ABSTRACT

WHELAN, THOMAS JAMES. Response Rates in 21st Century Organizational Survey Research: A Conceptual Model and Meta-analysis. (Under the direction of Lori Foster Thompson.)

The influence of survey features on response rates has been of interest to organizational researchers for decades, as both survey technologies and the use of response enhancing techniques continue to advance and expand. To explore this topic, the current study conducted a meta-analysis of response rates to evaluate a conceptual model of predictors comprised of survey content, survey methodology, and recipient characteristics. This model was assessed via a regression analysis conducted on recent empirical articles published in prominent organizational journals across the span of fifteen years (2000-2014). In addition, variability in response rates was examined through relative weights analysis (Johnson, 2000), to investigate which predictors accounted for the most unique variability, as well as via hierarchical linear modeling, to explore variation in response rates over time. Results from an analysis of 238 studies from six top-tier journals in the organizational sciences literature supported hypothesized relationships between lower response rates and longer survey length, Web-based administration, and recipient samples with higher average job complexity. Job complexity accounted for the highest percentage of explained variance in response rates compared to other predictors, per the results of the relative weights analysis. In addition, hierarchical linear modeling results showed that there was a significant negative relationship between job complexity and response rates when accounting for the publication year of primary studies. Implications include an updated benchmark for response rates in organizational surveys of 51%, based on the summary findings. Future research on the implications of technology for survey delivery media and response enhancing techniques are discussed.
Response Rates in 21st Century Organizational Survey Research:
A Conceptual Model and Meta-analysis

by
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>LIST OF TABLES</td>
<td>v</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td>vi</td>
</tr>
<tr>
<td>Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1. Response Behavior in Organizational Survey Research</td>
<td>3</td>
</tr>
<tr>
<td>a. Survey Content</td>
<td>4</td>
</tr>
<tr>
<td>b. Survey Methodology</td>
<td>5</td>
</tr>
<tr>
<td>c. Recipient Characteristics</td>
<td>11</td>
</tr>
<tr>
<td>2. Unique Variance in Response Rates</td>
<td>14</td>
</tr>
<tr>
<td>3. Longitudinal Variability in Response Rates</td>
<td>15</td>
</tr>
<tr>
<td>Method</td>
<td>16</td>
</tr>
<tr>
<td>1. Study Search and Inclusion Criteria</td>
<td>16</td>
</tr>
<tr>
<td>2. Meta-Analytic Coding Scheme</td>
<td>19</td>
</tr>
<tr>
<td>Results</td>
<td>22</td>
</tr>
<tr>
<td>1. Linear Regression Model</td>
<td>24</td>
</tr>
<tr>
<td>2. Relative Weights Regression Analysis</td>
<td>25</td>
</tr>
<tr>
<td>3. Hierarchical Linear Modeling Analyses</td>
<td>26</td>
</tr>
<tr>
<td>Discussion</td>
<td>30</td>
</tr>
<tr>
<td>1. Point Estimate for Response Rates</td>
<td>34</td>
</tr>
<tr>
<td>2. Practical Implications</td>
<td>35</td>
</tr>
<tr>
<td>3. Limitations</td>
<td>36</td>
</tr>
<tr>
<td>4. Future Research</td>
<td>37</td>
</tr>
<tr>
<td>REFERENCES</td>
<td>40</td>
</tr>
<tr>
<td>APPENDIX</td>
<td>82</td>
</tr>
<tr>
<td>1. Appendix A: Meta-Analysis Coding Rules</td>
<td>83</td>
</tr>
<tr>
<td>2. Appendix B: Proposal Document</td>
<td>87</td>
</tr>
</tbody>
</table>
LIST OF TABLES

Table 1. Excluded Studies from Meta-Analytic Coding .................................................. 74
Table 2. Descriptive Statistics by Journal ................................................................. 75
Table 3. Descriptive Statistics and Correlations for Study Variables ....................... 76
Table 4. Descriptive Statistics for Nominal Variables ................................................. 77
Table 5. Standardized, Unstandardized, and Relative Weight Regression Parameters for Predictors of Response Rates ................................................................. 78
Table 6. Estimates for Hierarchical Linear Models Predicting Response Rates .......... 79
LIST OF FIGURES

Figure 1. Conceptual model of response antecedents ............................................... 80

Figure 2. Boxplot of response rates by year ................................................................. 81
Introduction

Organizational surveys can be defined as tools to collect self-report data from and relevant to organizations. As stated by Tourangeau (2004), “surveys rest on a delicate and complicated relationship between those who conduct surveys and those who take part in them” (p. 776). The magnitude of the influence of survey characteristics on response rates and their importance over time warrants continued investigation, as empirical findings and technological advancements continue to change how organizations and researchers plan, collect, and analyze survey data. Accordingly, there is an ever-present need to understand from a broad perspective those factors that lead a recipient to answer or fail to complete a survey and the contemporary contexts in which these outcomes occur.

Response rates have been the primary outcome of interest in many reviews of survey response behavior in organizational science and related disciplines (e.g., Anseel, Lievens, Schollaert, & Choragwicka, 2010; Baruch, 1999; Baruch & Holtom, 2008; Cook, Heath, & Thompson, 2000; Cycyota & Harrison, 2006; Fox, Crask, & Kim, 1988; Goyder, 1982; Heberlein & Baumgartner, 1978; Manfreda, Bosnjak, Berzelak, Haas & Vehovar, 2008; Roth & BeVier, 1998; Sheehan, 2001; Shih & Fan, 2008; Van Horn, Green, & Martinussen, 2009; Yammarino, Skinner, & Childers, 1991; Yu & Cooper, 1983). A response rate can be defined as the number of complete responses from individual employees divided by the total number of eligible employees in the sampling frame (American Association for Public Opinion Research [AAPOR], 2011, p. 5). The ratio of returned surveys to distributed surveys has been seen as a proxy, albeit an imperfect one, for the quality of a data collection effort.

The historical attention paid to response rates in the research literature is not
unwarranted. Maximizing survey return whenever possible is of interest due to the implications for survey research and practice. There are a variety of reasons for survey sponsors to concern themselves with response rates. Without an adequate sample size, fewer data points due to low response rates can limit the statistical power needed to perform analyses of interest (Rogelberg & Stanton, 2007), subsequently requiring organizations to incur greater costs in soliciting additional respondents (Newell, Rosenfeld, Harris, & Hildelang, 2004). Low response rates may also damage the credibility of survey data in the views of organizational decision makers, stakeholders, and journal reviewers, regardless of the actual legitimacy of any inferences made from the data (e.g., Campion, 1993; Luong & Rogelberg, 1998). Lastly, a notable concern with low response rates pertains to the potential for nonresponse bias, or non-arbitrary differences between respondents and nonrespondents (Rogelberg & Luong, 1998). Such differences, although largely independent of response rates, can lead to range restriction, systematic bias in mean scores (e.g., Lynn, 2008; Taris & Schreurs, 2007), erroneous estimation of population parameters, and faulty conclusions regarding true relationships between variables (Allen, Stanley, Williams, & Ross, 2007; Newman, 2009).

Though there are several extant meta-analyses on response rates in organizational research, the present study contributes to the literature in three important ways. First, this study conducts a quantitative review of published response rates and factors related to survey content, survey methodology, and the recipient characteristics in top-tier journals in the fields of industrial-organizational (I-O) psychology and management and compares which factors are most influential on rates of survey return. This comparison is accomplished via multiple
regression analysis employing relative weights (Johnson, 2000), which has not previously been applied to meta-analytic data on response rates. Second, this study expands previous reviews such as those by Roth and BeVier (1998), Baruch and Holtom (2008), and Anseel et al. (2010), both by focusing exclusively on more recent volumes in the literature (2000-2014) than has been done previously and by including a range of variables related to the use of response enhancing techniques in organizational research. Third, this review examines variability in response rate trends over the span of fifteen years via hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002), which also has not been previously applied to meta-analytic data on response rates in organizational surveys. Given that surveys are utilized to measure a wide range of job-related constructs for a variety of purposes, it is critical to determine how effectively response enhancing techniques may be in influencing survey return in contemporary organizations.

**Response Behavior in Organizational Survey Research**

To consider the variety of ways that aspects of survey delivery and recipient characteristics may influence individuals’ propensity to respond to organizational surveys, an inductive model is proposed that takes into account common survey features and sample characteristics in the prediction of recipient behavior. The model found in Figure 1 is offered as an empirically-testable framework of the antecedents to survey return. Though this model is not intended to be an exhaustive list of all possible predictors of survey behavior, it is adapted from models proposed by Peytchev (2009) and draws from the framework of Rogelberg and colleagues (2000, 2003, 2006), in addition to themes common to previous meta-analyses of response rates.
The outcome of interest in the model concerns the endpoint of response behavior; specifically, the criterion of rate of survey return, calculated as the ratio of respondents to recipients. As shown in Figure 1, three general categories of antecedents to response rates are proposed: survey content, survey methodology, and recipient characteristics. The model assumes that although many of these antecedents are mutually exclusive (e.g., a sponsor cannot simultaneously use and not use incentives for the same recipient) any survey effort will inevitably include an assortment of these factors. The three general categories of antecedents will be described in detail, beginning with factors related to the content of a survey.

