8.02   0.0155 75.1%
group = 4000   1 1.7572 [1.5349;  2.0116]  0.00       --    --
group =  458   1 1.5676 [1.0620;  2.3139]  0.00       --    --
group = 1006   3 1.4510 [1.1553;  1.8223] 11.88   0.206  83.2%
group = 1388   1 1.3256 [1.0725;  1.6384]  0.00       --    --
group = 1332   3 1.1995 [0.9861;  1.4590]  4.52   0.038  55.7%
group = 1000   2 1.2816 [1.0074;  1.6304]  3.68   0.083  72.8%
group = 2913   3 2.0052 [1.6028;  2.5088] 15.86   0.2862 87.4%
group =   75   1 5.3478 [1.8260; 15.6622]  0.00       --    --
group =  485   1 1.1739 [0.8218;  1.6768]  0.00       --    --

Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
Between groups   27.30    9   0.0012

Results for subgroups (random effects model):
               k     OR             95%-CI     Q    tau^2   I^2
group = 3000   3 1.4717 [1.2507;  1.7318]  8.02   0.0155 75.1%
group = 4000   1 1.7572 [1.5349;  2.0116]  0.00       --    --
group =  458   1 1.5676 [1.0620;  2.3139]  0.00       --    --
group = 1006   3 1.4085 [0.8019;  2.4739] 11.88   0.206  83.2%
group = 1388   1 1.3256 [1.0725;  1.6384]  0.00       --    --
group = 1332   3 1.1938 [0.8884;  1.6042]  4.52   0.038  55.7%
group = 1000   2 1.3189 [0.8263;  2.1050]  3.68   0.083  72.8%
group = 2913   3 1.8556 [0.9706;  3.5473] 15.86   0.2862 87.4%
group =   75   1 5.3478 [1.8260; 15.6622]  0.00       --    --
group =  485   1 1.1739 [0.8218;  1.6768]  0.00       --    --

Test for subgroup differences (random effects model):
                     Q d.f.  p-value
Between groups   16.83    9   0.0514

Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
```

Participants' description

```
Number of studies combined: k = 19

                         OR            95%-CI     z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:
     Q d.f.  p-value
 70.16   18 < 0.0001

Results for subgroups (fixed effect model):
```

```
             k     OR            95%-CI     Q    tau^2   I^2
group = 2    8 1.5238 [1.4270; 1.6272] 24.06   0.0241 70.9%
group = 3    7 1.2812 [1.1171; 1.4693] 18.16   0.0705 67.0%
group = 1    1 1.3256 [1.0725; 1.6384]  0.00       --    --
group = 4    3 2.0052 [1.6028; 2.5088] 15.86   0.2862 87.4%

Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
Between groups   13.03    3   0.0046

Results for subgroups (random effects model):
             k     OR            95%-CI     Q    tau^2   I^2
group = 2    8 1.5247 [1.3237; 1.7561] 24.06   0.0241 70.9%
group = 3    7 1.2761 [1.0029; 1.6239] 18.16   0.0705 67.0%
group = 1    1 1.3256 [1.0725; 1.6384]  0.00       --    --
group = 4    3 1.8556 [0.9706; 3.5473] 15.86   0.2862 87.4%

Test for subgroup differences (random effects model):
                    Q d.f.  p-value
Between groups   2.76    3   0.4303

Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
```

Incentive Type

```
Number of studies combined: k = 19

                         OR           95%-CI     z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:
     Q d.f.  p-value
 70.16   18 < 0.0001

Results for subgroups (fixed effect model):
             k     OR             95%-CI     Q    tau^2   I^2
group = 1    4 1.5360 [1.4329;  1.6466] 13.19   0.0171 77.2%
group = 2    1 1.5676 [1.0620;  2.3139]  0.00       --    --
group = 5    9 1.4898 [1.3171;  1.6851] 42.75   0.1602 81.3%
group = 3    1 1.3256 [1.0725;  1.6384]  0.00       --    --
group = 4    3 1.2464 [1.0208;  1.5218]  3.86   0.0292 48.1%
group = 6    1 5.3478 [1.8260; 15.6622]  0.00       --    --

Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
Between groups   10.47    5   0.0629

Results for subgroups (random effects model):
             k     OR             95%-CI     Q    tau^2   I^2
group = 1    4 1.5395 [1.3303;  1.7815] 13.19   0.0171 77.2%
group = 2    1 1.5676 [1.0620;  2.3139]  0.00       --    --
group = 5    9 1.4578 [1.0902;  1.9494] 42.75   0.1602 81.3%
group = 3    1 1.3256 [1.0725;  1.6384]  0.00       --    --
group = 4    3 1.2630 [0.9559;  1.6689]  3.86   0.0292 48.1%
group = 6    1 5.3478 [1.8260; 15.6622]  0.00       --    --
```

```
Test for subgroup differences (random effects model):
                    Q d.f.  p-value
Between groups   8.08    5   0.1519

Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
```

Incentive Amount

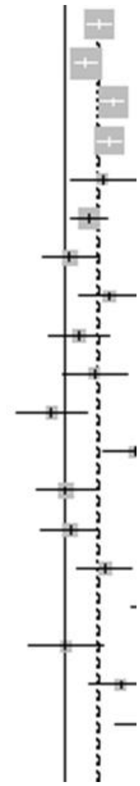
```
Number of studies combined: k = 19

                         OR           95%-CI      z  p-value
Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001
Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:
 tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:
     Q d.f.  p-value
 70.16   18 < 0.0001

Results for subgroups (fixed effect model):
            k     OR           95%-CI     Q    tau^2   I^2
group = 2   3 1.6468 [1.5181; 1.7863]  2.76   0.002  27.4%
group = 1  14 1.3348 [1.2359; 1.4417] 42.75   0.055  69.6%
group = 0   2 2.5106 [1.7526; 3.5964]  2.12   0.1893 52.8%

Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
Between groups   21.73    2 < 0.0001

Results for subgroups (random effects model):
            k     OR           95%-CI     Q    tau^2   I^2
group = 2   3 1.6455 [1.4954; 1.8105]  2.76   0.002  27.4%
group = 1  14 1.3519 [1.1598; 1.5757] 42.75   0.055  69.6%
group = 0   2 2.9991 [1.3854; 6.4924]  2.12   0.1893 52.8%

Test for subgroup differences (random effects model):
                    Q d.f.  p-value
Between groups   7.29    2   0.0262

Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
```

Appendix D
Data Output

Model 1 all

```
model.all <- metabin(tpos, (tpos + tneg), cpos, (cpos + cneg), data=
data1, sm="OR")

summary (model.all)

 Number of studies combined: k = 19

                        OR           95%-CI     z  p-value

Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001

Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001

Quantifying heterogeneity:

  tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

Test of heterogeneity:

     Q d.f.  p-value

 70.16   18 < 0.0001


 Details on meta-analytical method:

- Mantel-Haenszel method

- DerSimonian-Laird estimator for tau^2

forest.meta(model.all, rightcols=FALSE)
```

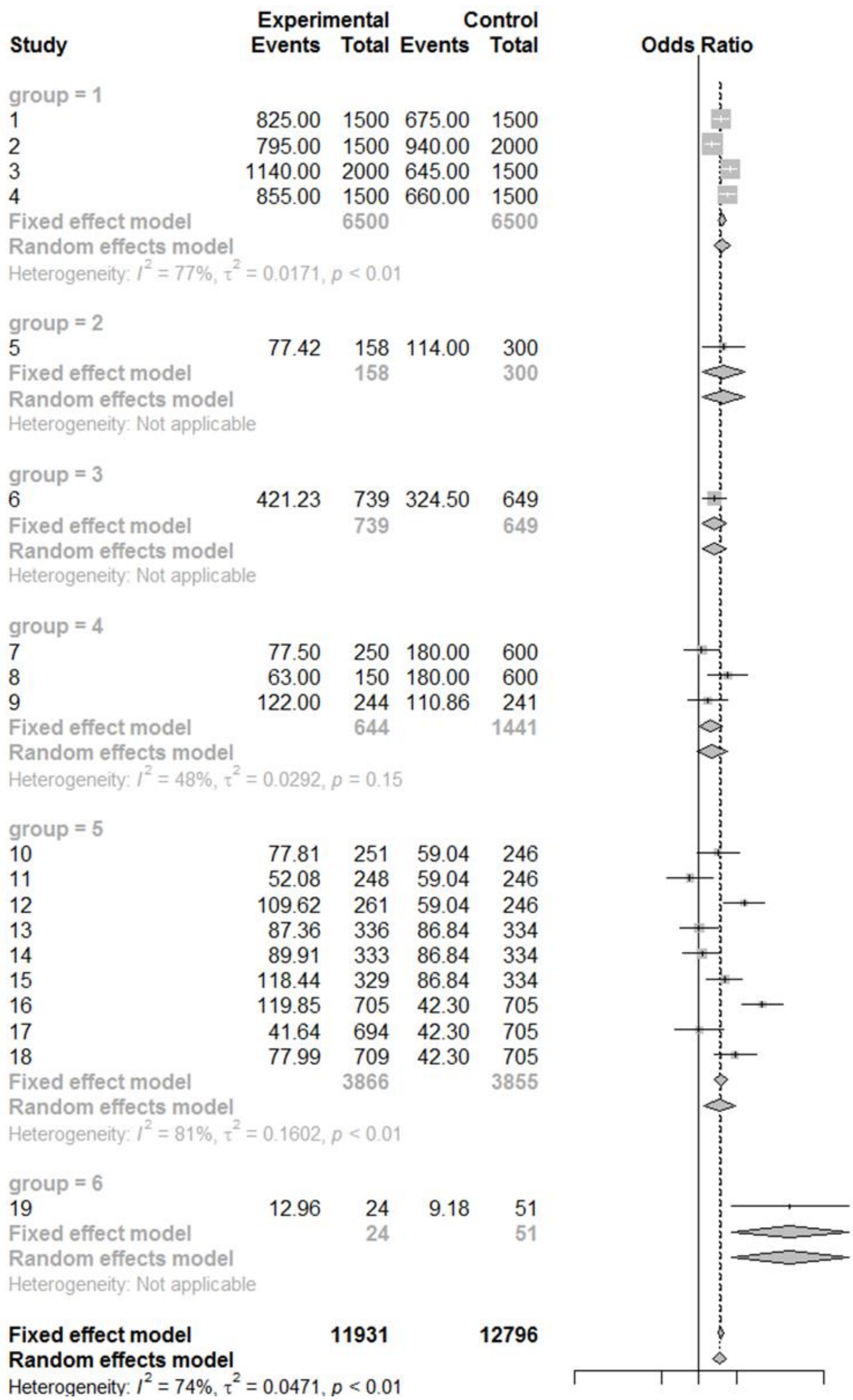
825.00	1500	675.00	1500
795.00	1500	940.00	2000
1140.00	2000	645.00	1500
855.00	1500	660.00	1500
77.42	158	114.00	300
421.23	739	324.50	649
77.50	250	180.00	600
63.00	150	180.00	600
122.00	244	110.86	241
77.81	251	59.04	246
52.08	248	59.04	246
109.62	261	59.04	246
87.36	336	86.84	334
89.91	333	86.84	334
118.44	329	86.84	334
119.85	705	42.30	705
41.64	694	42.30	705
77.99	709	42.30	705
12.96	24	9.18	51



Model 2: ANOVA

```
model.anova <- metabin(tpos, (tpos + tneg), cpos, (cpos + cneg),
byvar=data1$I_type, bylab= "group", data= data1, sm="OR")

summary(model.anova)