**Survey Content**

**Salience.** Multiple aspects of survey content can be influential in determining recipient behavior, such as topic salience and item sensitivity of the survey for an individual. Salience can be interpreted as the importance and timeliness of a survey’s content to a recipient, such that the items ask questions that are of interest to the recipient and related to the recipient’s current circumstances (Heberlein & Baumgartner, 1978). Past meta-analyses of response behavior such as Anseel et al. (2010), Cook et al. (2000), Cycyota and Harrison (2006), Roth and BeVier (1998), and Sheehan and McMillan (1999) concluded that issue salience was related to higher unit response rates. Accordingly, the more a recipient sees a survey as being pertinent to him- or herself, the more likely he or she should be to return the survey. Thus, the following hypothesis is proposed:

**Hypothesis 1:** Topic salience in a survey effort will have a positive, non-zero relationship with rates of survey response.
Sensitivity. The sensitivity of a survey topic can also influence a recipient’s willingness to provide substantive answers to a survey. A sensitive survey topic can be conceptualized as including three characteristics: the intrusiveness of the item content, the threat of potential consequences for responding to the item, and the social undesirability of a recipient’s answer to the item (Tourangeau & Yan, 2007). As the items contained in a survey are perceived to be increasingly sensitive, a recipient may feel more apprehensive about providing data to the survey sponsor (Dillman, 2000), which has been substantiated in a previous meta-analysis by Edwards et al. (2002). For sensitive survey topics, reluctance to provide answers to all or part of the survey may be motivated by a concern that the confidentiality afforded to recipients does not cover the potential risks of providing meaningful answers to sensitive items (Rasinski, Willis, Baldwin, Yeh, & Lee, 1999). Consequently, a recent review by McCluskey and Topping (2011) urged survey sponsors to carefully consider the sensitivity of item content and the appropriateness of such items to the target recipients to mitigate unnecessary negative effects on response rates. Therefore, the following hypothesis is proposed:

Hypothesis 2: Topic sensitivity will have a negative, non-zero relationship with rates of survey response.

Survey Methodology

The procedural and social characteristics of a survey’s methodology, such as the administration medium, anonymity or confidentiality assurances, and overall survey length, have received scrutiny in previous reviews to gauge the likely impact on response rates (e.g., Cook et al., 2000; Edwards et al., 2002; Heberlein & Baumgartner, 1978; Roth & BeVier,
1998; Shih & Fan, 2008). Though aspects of survey methodology may not be as conspicuous to some recipients as the topic of a survey, past research has demonstrated that administration methods affect response rates (e.g., Armstrong & Lusk, 1987; Church, 1993; Fox et al., 1988; Manfreda et al., 2008; Weathers et al., 1993; Yammarino et al., 1991; Yu & Cooper, 1983).

**Salutation specificity.** Personalizing the salutation on a survey solicitation, such as addressing the recipient by name, has been suggested as a way to encourage survey return (e.g., Dillman et al., 2009; Rogelberg & Luong, 1998), and has been shown to increase response rates in past research (e.g., Bosnjak, Tuten, & Wittmann, 2005; Cook et al., 2000; Heerwegh, Vanhove, Matthijs & Loosveldt, 2005). Personalization plays an integral part of Dillman and colleagues’ (2000; 2009) tailored design method for surveys, with the assumption that the more important a recipient is led to believe he or she is to the survey effort, the more that recipient feels the benefit of responding outweighs the cost in time and effort. The majority of existing meta-analyses (e.g., Anseel et al., 2010; Edwards et al., 2002; Fox et al., 1988; Yu & Cooper, 1983) have found a significant effect for this methodological device in improving response rates. Accordingly, the following hypothesis is proposed:

Hypothesis 3: Personalization of survey salutations will have a positive, non-zero relationship with rates of survey response.

**Identification likelihood.** Most survey efforts collect names or other personally identifying information from recipients, such as their date of birth, employee number, or other information that could be used to distinguish an individual’s identity. Recipients who question the privacy afforded by a survey may be reluctant to provide answers to items that could reflect poorly on them or otherwise instigate some form of reprisal (e.g., Rogelberg et
al., 2006; Thompson, Surface, Martin, & Sanders, 2003). Past research supports this view, suggesting that requiring recipients to identify themselves can exacerbate low response rates. For instance, meta-analyses by Anseel et al. (2010) and Roth and BeVier (1998) found that the use of identification numbers instead of names significantly increased unit response. As the emphasis on privacy assurances may not be the same across surveys (Sobal, 1984), recipients may see their likelihood of being identified differently under assorted conditions even when there are justifiable reasons to track individual recipients, such as when there is a need to link response data to ratings provided on another survey or to archival information stored in an organization’s database. Particularly when completing a survey is voluntary on the part of the recipient, provisions for privacy should encourage response. Thus, the following hypothesis is proposed:

Hypothesis 4: Identification likelihood will have a negative, non-zero relationship with rates of survey response.

**Survey length.** The number of items on a survey instrument may significantly impact the likelihood of response as well, such that shorter surveys that demand fewer resources from the survey recipient are more likely to be returned (Rogelberg & Stanton, 2007). For instance, a meta-analysis by Edwards, Roberts, Sandecock, and Frost (2004) found that the odds of a recipient returning a survey decreased significantly for longer questionnaires.

However, past reviews such as Yammarino et al. (1991) have operationalized survey length as the total page count of each primary study’s survey instrument. As noted by Dillman (2000), “there is more to length than a simple count of pages… (putting) more questions into fewer pages to make a questionnaire shorter is not likely to accomplish its
intended purpose” (p. 306). Accordingly, in the current study this variable will be treated as the total number of items reported in each primary article that meets inclusion criteria, as was done by Roth and BeVier (1998). Given the evidence that survey length does influence response rates, the following hypothesis is proposed:

Hypothesis 5: The total number of survey items will have a negative, non-zero relationship with rates of survey response.

**Advanced notice/follow-up contacts.** Two recommended methods to increase response rates are the use of advanced notice and follow-up contacts, which are intended to notify, encourage, and remind individuals to complete and return survey materials (Bosnjak et al., 2005; Dillman et al., 2009; Rogelberg & Luong, 1998; Rogelberg & Stanton, 2007). The contacts between a survey sponsor and recipient in contemporary survey efforts can be made through a variety of methods, including postal mail, email, or text messages on mobile devices (e.g., LaRose & Tsai, 2014; Mavletova, 2013; van Heerden, Norris, Tollman, Stein, & Richter, 2014).

Advanced notice of an upcoming survey has been shown to result in improved response rates in several past reviews (Edwards et al., 2002; Fox et al., 1988; Heberlein & Baumgartner, 1978; Roth & BeVier, 1998; Weathers et al., 1993; Yu & Cooper, 1983). While a recent review by Anseel et al. (2010) suggested that the gains in curbing low response rates via advanced notice may be slightly declining over time, the overwhelming pattern in past reviews (including Anseel and colleagues) suggests that this tactic is effective in significantly increasing response rates. Therefore, the following hypothesis is proposed:

Hypothesis 6: The number of advanced survey notifications will have a positive, non-
zero relationship with rates of survey response.

Past reviews have identified follow-up contacts as a means to effectively increase response rates by providing recipients multiple opportunities and encouragement to complete a survey (Edwards et al., 2002; Fan & Yan, 2010; Fox et al., 1998; Sheehan, 2001; Yammarino et al., 1991; Yu & Cooper, 1983). However, follow-ups may discourage some recipients from responding to a survey, as suggested by the lower response rates for reminders reported in reviews by Cycyota and Harrison (2006) and Baruch and Holtom (2008). Nonetheless, reminders have historically been recommended as a means through which to increase response rates, and the majority of quantitative reviews support their use. Therefore, the following hypothesis is proposed:

Hypothesis 7: The number of follow-up contacts will have a positive, non-zero relationship with rates of survey response.

**Administration medium.** The medium through which an organizational survey is administered has garnered significant attention from both scientists and practitioners (e.g., Naus, Phillipp, & Samsi, 2009; Stanton, 1998; Thompson, Surface, Martin, & Sanders, 2003; Yost & Homer, 1998). In the current study, the focus is on the comparison between paper and Web-delivered surveys, as has been the case in several recent meta-analyses of response behavior (Anseel et al., 2010; Baruch & Holtom, 2008; Groves & Peytcheva, 2008). The prevailing mode of thought in the literature suggests that electronic surveys will yield lower levels of response compared to paper surveys (Crawford, Couper, & Lamias, 2001; Cronk & West, 2002; Kaplowitz, Hadlock, & Levine, 2004), despite the fact that electronic surveys can be fully automated to reduce issues with the return and conversion of data for analysis.
For survey recipients, Web-based surveys can be adversely affected by factors such as connectivity issues or low Internet self-efficacy, leading to frustration and ultimately discouraging survey completion (Medway & Fulton, 2012). Recipients may also be less willing to respond to Web surveys due to concerns about data privacy, perceptions that sponsors of Web surveys might not be legitimate, or the perceived nuisance of higher volumes of survey requests owing to the lower material costs for soliciting recipients via the Web (Manfreda et al., 2008). Though Baruch and Holtom (2008) did not find significantly different levels of unit response across administration media in their review, meta-analyses by Manfreda et al. and Shih and Fan (2008) concluded that while there is variability in response rates within media, Web surveys tend to have significantly worse response rates than paper surveys. Accordingly, the following hypothesis is proposed:

**Hypothesis 8:** Administration medium will have a significant relationship with rates of survey response, such that Web-based surveys will yield lower rates of survey response compared to paper surveys.

**Incentives.** The use of incentives has been championed as a way to motivate recipients to complete and subsequently return a survey instrument to a survey sponsor (e.g., Bosnjak et al., 2005; Dillman, 2000; Helgeson et al., 2002; Rogelberg & Luong, 1998; Rogelberg & Stanton, 2007; Rose, Sidle, & Griffith, 2007). Incentives can be monetary, such that they offer some form of cash or check to the survey recipient, or nonmonetary, the latter of which Church (1993) defined as any extra item or token that would be considered above and beyond the normal procedure for most surveys. The underlying reason to encourage survey completion through incentives is that their use creates a social exchange relationship
between the survey sponsor and recipients, whereby the benefit to recipients is tangibly increased compared to the perceived material and psychological costs of responding (Dillman et al., 2009). In several previous reviews of survey response rates, incentives have been shown to increase response rates (e.g., Church, 1993; Fox et al., 1988; Yammarino et al., 1991; Yu & Cooper, 1983). As the majority of research suggests that the use of incentives by a survey sponsor either before or after survey completion should lead to higher levels of response, the following hypothesis is proposed:

Hypothesis 9: Incentives will have a positive, non-zero relationship with rates of survey response.

**Recipient Characteristics**

While much attention has been paid to the external characteristics of a survey effort, an equally important though often underemphasized factor in response behavior concerns the composition of the recipient sample, i.e., recipient characteristics, as shown in Figure 1. The type of target recipients and demographic characteristics of a given sample may be significantly related to observed response rates (e.g., Anseel et al., 2010). The following hypotheses explore the relationship of response rates with the composition of respondents in a primary study considered in aggregate (the modal or most prevalent education level, target population, and job complexity of a sample of respondents), consistent with past meta-analysis efforts (e.g., Baruch, 1999; Edwards et al., 2004; Shih & Fan, 2008; Yammarino et al., 1991).

**Education level.** The level of a recipient’s education has been found to relate to response behavior, as past research has demonstrated that recipients who failed to return a
survey tend to have less education compared to respondents who completed the survey (Rogelberg & Luong, 1998). This effect has been demonstrated for mailed surveys (e.g., Gannon, Nothern, & Carroll, 1971) as well as for surveys administered on newer technologies such as mobile phones (e.g., Mavletova, 2013). Though education is not necessarily a proxy for cognitive ability, a study by Holbrook, Cho, and Johnson (2006) found that education level was related to fewer difficulties comprehending a survey item or with mapping a judgment to response categories. The meta-analysis by Roth and BeVier (1998) suggested that the modal education level for a sample of recipients was a significant factor influencing response rates to a survey, such that a group of more educated recipients demonstrated higher observed response rates. In addition, Goyder (1982) found that education appeared to be a contributing factor to survey return when considered across studies. Thus, the following hypothesis is proposed:

Hypothesis 10: The modal education level of samples will have a positive, non-zero relationship with rates of survey response.

**Target population.** A target population for a survey can be defined a number of ways, depending on the field of study, relevant sampling frame, or objective of the survey. Examples of different target populations include nationalities, specific occupational groups, customers and consumers, opinion panels, special interest groups, students, or employees within a specific organization (e.g., Groves & Peytcheva, 2008). Groups of employee recipients can vary in the number of survey requests they typically receive and subsequently attend to, as well as in the amount of time available to complete surveys that may otherwise be low-priority activities (e.g., Cycyota & Harrison, 2006). Past meta-analyses have shown
some agreement on the pattern of response rates depending on the sample of recipients (e.g., Groves & Peytcheva, 2008; Heberlein & Baumgartner, 1978; Van Horn et al., 2009; Yammarino et al., 1991). The current study focused on organizationally-relevant samples that researchers have used to make inferences about organizational behavior. Anseel et al. (2010) found a significant effect for the type of recipient such that non-working and non-managerial recipients were most likely to return a survey compared to consumer, managerial, and executive groups, respectively. Similarly, Shih and Fan (2008) noted that university samples tend to have better response rates than employee or general samples. Given the patterns in response rates reported by past reviews, the following hypothesis is proposed:

Hypothesis 11: Target population will have a non-zero relationship with rates of survey response, such that university-sourced groups of survey recipients will have higher rates of survey response compared to professional groups of survey recipients.

Job complexity. The complexity of a recipient’s job may also influence whether he or she completes a survey. Job complexity can be defined as “the extent to which a job entails autonomy or less routine and the extent to which it allows for decision latitude” (Shalley, Gibson, & Blum, 2009, p. 493). Given that jobs higher in complexity involve more multifaceted tasks that are difficult to perform (e.g., Morgeson & Humphrey, 2006), individuals who hold positions higher in complexity may have fewer opportunities to respond to a survey due to the regular demands of their occupation.

Past meta-analytic results support the relationship between job complexity and response rates. Reviews by both Cycyota and Harrison (2006) and Baruch and Holtom (2008) found that individuals holding jobs with more stature in the target organization were
significantly less likely to complete and return a survey. As suggested by current theory about task complexity as well as past meta-analytic results, the following hypothesis is proposed:

Hypothesis 12: Job complexity will have a negative, non-zero relationship with rates of survey response.

**Unique Variance in Response Rates**

As there are a number of hypotheses concerning predictors of response rates, knowledge of which predictors account for the most variance in survey return would be of great value to researchers and practitioners designing and administering surveys in organizational research. In other words, which aspects of survey content, survey administration, and recipient characteristics are playing the largest role in predicting response rates?

Relative importance analysis, as described by LeBreton, Hargis, Griepentrog, Oswald, and Ployhart (2007), provides an alternative source of information as to which predictors are making substantial contributions to explainable variance in a regression model. In situations where organizational or methodological constraints preclude an optimal survey effort, information concerning the predictive capacity of the variables under study could assist researchers and practitioners in prioritizing resources and making informed decisions about investing time and effort in tactics to increase survey return. Therefore, the following research question is posed:

Research Question 1: What is the relative importance of predictors that account for variance in rates of survey response?
Longitudinal Variability in Response Rates

For a quantitative review of response rates, a question of interest to researchers and practitioners concerns the existence and directionality of trends over time. There are a number of factors that may contribute to declining response rates, such as lower budgets for the supplemental use of response enhancing techniques, ”oversurveying” from sponsors who prefer administering longer questionnaires, and increased popularity of surveys with organizational decision-makers (Manfreda et al., 2008; Rogelberg & Stanton, 2007). However, past reviews do not show consensus on patterns of response rates over time. Cycyota and Harrison (2006) found that response rates appeared to be declining for the 1992-2003 window included in the authors’ analysis. Despite Baruch’s (1999) conclusion that response rates have been declining, Baruch and Holtom (2008) did not find a significant difference in overall response rate trends in the 2000-2005 time period considered in their review. However, Baruch and Holtom employed a t-test to compare mean response rates, and both Anseel et al. (2010) as well as Cycyota and Harrison included year of publication as a variable in their main effects regression models. Ignoring a structural grouping in data when using regression—such as year of publication—can lead to underestimation of standard errors and put subsequent conclusions at risk of Type I error, as traditional regression techniques assume independence of observations (Hox, 2010). The current study will utilize hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002), an analytical approach that permits consideration of the amount of variance both within years and across years. As primary studies are nested within each publication year, this analytical approach accounts for the hierarchical nature of the meta-analytic data. Given that the current study will be the first
known application of HLM to data on response rates to organizational surveys, a hypothesized relationship is difficult to presume based on the conflicting results of past quantitative reviews. As such, the following research question is proposed:

Research Question 2: Is there significant variation in published rates of survey response from 2000 to 2014?

Although there is benefit to knowing which antecedents of survey response account for unique variance (i.e., Research Question 1), no less important is information about the significance of each predictor when considered over time. There is utility to both researchers and practitioners in knowing which factors are especially likely to drive response rates in present day survey efforts, and in knowing which factors have shown diminishing returns when considered over time. As such, the following research question is posed:

Research Question 3: Has there been significant variation in response rates over time related to survey content, survey methodology, and recipient characteristics?

Method

Study Search and Inclusion Criteria

This study employed the following strategy to identify published research for the purpose of meta-analysis, focused on empirical research reports published between 2000 and 2014 in the following journals: Journal of Applied Psychology, Personnel Psychology, Academy of Management Journal, Journal of Management, Organizational Research Methods, and Management Information Science Quarterly. These journals were selected from lists of the top-ranked journals in the fields of applied psychology and management, according to Journal Citation Reports (Thomson Corporation, 2012). These outlets were
chosen as they routinely and primarily publish empirical articles that report findings relevant to the study of I-O psychology and organizational science, and with the exception of MISQ all appear in Zickar and Highhouse’s (2001) list of top publication outlets in the field of I-O psychology. The time period of primary studies was chosen to constrain the data set to literature most likely to include Web-based survey administration technology circa 2000 or later.

As with past meta-analyses of response rates, it was not feasible to examine all published journals and unpublished manuscripts for information related to the hypotheses of this review. Accordingly, the top-ranked empirical journals selected presented a cross-section of publications regarded as having especially high standards of rigor and likely to routinely report methodological information for each primary study. As such, these outlets serve as a normative indicator for organizational researchers as to what is methodologically acceptable (e.g., Cycyota & Harrison, 2006). To facilitate the identification of primary studies, literature searches were conducted within each of these top-ranked journal using computerized databases of journal archives (e.g., Business Source Premier, EBSCO Host, Sage Premier). Keywords for the searches included survey, questionnaire, instrument, self-report, and self-administered, with the qualifying term of response rate contained in the full text of each article.

Of the following inclusion criteria, primary studies were required to meet criteria 1 through 3, and at least two criteria from 4 through 6 to be included in this meta-analysis:

1. Data in the primary study were collected through surveys or questionnaires;
2. Information regarding response rate or information that permits calculation of the
rate of survey return was available;

3. The survey procedure must not have required mandatory response from recipients, which fails to provide information regarding the variables affecting response rates (e.g., Cook et al., 2000);

4. Information concerning at least one of the variables identified as possible survey content predictors of response rates in the hypotheses was available;

5. Information detailing two or more aspects of the methods used for data collection (e.g., paper or Web medium, use of advance notification and/or follow-up contacts, etc.) was available;

6. Information concerning one or more of the recipient characteristics (e.g., education, target population, etc.) of the observed sample was available.

The following types of primary research studies identified in the literature search were excluded: (a) studies that involved interviews, whether self-administered or conducted by an interviewer, or daily diary study designs; (b) studies failing to report information that permitted an inference to be made about criterion 3 as stated above; (c) studies that used archival data; and, (d) studies where the primary level of analysis was not at the individual level (e.g., matched samples, teams, or dyads).

The literature search resulted in a total of 1,493 citations across all keywords, representing 701 unique primary studies. Of these, 238 studies met the inclusion criteria (33.9%), reflecting a total of 159,218 survey recipients. A frequency table of the reasons for which studies were excluded from further coding is presented in Table 1.
Meta-Analytic Coding Scheme

To address the hypotheses posited above, study characteristic codes were adapted from coding schemes from previous summaries of response rates such as Heberlein and Baumgartner (1978), Yammarino et al. (1991), and Roth and BeVier (1998). In addition to the codes described below, the year of publication and final sample size were recorded.

Survey content characteristics codes included topic salience and topic sensitivity. Topic salience, adapted from Heberlein and Baumgartner (1978), was coded on a three-point scale of salient (important and of current interest to the recipient), possibly salient (important though not necessarily current), or nonsalient (neither important nor current). Topic sensitivity was also coded on a three-point scale of sensitive (intrusive, overtly embarrassing), possibly sensitive (intrusive, not likely to be embarrassing), or nonsensitive (neither intrusive nor embarrassing; Tourangeau & Yan, 2007).