 Number of studies combined: k = 19

                        OR            95%-CI     z  p-value

 Fixed effect model   1.4932 [1.4130; 1.5779] 14.24 < 0.0001

 Random effects model 1.4706 [1.3001; 1.6635]  6.13 < 0.0001


 Quantifying heterogeneity:

  tau^2 = 0.0471; H = 1.97 [1.58; 2.47]; I^2 = 74.3% [59.8%; 83.6%]

 Test of heterogeneity:

      Q d.f.  p-value

  70.16   18 < 0.0001

Results for subgroups (fixed effect model):

            k     OR            95%-CI     Q    tau^2   I^2
```

```
 group = 1   4 1.5360 [1.4329;  1.6466] 13.19   0.0171 77.2%
 group = 2   1 1.5676 [1.0620;  2.3139]  0.00       --    --
 group = 3   1 1.3256 [1.0725;  1.6384]  0.00       --    --
 group = 4   3 1.2464 [1.0208;  1.5218]  3.86   0.0292 48.1%
 group = 5   9 1.4898 [1.3171;  1.6851] 42.75   0.1602 81.3%
 group = 6   1 5.3478 [1.8260; 15.6622]  0.00       --    --

 Test for subgroup differences (fixed effect model):
                     Q d.f.  p-value
 Between groups   10.47    5   0.0629

 Results for subgroups (random effects model):
            k     OR            95%-CI     Q    tau^2   I^2
 group = 1   4 1.5395 [1.3303;  1.7815] 13.19   0.0171 77.2%
 group = 2   1 1.5676 [1.0620;  2.3139]  0.00       --    --
 group = 3   1 1.3256 [1.0725;  1.6384]  0.00       --    --
 group = 4   3 1.2630 [0.9559;  1.6689]  3.86   0.0292 48.1%
 group = 5   9 1.4578 [1.0902;  1.9494] 42.75   0.1602 81.3%
 group = 6   1 5.3478 [1.8260; 15.6622]  0.00       --    --

 Test for subgroup differences (random effects model):
                    Q d.f.  p-value
 Between groups   8.08    5   0.1519
 Details on meta-analytical method:
- Mantel-Haenszel method
- DerSimonian-Laird estimator for tau^2
forest.meta(model.anova, rightcols=FALSE)
```


Experimental Control
Study Events Total Events Total
Odds Ratio
group = 1
1 825.00 1500 675.00 1500
2 795.00 1500 940.00 2000
3 1140.00 2000 645.00 1500
4 855.00 1500 660.00 1500
Fixed effect model 6500 6500
Random effects model
Heterogeneity: I^2 = 77%, τ^2 = 0.0171, p < 0.01
group = 2
5 77.42 158 114.00 300
Fixed effect model 158 300
Random effects model
Heterogeneity: Not applicable
group = 3
6 421.23 739 324.50 649
Fixed effect model 739 649
Random effects model
Heterogeneity: Not applicable
group = 4
7 77.50 250 180.00 600
8 63.00 150 180.00 600
9 122.00 244 110.86 241
Fixed effect model 644 1441
Random effects model
Heterogeneity: I^2 = 48%, τ^2 = 0.0292, p = 0.15
group = 5
10 77.81 251 59.04 246
11 52.08 248 59.04 246
12 109.62 261 59.04 246
13 87.36 336 86.84 334
14 89.91 333 86.84 334
15 118.44 329 86.84 334
16 119.85 705 42.30 705
17 41.64 694 42.30 705
18 77.99 709 42.30 705
Fixed effect model 3866 3855
Random effects model
Heterogeneity: I^2 = 81%, τ^2 = 0.1602, p < 0.01
group = 6
19 12.96 24 9.18 51
Fixed effect model 24 51
Random effects model
Heterogeneity: Not applicable
Fixed effect model 11931 12796
Random effects model
Heterogeneity: I^2 = 74%, τ^2 = 0.0471, p < 0.01

Appendix E
Dedication

This thesis study is dedicated to my sons, Ziyad and Abdullah, whose love and courage carried me through the toughest of times. You, Ziyad and Abdullah, are and will always be the most important individuals in my life.