Methodological characteristics codes included salutation specificity, identification likelihood, survey length, the total number of advanced notice and follow-up contacts, the administration medium, and the use of incentives. Salutation specificity was coded as a dichotomous variable of no personalization or personalization of the recipient. Identification likelihood was coded on a three-point scale of fully identified (name or other personal information required), partially identified (non-personal identifier assigned for the purpose of the survey), and anonymous. Survey length was coded as the total number of items for all collected measures as reported by the authors of a primary study. The frequency of advanced notice and follow-up contacts were coded separately for both variables on a four-point scale of no contact, 1 contact, 2 contacts, or 3 or more contacts. The medium used to administer
the survey was coded to indicate the use of a mailed/paper survey or a computer-/Web-based survey. Incentives were coded to indicate the presence or absence of monetary and nonmonetary recipient incentives on return of the survey materials.

Recipient characteristics codes included the modal educational level (high school diploma, some college, Bachelor’s degree, graduate degree; Roth & BeVier, 1998), the target population or source of the recipients (i.e., university population, single organization/specific occupational population, or multiple-organization general occupational population; Shih & Fan, 2008), and job complexity. Job complexity was coded on a three-point scale of low (i.e., hourly workers, clerical jobs), medium (lower- to mid-level managers), and high (executives, professions such as lawyer or physician); the code assigned for job complexity was based on the occupation held by the preponderance of the sample when available and appropriate (i.e., this variable was not coded for academic samples). It should be noted that as these variables represent an aggregation of recipient characteristics in a given study and do not capture demographic diversity within a single sample, each variable noted above was coded at the study level such that one code was assigned based on the most prevalent characteristic of participants in the same study.

For the criterion variable, response rate was recorded when reported by the primary study authors or computed from information available in the method section for each primary study. In the case of the latter, the rate of survey return was calculated so resulting values were scaled in the direction of increasing response, by dividing the final number of usable surveys returned by the total number of recipients solicited. A requirement of meta-analytic data sets is independence of data points, such that each study does not contribute more than
one observation to aggregate data. In the case of articles that contain multiple waves of data
collection or a “study 1—study 2” sequential hypothesis-testing design, only codes from the
survey administration with the largest sample size were used. Table 2 contains descriptive
statistics for each of the six journals included in the literature search.

The table presented in Appendix A served as the guideline for coding all variables
from the 238 primary studies. During coding, the number of times codes had to be inferred
from the study were as follows: salutation specificity (6), identification likelihood (19),
advanced notice and follow-up contacts (9), administration mode (7), modal education (22),
and job complexity (10). Variables were coded as absent when a rater was unable to gauge
the presence or absence of a predictor variable, consistent with previous reviews of response
rates in organizational research (e.g., Anseel et al., 2010; Cycyota & Harrison, 2006). This
was not done for the survey length, modal education level, or modal job complexity codes, as
an inferred zero value could bias the interpretability of the analysis results.

Two raters recorded all study codes, both of whom held graduate degrees in I-O
psychology and have experience publishing and presenting peer-reviewed research. An
intrarater agreement analysis was performed on a random subset of 30 studies that met the
inclusion criteria, after which the remainder of the studies were coded by a single rater. To
assess the degree to which raters assigned similar codes to categorical variables (e.g.,
salutation specificity and administration mode), Cohen’s (1960) kappa (κ) index provided a
measure of intrarater agreement for dichotomous codes. A two-way single measures
intraclass coefficient was calculated for nominal variables with three levels (e.g., incentives
and target population), which is statistically interchangeable with a weighted kappa for
ordinal scales (Cohen, 1968; Norman & Streiner, 2008). The resulting estimates indicated excellent agreement in coding for salutation specificity, $\kappa = 1.00, p < .01$, and administration mode, $\kappa = 1.00, p < .01$, as did the coefficients for coding the use of incentives, $\text{ICC} = 0.98, p < .01$, and each study’s target population, $\text{ICC} = 0.92, p < .01$ (Fleiss, Levin, & Palk, 2003). The interrater agreement for all other variables was assessed using a two-way mixed, single measures ICC to test the degree to which agreement across raters generalized to a single rater. The resulting ICC estimates for topic salience (0.90), topic sensitivity (0.91), identification likelihood (0.95), survey length (0.97), advanced notice (0.89), follow-up contacts (0.98), modal education (0.88), and job complexity (0.96) indicated that coders had an acceptable degree of agreement across study codes, $p < .05$ (Cicchetti, 1994). It should be noted that pertinent details in the method section for each study in the interrater analyses were highlighted to ensure both raters were considering the same source information while coding. Given acceptable levels of rating agreement, study codes were deemed to be suitable for use in the hypothesis tests of the present study.

**Results**

Means, standard deviations, and correlations of the response rate criterion with coded study variables are reported in Table 3. Summary statistics for nominal variables are reported in Table 4.

All of the hypothesis test results that follow are organized and presented by the type of analysis. First, to provide a test of the hypotheses for coded variables at the nominal level of measurement (e.g., salutation specificity, administration mode, use of incentives, target population), $t$-tests and ANOVAs with pertinent post-hoc analyses were conducted to
determine whether response rates were significantly different across levels of these variables.

For salutation specificity, Hypothesis 3 predicted that the personalization of survey salutations would have a positive, non-zero relationship with rates of survey response. The results of a one-tailed $t$-test demonstrated that the response rates for personalized survey invitations were not significantly different than generic invitations, $t(155) = 0.37, p = 0.64$. Therefore, Hypothesis 3 was not supported. For administration mode, Hypothesis 8 predicted that Web-based surveys would yield lower rates of survey response compared to paper surveys. The results of a one-tailed $t$-test demonstrated that the response rate for paper surveys were found to be significantly higher compared to Web-based surveys, $t(212) = 1.72, p = 0.04$. Therefore, Hypothesis 8 was supported.

Hypothesis 9 predicted that the use of survey incentives would have a positive, non-zero relationship with rates of survey response. An ANOVA conducted on the use of monetary and nonmonetary incentives was not significant, $F(2, 235) = 1.15, p = .32, \eta^2 = 0.01$. Therefore, Hypothesis 9 was not supported. For the target population of a survey, Hypothesis 11 predicted that university survey recipients would have higher rates of survey response compared to professional groups of survey recipients. An ANOVA conducted on the target population of a survey was significant, $F(2, 235) = 8.17, p < .001, \eta^2 = 0.07$. Planned Bonferroni post-hoc comparisons ($\alpha = 0.05$) indicated that university samples ($M = 63.0\%, SD = 28.0\%$) had a significantly higher response rate compared to multi-organization field samples ($M = 44.9\%, SD = 22.0\%$). However, the comparisons did not find a difference between university samples and single-organization field samples ($M = 54.7\%, SD = 20.7\%$). Therefore, Hypothesis 11 was partially supported.
Linear Regression Model

To provide a test of the remaining hypotheses, all study codes were entered into a meta-analytic regression analysis (e.g., Huffcutt & Woehr, 1999; Judge & Piccolo, 2004; Riketta, 2008; Viswesvaran & Ones, 1995) utilizing the SAS Institute’s (2012) PROC REG program. For a power level of 0.80, Cohen’s (1988) convention for an effect size of .02, .15, and .35 for small, medium, and large effects, for a multiple regression in a meta-analytic context would require a $k$ of 406, 66, and 36 studies, respectively. Accordingly, the regression analysis in the current study ($k=238$) had sufficient power to detect small-to-medium effect sizes.

All variables from Figure 1 were entered simultaneously as main effects in a regression model. Continuous variables were mean-centered to reduce the effects of multicollinearity (Aiken & West, 1991), and the use of incentives and the target population were dummy-coded before being entered in the analysis. The overall model was significant, $F(15, 198) = 2.99, p < .001$, with a $R^2$ of .185 indicating the predictors in the model accounted for 18.5% of variance in the dependent variable of response rates (adjusted $R^2 = .123$). Parameter estimates from the regression analysis are presented in Table 5.

In this main effects regression model, survey length ($\beta = -0.13, p = .01$), and the modal job complexity of survey recipients ($\beta = -0.23, p < .01$) were significant predictors of response rates. Therefore, Hypothesis 5 was supported by the results of the main effects regression analysis, which predicted that the total number of survey items would have a negative relationship with response rates, as was Hypothesis 12, which predicted that job complexity would have a negative relationship with response rates. Although not significant
in the regression model, the modal education level of survey recipients was significantly correlated with response rates, \( r = -0.23, p = 0.01 \) (see Table 3). Therefore, Hypothesis 10 was partially supported. No other significant relationships were detectable in the regression analysis of an effect on response rates for topic salience (Hypothesis 1), topic sensitivity (Hypothesis 2), identification likelihood (Hypothesis 4), advanced notice (Hypothesis 6), follow-up contacts (Hypothesis 7), or modal education level (Hypothesis 10).

**Relative Weights Regression Analysis**

With meta-analytic data, there are often potential issues with multicollinearity among predictors, which relative importance analysis as described by Johnson (2000) is particularly suited to address. Relative importance was defined by Johnson and LeBreton (2004) as “the proportionate contribution each predictor makes to \( R^2 \), considering both its direct effect (i.e., its correlation with the criterion) and its effect when combined with the other variables in the regression equation” (p. 240). This analytical strategy provides a means by which to gauge the relationship between response rates and response enhancement techniques by providing more information as to the unique contribution of each predictor in the model. Relative importance analysis has been used in the organizational research domain in meta-analyses of relationships between cognitive ability and job performance (Lang, Kersting, Hülsheger, & Lang, 2010), emotional intelligence and job performance (O’Boyle, Humphrey, Pollack, Hawver, & Story, 2011), and transformational leadership and follower performance (Wang, Oh, Courtright, & Colbert, 2011), but to date has not been utilized in a meta-analysis on determinants of survey response.

To investigate Research Question 1 examining unique variance in response rates, the
potential predictors of rate of return that were measured on at least an ordinal scale were compared via relative weights analysis (Johnson, 2000). This analysis used the study-level data to provide a weighting scheme which indicates the predictor variables that account for greater or lesser proportions of the total explained variance in the regression model. This analytic strategy regressed the criterion of response rate on orthogonal transformations of the predictor variables to remove the effect of intercorrelations that may bias standardized regression weights. The resulting analysis provides coefficients (denoted $\varepsilon$; Johnson, 2000) that represent the contribution each predictor makes to variance in the criterion when the predictor is considered both uniquely and in the full regression model (Tonidandel & LeBreton, 2011). Each relative weight ($\varepsilon_j$) is scaled in the metric of variance explained, such that it represents the proportion of $R^2$ attributable to each predictor.

The parameter estimates from the relative weights analysis are shown in the rightmost column of Table 5. For Research Question 1, results showed that the modal job complexity of recipients accounted for the highest proportion of explained variance in response rates ($\varepsilon = 45.5\%$), followed by administration mode ($\varepsilon = 19.2\%$) and follow-up contacts ($\varepsilon = 16.1\%$).  

**Hierarchical Linear Modeling Analyses**

To investigate Research Questions 2 and 3, a series of multilevel models were fitted to the data to examine the variance in published response rates over time, and the extent to which study characteristics account for that variability within years and between years (Raudenbush & Bryk, 2002). This analysis was accomplished through the use of the SAS Institute’s (2012) PROC MIXED program. As noted previously, this represents the first use of HLM in meta-analytic research on response rates in published organizational literature.
There are several reasons for the appropriateness of utilizing HLM in the current study. First, the nested structure inherent in examining studies across time precludes an assumption of independent observations, and ignoring dependencies that exist in the data may result in significantly increased Type I error (Tabachnick & Fidell, 2007). In addition, Raudenbush and Bryk (2002) described the random effects model for meta-analysis as a special case of a multilevel regression model, as study characteristics that are often part of meta-analytic coding frameworks inherently represent variables across levels (i.e., characteristics across studies). Indeed, Hox (2010) noted that the formula for a fully unconditional model (also called an intercept-only, null, or empty model) in HLM is equivalent to the random effects model for meta-analysis as described by Hedges and Olkin (1985), and in practice the two computational approaches will produce convergent results. As Research Questions 2 and 3 in the current study sought to decompose the variability in survey return over time, a multilevel approach to study characteristics was suited to examining these trends that past reviews of response rates such as Anseel et al. (2010) have sought to do via examining regression coefficients with interaction terms between study characteristics and survey year in an ordinary least-squares regression model.

First, a fully unconditional model was fitted to the data to test for the presence of significant variability in response rates for the collected primary studies between and within years of publication. In other words, to test whether there were differences between average response rates over the years 2000 to 2014 as described in Research Question 2. This model was specified as a baseline assessment of variance to obtain estimates of within-year (\(\sigma^2\)) and between-year (\(\tau_{00}\)) variability in response rates (Raudenbush & Bryk, 2002). These estimates
were then used to obtain an intraclass correlation coefficient (ICC) through the formula, \( \rho_I = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \), which indicates the proportion of variance between years; the proportion of within-year variance is then equivalent to \( 1 - \rho_I \). As shown in Table 6 (see column for Model 1), there was significant variability in response rates at Level 2 (ICC = 0.37). The model intercept (\( \gamma_{00} \)) represents an average response rate of 51.2% across studies across years (\( t = 34.53, p < .001 \)). Results of the unconditional model showed that 63% of the variance in response rates can be potentially explained by differences in primary studies at Level 1 (\( \sigma^2 = 0.031, z = 3.41, p < .001 \)), and 37% of the variance in response rates can be accounted for by publication year (\( \tau_{00} = 0.019, p < .025 \)). Thus, there has been significant variation in response rates between years during the period under study (2000-2014). Figure 2 presents a boxplot of response rates from 2000-2014, as reported in the articles that met the inclusion criteria for meta-analysis. As publication year can be considered to be monotonically related to response rates, as suggested by Cycyota and Harrison (2006), a post-hoc Spearman rank-order correlation was conducted between response rates and publication year. The Spearman correlation showed no significant directional trend in response rates over time (\( r_s = 0.04, p = 0.54 \)), concurring with the Pearson correlation reported in Table 3 (\( r = 0.04, p = 0.57 \)). Further, the main effects regression did not show a significant relationship between year of publication and response rates (\( \beta = 0.06, p = 0.40 \)). As such, Research Question 2 found that although there was significant variation between years, there was not a significant directionality to the relationship.

Following the unconditional model, continuous study-level codes (i.e., continuous variables at Level 1) were entered into the model to determine the extent to which they
explained within-group variance in response rates, while allowing response rate intercepts to randomly vary at the higher levels of the model (i.e., an ANCOVA with random intercepts regression model; Raudenbush & Bryk, 2002). This examines whether the predictors of response rates from Figure 1 are related to response rates when accounting for publication year, as described in Research Question 3. All parameter estimates for this model are shown in Table 6 (see column for Model 2). Predictor variables were centered on the grand mean, such that the resulting parameter estimate for each predictor represents the effect on response rates adjusted for the means of other predictors in the model; this linear transformation also allows the variances of the intercept and slopes for response rates to be interpreted as the expected variances when all predictors are at their means and have a value of zero (Hox, 2010). The results of the model found that higher modal job complexity ($\gamma_{80} = -0.091$, $t = -3.64$, $p < 0.01$) exhibited a negative and statistically significant relationship with response rates. There were no other significant predictors of response rates in Model 2. The proportion of variance in response rates at Level 1 can be derived through the formula, $R^2_w = (\sigma^2_u + \hat{s}^2)/\sigma^2_u$, where $\sigma^2_u$ represents the Level 1 variance from Model 1. From the Level 1 residual variance ($\hat{s}^2$) in this model, 18.6% of the variance in response rates at Level 1 was accounted for by the predictors added to the regression equation in Model 2.

Finally, a random-coefficients regression model (Raudenbush & Bryk, 2002) was specified where the between-year constraint on parameter estimates for slopes were freed for job complexity. This model allowed both slopes and intercepts for job complexity to randomly vary at Level 2 (i.e., by publication year) while constraining the slopes for variables that were not significant in Model 2. Parameter estimates for this model are shown
in Table 6 (see column for Model 3). As with the previous model, job complexity ($\gamma_{80} = -0.087$, $t = -3.40$, $p < 0.01$) was associated with significant decreases in response rates. However, there were not significant differences in slopes between years for job complexity. There were no other significant predictors of response rates in Model 3. Thus, Research Question 3 found that the modal job complexity of a sample was significantly and negatively related to response rates, though this relationship does not significantly vary in its slope across years.

**Discussion**

This study tested a conceptual model that considered the influence of the content of a survey, the administration of a survey, and the characteristics of the target recipients on response rates in organizational research settings. The analyses that were performed offer a quantitative exploration of the use of surveys in representative published literature, and provide a summative and comparative analysis of the contributors to survey return over the course of 15 years in contemporary organizational research. In addition, the relative importance and HLM analyses conducted in the current study are the first known application of these statistical techniques to a meta-analysis of survey response rates in the organizational sciences, providing a perspective on trends in survey return that has not been previously available in past reviews. Therefore, this study broadens both the understanding of response behavior in organizational research and illustrates the potential statistical applications with meta-analytic data sets of study methodology.

Overall, mixed support was found for the hypothesized relationships depicted in Figure 1. In the predictor category involving aspects of survey content, two variables were
expected to influence response rates, though neither of them did. Specifically, there was not a significant relationship between response rates and the salience of a survey topic, despite previous meta-analytic findings for an effect of salience on response rates in organizational literature (e.g., Anseel et al., 2010, Cycyota & Harrison, 2006, Roth & BeVier, 1998).

Similarly, no effect was found for survey topic sensitivity on response rates, which replicates previous selected interdisciplinary meta-analytic findings (Cook et al., 2000; Edwards et al., 2002) despite justification for expecting an effect (e.g., Tourangeau, Groves, & Redline, 2010; Tourangeau & Yan., 2007). Accordingly, the results of the present meta-analysis did not suggest that aspects of survey content play a significant role in driving response rates to organizational surveys.

For the second predictor category in Figure 1 involving aspects of survey methodology, seven methodological characteristics of surveys were expected to influence response rates. Response rates were not related to personalized invitations to encourage completion rates when contacting survey recipients, despite the results of previous reviews (e.g., Anseel et al., 2010; Edwards et al., 2002; Fox et al., 1988; Yu & Cooper, 1983). Cycyota and Harrison (2006) similarly failed to find an effect for salutation specificity in their review of executive samples, and concluded that the effort involved with making survey invitations specific to survey recipients may not be worth the expenditure of resources as the practice did not appear to influence response rates in a meaningful way. Despite accounting for the use of identification numbers to protect confidentiality, which had not been done in many previous meta-analyses (e.g., Cook et al., 2000; Yammarino et al., 1991; Yu & Cooper, 1983), the results of the current study failed to find a significant relationship between when
sponsors made provisions for the privacy of survey recipients and subsequent response rates.

Although several past meta-analyses have not found longer surveys to influence response rates (e.g., Goyder, 1982; Roth & BeVier, 1998; Yu & Cooper, 1983), results did support an effect of survey length on response rates. As previous reviews such as Heberlein and Baumgartner (1978) considered survey length as a metric of the total number of pages, the reported results suggest that future meta-analyses should consider treating survey length as the total number of items. The current study did not find an effect of either advanced notice or follow-up contacts on response rates. As noted previously, Anseel et al. (2010) found that the gains in curbing low response rates via advanced notice appeared to be declining, and speculated that follow-up contacts were typically employed as an ad hoc tactic. However, Manfreda et al. (2008) posited that as computers are increasingly utilized to deliver surveys, electronic reminders may increasingly be seen by some recipients as intrusive and unwanted contact by the survey sponsor. Although one cannot accept a null hypothesis, the lack of results for the use of these techniques could reflect survey sponsors’ efforts to mitigate low response rates rather than to enhance them through multiple contacts.

The results supported an effect for a survey’s administration medium on response rates, such that Web-based surveys had significantly lower rates of completion compared to paper surveys. This finding is in line with the results of previous research and recommendations across a variety of disciplines (e.g., Crawford, Couper, & Lamias, 2001; Cronk & West, 2002; Dillman, 2000; Fan & Yan, 2010; Kaplowitz, Hadlock, & Levine, 2004). Though the Internet provides inexpensive and theoretically unlimited capacity as a survey administration medium, there are a number of technical failure points with online
surveys that do not have a counterpart in paper surveys. For example, a paper survey does not have to contend with a browser software crashing, or a broken hyperlink, or server downtime where the survey is hosted, or automated “spam” folders that may delete some or all attempted contacts from a survey sponsor, all of which could in part or in combination contribute to lower response rates for Web-based surveys. Finally, no effect was found for the use of incentives on response rates, in accordance with several past meta-analytic results (Baruch & Holtom, 2008; Cycyota & Harrison, 2006; Manfreda et al., 2008).

For the third category in Figure 1 concerning characteristics of survey recipients, results showed a mixed pattern of support for the three predictors considered. No significant effect was found for the modal education level of respondents on response rates, and despite a significant negative correlation this variable did not account for a large amount of variance in response rates as shown in Table 5. A partial effect was found for the source of an organizational sample on response rates. More specifically, university samples had significantly higher response rates compared to samples from multiple organizations, but university samples were not significantly different compared to surveys that sampled a single organization.

The results of the meta-analysis did support an effect of respondent job complexity on response rates, as hypothesized. Further, the findings for Research Questions 1 and 3 provided additional support for the meaningfulness of job complexity as a predictor of response rates to organizational surveys. It may be that individuals with more complex jobs tend to have more power within the organization and therefore more opportunities outside of a survey effort to influence organizational decisions. For those lower in stature, survey input
could be their primary opportunity for voice. In addition, as firm-level surveys historically tend to target individuals higher in organizational rank (e.g., Cycyota & Harrison, 2002), high complexity jobs may receive higher volumes of survey requests. As the slope coefficient for job complexity in Table 6 did not significantly vary across the 15 years under study, the results for Research Question 3 suggested that the downward influence of higher job complexity on response rates has been relatively stable over time.

**Point Estimate for Response Rates**

Several relatively recent meta-analyses have sought to provide benchmarks for researchers and practitioners in organizational science, given variability observed in response rates and strategies to increase response rates as identified in primary study designs. Among oft-used benchmarks, Baruch (1999) estimated an average response rate of 55.6% across studies published in several management journals over three decades. Other quantitative reviews have found comparable numbers; Anseel et al. (2010) reported an average response rate of 52.3%, and Roth and BeVier (1998) reported 57% in their meta-analysis. In the current study, the arithmetic mean response rate across all studies was 51%; all three HLM models also resulted in a point estimate for a mean response rate of 51%, as shown in Table 5. Accordingly, these convergent results accomplished the noteworthy aim of providing a benchmark as to the average response rate for survey data collection efforts in 21st century organizational research.

The findings of Research Question 2 provided further insight into response rates. Results showed that while there is significant variability in response rates between years, there does not appear to be a significant directional trend in response rates.
Practical Implications

For organizations and practitioners, the results reported above have implications for the design of applied survey research. The results of this meta-analysis should assist survey sponsors and researchers in making informed decisions about investing resources in the use of response enhancing techniques. As the majority of predictors in the model represent widely-accepted practices to encourage survey return, a lack of findings could indicate that either the techniques are less effective than what has been observed in the past, they are not relevant to organizational populations (e.g., Cycyota & Harrison, 2002), or that their current utility is primarily to compensate for known shortcomings with survey design or administration across data collection efforts as preventative measures.

The investigation of response behavior in organizational research accomplished in this study appreciably expands the scope of previous reviews of response rates such as those conducted by Anseel et al. (2010), Baruch (1999), Baruch and Holtom (2008), Roth and BeVier (1998), and Yammarino et al. (1991). The results of the current study also permit a description of the prototypical survey design in top-tier journals for organizational science. Given that all continuous variables were grand mean centered in the HLM analysis, the model intercept represents the adjusted mean for response rates, holding the predictors constant at their respective mean (i.e., zero for continuous variables) across publication years. In other words, the average survey research effort for the time period of 2000-2014 had a response rate of approximately 51%, a topic that was mildly salient and sensitive to recipients, likely used identification numbers to track recipients, contained 41 items, was not accompanied by respondent incentives, and was usually administered on paper with no
advanced notice of the survey and one follow-up contact. The recipients of this illustrative survey effort were likely to be employees within the same organization, with at least some college education, in moderately complex jobs.

**Limitations**

While care was taken to encapsulate a broad spectrum of potential influences on response behavior, this study is not without limitations. As survey methods continue to evolve, no single study will provide incontrovertible evidence that a given variable affects recipients’ behavior—the dynamic relationship of survey sponsor, survey administration, and survey recipient will continually call for empirical inquiry. There are other theoretically interesting study characteristics that could not be included due to the scope or specificity of the variables and the amount of information that can be reliably collected from method sections of published research. For example, Church (1993) commented that although an effort was made to include variables such as survey length or topic salience in his meta-analysis, “many of the authors were too scant in their methodological descriptions to determine these details with any accuracy” (p. 66). In another instance, Kaplowitz, Lupi, Couper and Thorp (2012) found effects for survey invitation manipulations on response rates in a university population, but these effects differed between faculty, staff, and student respondents—distinctions in recipient groups that may be too granular to code reliably across studies. Further, there are likely potential antecedents to survey return that are not reported or studied prevalently enough in the extant organizational literature to facilitate meta-analysis.

It should also be noted that some researchers have posed alternative taxonomies of response behavior that are not captured in the model proposed in the current study. Many
employees may fail to complete and return surveys for reasons such as neglect (Rogelberg & Luong, 1998; Viswesvaran, Barrick, & Ones, 1993), and overt refusal (Groves & Couper, 1998). Relatedly, Newman (2009) provided a quantifiable taxonomy for incomplete surveys: item-level nonresponse, where data are missing for only a few items; scale-level nonresponse, where data are missing for an entire measured construct; and unit nonresponse, where data were never provided by the survey recipient. While many of these distinctions cannot be directly assessed through meta-analytic techniques without access to primary study data, they bear mention as complementary conceptualizations of response behavior.

Lastly, this meta-analysis only considered published research in top-tier journals in the fields of applied psychology and management, which may be a concern with the inclusion criteria for primary studies. In a previous review, Baruch and Holtom (2008) found no significant difference in response rates across 17 journals spanning first- and second-tier rankings that primarily published organizational research. However, the authors found that journals did appreciably differ in the number of studies that reported procedural details in the “Methods” section of each individual study, such that journals considered top-tier were more likely to report richer detail on aspects of survey administration. The current study focuses on a selection of top-tier outlets to provide a cumulative quantitative analysis of what may be considered the most methodologically rigorous survey efforts, as was the case in the meta-analysis by Baruch (1999). As such, the sample of studies analyzed in the current research can be taken as likely to reflect the larger population of published organizational survey research that satisfied the inclusion criteria.

**Future Research**

As technology continues to transform the business landscape, the methods through
which employees are surveyed have increasingly been computer-based (Naglieri et al., 2004; Tourangeau, 2004). Accordingly, studies of survey methodology will likely require constant review and revisions to best practices. While advancements in paper production or pen design have little bearing on survey recipient behavior, browser interfaces and innovations in computer displays can have a non-arbitrary impact on how a recipient navigates, interprets, and responds to the questions being asked. Continued research on response behavior is certainly warranted as Web-based survey delivery practices continue to evolve with new software technologies and delivery platforms such as mobile devices and social media frameworks. In particular, surveys delivered over mobile phones may have to contend with issues such as insufficient attention caused by environmental distractions and multitasking (Lynn & Kaminska, 2012), or complications with surveys delivered through “apps” that can be unintentionally corrupted, deleted, or blocked (van Heerden et al., 2014).

Future research should also seek to better elucidate the role of technology on response enhancing techniques that may account for variance in response rates. For instance, sponsors will need to better adapt survey practices such as incentives to the Internet, where the form of an incentive or the actions required by a survey recipient to redeem an incentive may be subject to obstacles not present with mailed surveys. Larose and Tsai (2014) posited that online incentives for Web surveys, such as a gift card or some form of online payment to a recipient’s account, may suffer from issues related to their credibility (e.g., trust that the code to redeem the incentive truly works), coverage (e.g., a recipient lacking the right type of account through which to receive the incentive), and convenience (e.g., the effort required for a participant to log-in to an account or otherwise verify his or her identity). Although a cash
inventive may circumvent such issues, preliminary results are mixed on whether using a mailed pre-paid incentive with a Web-based survey can lead to nonresponse bias with regard to the demographics of respondents (e.g., Dykema et al., 2013; Parsons & Manierre, 2014).

Future research should also seek to assess trends between the meta-analyses conducted on response rates. For instance, seeking to understand and/or replicate reviews using different coding schemes and inclusion criteria may serve to better illuminate which approaches yield the most methodologically sound results. Lipsey and Wilson (2001) noted that qualitative characteristics between studies were more difficult to account for in meta-analysis due to the need to transform design or analysis features into an interpretable code that adequately captures enough information for analysis, compared to the palpability of summarizing numerical effect sizes. Correspondingly, greater specificity in coding may limit the statistical power available to a meta-analyst to test for method effects. Future investigations of meta-analytic techniques would benefit from a scoring or coding system for the analytical sophistication of quantitative reviews and how researchers manage what is often a trade-off between complexity and interpretability.
REFERENCES

References marked with an asterisk indicate studies included in the meta-analysis.


American Psychological Association (2010). *Publication manual of the American


*Caligiuri, P. M. (2000). The Big Five personality characteristics as predictors of expatriate’s desire to terminate the assignment and supervisor-rated performance. Personnel


burden. *Social Science Computer Review, 19*, 146-162.


Helgeson, J. C., Voss, K. E., & Terpening, W. D. (2002). Determinants of mail-survey


Judge, T. A., & Piccolo, R. F. (2004). Transformational and transactional leadership: A meta-


Kepes, S., McDaniels, M. A., Brannick, M. T., & Banks, G. C. (2013). Meta-analytic reviews in the organizational sciences: Two meta-analytic schools on the way to MARS (the


What will the boss think? The impression management implications of supportive relationships with star and project peers. *Personnel Psychology*, n/a–n/a. 
http://doi.org/10.1111/peps.12091


Mason, C., Allam, R., & Brannick, M. T. (2007). How to meta-analyze coefficient-of-


*Rogelberg, S. G., Conway, J. M., Sederburg, M. E., Spitzmüller, C., Aziz, S., & Knight, W.


Thomson Corporation. (2012). *Institute for Scientific Information (ISI). Social Science Citation Index-Journal Citation Reports*. Online resource.


Table 1

*Excluded Studies from Meta-Analytic Coding*

<table>
<thead>
<tr>
<th>Reason</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incorrect level of analysis</td>
<td>208</td>
</tr>
<tr>
<td>Not enough information to determine if inclusion criteria were met</td>
<td>78</td>
</tr>
<tr>
<td>Use of archival data</td>
<td>68</td>
</tr>
<tr>
<td>Interviews/diary design</td>
<td>34</td>
</tr>
<tr>
<td>Not an empirical study (e.g., theory/methods article)</td>
<td>30</td>
</tr>
<tr>
<td>Lab study/experimental design</td>
<td>18</td>
</tr>
<tr>
<td>Not an organizationally-relevant sample</td>
<td>15</td>
</tr>
<tr>
<td>Previous meta-analysis</td>
<td>10</td>
</tr>
<tr>
<td>Mandatory survey</td>
<td>2</td>
</tr>
</tbody>
</table>
Table 2

*Descriptive Statistics by Journal*

<table>
<thead>
<tr>
<th>Journal</th>
<th>RR</th>
<th>SD</th>
<th>k by journal</th>
<th>% of k studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>JAP</td>
<td>53.9%</td>
<td>22.3%</td>
<td>45</td>
<td>18.9%</td>
</tr>
<tr>
<td>PPsy</td>
<td>51.4%</td>
<td>22.5%</td>
<td>61</td>
<td>25.6%</td>
</tr>
<tr>
<td>AMJ</td>
<td>59.1%</td>
<td>24.8%</td>
<td>14</td>
<td>5.9%</td>
</tr>
<tr>
<td>JOM</td>
<td>50.1%</td>
<td>22.3%</td>
<td>91</td>
<td>38.2%</td>
</tr>
<tr>
<td>ORM</td>
<td>54.8%</td>
<td>21.1%</td>
<td>16</td>
<td>6.7%</td>
</tr>
<tr>
<td>MISQ</td>
<td>34.1%</td>
<td>12.3%</td>
<td>11</td>
<td>4.6%</td>
</tr>
</tbody>
</table>

Notes: Total $k = 238$; $^a$JAP = Journal of Applied Psychology, PPsy = Personnel Psychology, AMJ = Academy of Management Journal, JOM = Journal of Management, ORM = Organizational Research Methods, MISQ = Management Information Systems Quarterly; $^b$ RR = average response rate per journal; $^c$ Percentage of total $k$ by the number of studies from each journal.
Table 3

*Descriptive Statistics and Correlations for Study Variables*

<table>
<thead>
<tr>
<th>Variablea</th>
<th>M</th>
<th>SD</th>
<th>1.</th>
<th>2.</th>
<th>3.</th>
<th>4.</th>
<th>5.</th>
<th>6.</th>
<th>7.</th>
<th>8.</th>
<th>9.</th>
<th>10.</th>
<th>11.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Response rate</td>
<td>51.3%</td>
<td>22.3%</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Year of publication</td>
<td>-</td>
<td>-</td>
<td>0.04</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Salience</td>
<td>1.84</td>
<td>0.75</td>
<td>-0.03</td>
<td>0.04</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Sensitivity</td>
<td>1.95</td>
<td>0.77</td>
<td>-0.08</td>
<td>-0.01</td>
<td>0.49**</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Salutation specificityb</td>
<td>0.12</td>
<td>0.33</td>
<td>-0.03</td>
<td>-0.16*</td>
<td>-0.04</td>
<td>0.07</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Identification likelihood</td>
<td>2.14</td>
<td>0.73</td>
<td>0.05</td>
<td>0.10</td>
<td>-0.05</td>
<td>-0.01</td>
<td>0.10</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Survey length</td>
<td>41.08</td>
<td>25.89</td>
<td>-0.12</td>
<td>0.02</td>
<td>0.09</td>
<td>-0.08</td>
<td>-0.05</td>
<td>-0.04</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Advance notice</td>
<td>0.31</td>
<td>0.53</td>
<td>-0.07</td>
<td>0.02</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.28**</td>
<td>0.09</td>
<td>0.03</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9. Follow-up contacts</td>
<td>0.47</td>
<td>0.79</td>
<td>-0.14</td>
<td>0.07</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.21*</td>
<td>0.08</td>
<td>-0.08</td>
<td>0.25**</td>
<td>-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Administration mediumc</td>
<td>0.33</td>
<td>0.47</td>
<td>-0.12</td>
<td>0.46**</td>
<td>0.03</td>
<td>-0.02</td>
<td>-0.03</td>
<td>-0.06</td>
<td>-0.07</td>
<td>0.07</td>
<td>-0.07</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>11. Modal education</td>
<td>2.76</td>
<td>0.81</td>
<td>-0.23**</td>
<td>0.11</td>
<td>0.12</td>
<td>0.32**</td>
<td>0.04</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.07</td>
<td>0.06</td>
<td>0.09</td>
<td>-</td>
</tr>
<tr>
<td>12. Modal job complexity</td>
<td>1.88</td>
<td>0.69</td>
<td>-0.32**</td>
<td>-0.05</td>
<td>0.06</td>
<td>0.25**</td>
<td>0.19*</td>
<td>0.05</td>
<td>0.03</td>
<td>0.13</td>
<td>0.09</td>
<td>0.06</td>
<td>0.69**</td>
</tr>
</tbody>
</table>

*Notes: aN = 238 for all variables except survey length (N = 216), modal education (N = 132), and modal job complexity (N = 198); b 0 = no personalization, 1 = personalized survey invite; c 0 = paper survey, 1 = Web survey; *p < .05, **p < .01.*
Table 4
*Descriptive Statistics for Nominal Variables*

<table>
<thead>
<tr>
<th>Variable</th>
<th>( k )</th>
<th>RR(^a)</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Salutation specificity</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No personalization</td>
<td>138</td>
<td>51.4%</td>
<td>22.2%</td>
</tr>
<tr>
<td>Personalized invitation</td>
<td>19</td>
<td>49.3%</td>
<td>23.1%</td>
</tr>
<tr>
<td><strong>Administration medium</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Paper</td>
<td>144</td>
<td>50.7%</td>
<td>21.4%</td>
</tr>
<tr>
<td>Web</td>
<td>70</td>
<td>45.4%</td>
<td>20.9%</td>
</tr>
<tr>
<td><strong>Incentives</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No incentives</td>
<td>192</td>
<td>51.7%</td>
<td>22.4%</td>
</tr>
<tr>
<td>Nonmonetary</td>
<td>23</td>
<td>54.1%</td>
<td>24.1%</td>
</tr>
<tr>
<td>Monetary</td>
<td>23</td>
<td>44.9%</td>
<td>19.6%</td>
</tr>
<tr>
<td><strong>Target population</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University/lab sample</td>
<td>16</td>
<td>63.0%</td>
<td>28.0%</td>
</tr>
<tr>
<td>Single organization/specific occupation sample</td>
<td>124</td>
<td>54.8%</td>
<td>20.7%</td>
</tr>
<tr>
<td>Multiple organization/general employee sample</td>
<td>98</td>
<td>44.9%</td>
<td>22.0%</td>
</tr>
</tbody>
</table>

*Notes:* \(^a\) Mean response rate by nominal group.
Table 5
Standardized, Unstandardized, and Relative Weight Regression Parameters for Predictors of Response Rates

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\beta$</th>
<th>$B$</th>
<th>$SE$</th>
<th>$t$</th>
<th>$\varepsilon_j$ $^b$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.00</td>
<td>-5.47</td>
<td>7.11</td>
<td>-0.77</td>
<td>-</td>
</tr>
<tr>
<td>Year</td>
<td>0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>0.85</td>
<td>5.3%</td>
</tr>
<tr>
<td>Salience</td>
<td>0.06</td>
<td>0.02</td>
<td>0.02</td>
<td>0.78</td>
<td>0.4%</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>-0.08</td>
<td>-0.02</td>
<td>0.02</td>
<td>-1.00</td>
<td>4.3%</td>
</tr>
<tr>
<td>Salutation specificity</td>
<td>0.06</td>
<td>0.04</td>
<td>0.05</td>
<td>0.82</td>
<td>0.6%</td>
</tr>
<tr>
<td>Identification likelihood</td>
<td>0.06</td>
<td>0.02</td>
<td>0.02</td>
<td>0.88</td>
<td>0.4%</td>
</tr>
<tr>
<td>Survey length</td>
<td>-0.13</td>
<td>0.00</td>
<td>0.00</td>
<td>-1.99*</td>
<td>2.7%</td>
</tr>
<tr>
<td>Advanced notice</td>
<td>0.01</td>
<td>0.00</td>
<td>0.03</td>
<td>0.13</td>
<td>3.8%</td>
</tr>
<tr>
<td>Follow-up contacts</td>
<td>-0.11</td>
<td>-0.04</td>
<td>0.02</td>
<td>-1.67</td>
<td>16.1%</td>
</tr>
<tr>
<td>Administration medium</td>
<td>-0.12</td>
<td>-0.06</td>
<td>0.04</td>
<td>-1.61</td>
<td>19.2%</td>
</tr>
<tr>
<td>Incentives (nonmonetary) $^c$</td>
<td>0.08</td>
<td>0.05</td>
<td>0.05</td>
<td>1.10</td>
<td>-</td>
</tr>
<tr>
<td>Incentives (monetary) $^c$</td>
<td>-0.06</td>
<td>-0.04</td>
<td>0.05</td>
<td>-0.80</td>
<td>-</td>
</tr>
<tr>
<td>Modal education</td>
<td>-0.05</td>
<td>-0.02</td>
<td>0.03</td>
<td>-0.63</td>
<td>1.9%</td>
</tr>
<tr>
<td>Target population (single organization sample)$^d$</td>
<td>-0.10</td>
<td>-0.04</td>
<td>0.06</td>
<td>-0.71</td>
<td>-</td>
</tr>
<tr>
<td>Target population (multiple organization sample)$^d$</td>
<td>-0.25</td>
<td>-0.11</td>
<td>0.06</td>
<td>-1.81</td>
<td>-</td>
</tr>
<tr>
<td>Modal job complexity</td>
<td>-0.23</td>
<td>-0.08</td>
<td>0.03</td>
<td></td>
<td>2.83** 45.5%</td>
</tr>
</tbody>
</table>

Notes: $^a$ Overall $R^2 = 0.185$, $F(15, 198) = 2.99$, $p < .01$; $^b$ relative weights (Johnson, 2000); $^c$ dummy coded using ‘no incentives’ as the reference group; $^d$ dummy coded using university/lab sample as the reference group.
Table 6

*Estimates for Hierarchical Linear Models Predicting Response Rates*

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3 $^a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\gamma_{00}$)</td>
<td>0.51* (0.01)</td>
<td>0.51* (0.01)</td>
<td>0.51* (0.01)</td>
</tr>
<tr>
<td>Salience ($\gamma_{10}$)</td>
<td>0.01 (0.02)</td>
<td>0.01 (0.02)</td>
<td></td>
</tr>
<tr>
<td>Sensitivity ($\gamma_{20}$)</td>
<td>-0.01 (0.02)</td>
<td>-0.01 (0.02)</td>
<td></td>
</tr>
<tr>
<td>Identification likelihood ($\gamma_{30}$)</td>
<td>0.02 (0.02)</td>
<td>0.02 (0.02)</td>
<td></td>
</tr>
<tr>
<td>Survey length ($\gamma_{40}$)</td>
<td>-0.01 (0.01)</td>
<td>-0.01 (0.01)</td>
<td></td>
</tr>
<tr>
<td>Advanced notice ($\gamma_{50}$)</td>
<td>-0.01 (0.03)</td>
<td>-0.01 (0.03)</td>
<td></td>
</tr>
<tr>
<td>Follow-up contacts ($\gamma_{60}$)</td>
<td>-0.04 (0.02)</td>
<td>-0.04 (0.02)</td>
<td></td>
</tr>
<tr>
<td>Modal education ($\gamma_{70}$)</td>
<td>-0.02 (0.03)</td>
<td>-0.02 (0.03)</td>
<td></td>
</tr>
<tr>
<td>Modal job complexity ($\gamma_{80}$)</td>
<td>-0.09* (0.03)</td>
<td>-0.09* (0.03)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 ($\sigma^2$)</td>
<td>0.03* (0.01)</td>
<td>0.03* (0.01)</td>
<td>0.03* (0.01)</td>
</tr>
<tr>
<td>Level 2 ($\tau_{00}$)</td>
<td>0.02* (0.01)</td>
<td>0.02* (0.01)</td>
<td>0.02* (0.01)</td>
</tr>
<tr>
<td>Slope for job complexity ($\tau_{11}$)</td>
<td></td>
<td></td>
<td>0.00 (0.00)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model Fit</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log likelihood ($\chi^2$)</td>
<td>-36.1</td>
<td>-12.0</td>
<td>-12.7</td>
</tr>
<tr>
<td>AIC</td>
<td>-32.1</td>
<td>-8.0</td>
<td>-6.7</td>
</tr>
<tr>
<td>BIC</td>
<td>-25.3</td>
<td>-1.2</td>
<td>3.4</td>
</tr>
</tbody>
</table>

*Notes:* Entries show parameter estimates with standard errors in parentheses; $^a$ Regression slope for job complexity allowed to vary across publication year; *$p < .05$. 
Figure 1. Conceptual model of response antecedents.
Figure 2. Boxplot of response rates by year.

Note: The length of the box represents the interquartile range, the diamond represents the mean, the horizontal line represents the median, and the vertical lines extend to the minimum and maximum values of response rates for each year.
APPENDIX
## Appendix A

**Meta-Analysis Coding Rules**

<table>
<thead>
<tr>
<th>Category</th>
<th>Code Name</th>
<th>Explanation</th>
<th>Rating Scale</th>
</tr>
</thead>
</table>
| General     | Year of publication| The year the primary study was published  
Objective: “When was the study published?” | Numerical                  |
|             | Sample size        | $N$ of relevant study (if study1-study2, use study with larger $N$)  
Objective: “How many respondents answered the survey?” | Numerical                  |
|             | Response rate      | Ratio of total usable surveys to total surveys administered  
Objective: “What was the ratio of survey respondents to survey recipients?” | Total usable surveys total administered |
<table>
<thead>
<tr>
<th>Category</th>
<th>Code Name</th>
<th>Explanation</th>
<th>Rating Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Survey Content</strong></td>
<td>Topic salience</td>
<td>Salience of topic to target recipients</td>
<td>1 = Salient (important and current), 2 = Possibly salient (important though not necessarily current), 3 = Nonsalient (neither important or current)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How personally relevant and timely was the topic to the survey recipients in the primary study?”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Topic sensitivity</td>
<td>Sensitivity of topic to target recipients</td>
<td>1 = Sensitive (intrusive, embarrassing), 2 = Possibly sensitive (intrusive, not likely to be embarrassing), 3 = Nonsensitive (neither intrusive nor embarrassing)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “Were survey recipients likely to perceive the survey topic as sensitive/personally revealing?”</td>
<td></td>
</tr>
<tr>
<td><strong>Methodology</strong></td>
<td>Salutation specificity</td>
<td>Personalization of the recipient in the survey invitation</td>
<td>. = not reported, 1 = No personalization, 2 = personalization of recipient,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “Was the survey invitation customized to send to each recipient?”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Identification likelihood</td>
<td>Probability of recipient identification</td>
<td>. = not reported, 1 = Fully identified (name or other personal information required), 2 = Partially identified (identification number or other non-personal identifier), 3 = Anonymous (no identifier)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How likely were recipients to feel they could be identified by the survey sponsor?”</td>
<td></td>
</tr>
<tr>
<td>Category</td>
<td>Code Name</td>
<td>Explanation</td>
<td>Rating Scale</td>
</tr>
<tr>
<td>---------------------</td>
<td>----------------------------</td>
<td>----------------------------------------------------------------------------</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td><strong>Methodology (cont.)</strong></td>
<td>Survey length</td>
<td>Total number of items in administered survey</td>
<td>N/A; . = not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How many questions were on the survey?”</td>
<td></td>
</tr>
<tr>
<td>Advanced notice</td>
<td>contacts</td>
<td>Total number of initial contacts prior to survey administration (e.g., pre-</td>
<td>0 = No contacts, 1 = 1 contact,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>notification)</td>
<td>2 = 2 contacts, 3 = 3 or more contacts; . = not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How many contacts were sent ahead of the survey itself?”</td>
<td></td>
</tr>
<tr>
<td>Follow-up contacts</td>
<td></td>
<td>Total number of follow-up contacts to unit nonrespondents</td>
<td>0 = No contacts, 1 = 1 contact,</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How many contacts were sent after the first contact with the</td>
<td>2 = 2 contacts, 3 = 3 or more contacts; . = not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td>recipient?”</td>
<td></td>
</tr>
<tr>
<td>Administration</td>
<td>medium</td>
<td>Media used to administer survey to target recipients</td>
<td>1 = Paper, 2 = Web-based; . = not reported</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “How were recipients to access the survey?”</td>
<td></td>
</tr>
<tr>
<td>Incentives</td>
<td></td>
<td>Use of incentives to encourage unit response</td>
<td>1 = No incentives, 2 = Monetary incentives, 3 =</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Objective: “What type of incentive was given for participation in the survey?”</td>
<td>Nonmonetary incentives</td>
</tr>
<tr>
<td>Category</td>
<td>Code Name</td>
<td>Explanation</td>
<td>Rating Scale</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>Recipient Characteristics</strong></td>
<td>Education</td>
<td>Average educational level of respondents&lt;br&gt;Objective: “How educated were the majority of respondents in the primary study?”</td>
<td>. = not reported, 1 = low (HS diploma or lower), 2 = medium (some college), 3 = high (Bachelor's degree), 4 = expert (graduate degree)</td>
</tr>
<tr>
<td><strong>Target population</strong></td>
<td></td>
<td>Origin of target recipients (if study1-study 2, use study with larger N)&lt;br&gt;Objective: “What type of audience was the survey administered to?”</td>
<td>1 = University/lab sample, 2 = Single organization/specific occupation sample, 3 = Multiple organization/general sample</td>
</tr>
<tr>
<td><strong>Job complexity</strong></td>
<td></td>
<td>Relative complexity of respondents occupation&lt;br&gt;Objective: “How complex were the occupations for the majority of respondents in the primary study?”</td>
<td>. = not reported, 1 = Low (hourly workers, clerical workers), 2 = Medium (lower to mid-level managers) 3 = High (executive management; professions, e.g., lawyer, physician)</td>
</tr>
</tbody>
</table>
Appendix B

Proposal Document

The influence of survey characteristics on individual response behavior has been a constant interest of researchers for several decades. Survey methodology has benefited over time from an influx of empirical findings, technological advancements, and theoretical insights into response behavior, which have necessitated and instigated revisions to what is commonly accepted as best practices for survey administration (Krosnick, 1999). The interaction between an individual and a survey instrument is of particular importance for applied organizational research, as it facilitates testing a wide range of hypotheses which rely on self-reports of respondents. For researchers and practitioners in industrial and organizational (I/O) psychology and related disciplines, self-reports comprise one of the most readily available and widely utilized approaches to gathering information about work attitudes and work-related behavior. In practice, contemporary organizations often rely on self-report questionnaires as an efficient means to collect data on which to base decisions (e.g., Schmitt, 1994). In research, employee self-reports provide a foundation for the vast majority of scientific inquiries into work behavior (e.g., Aguinis, Pierce, Bosco, & Muslin, 2009; Podsakoff & Dalton, 1987). Surveys are the primary means of operationalizing a variety of constructs, and theories of work behavior depend on the validity of the measurement of these constructs.

Organizational surveys can be defined as a tool to collect self-report data from and relevant to organizations. Surveys focus on one or more levels of analysis, being utilized to
collect information on the organization itself, groups within the organization, or individual employees (Dutka & Frankel, 1993). Organizational surveys have applications that pertain to a variety of purposes, such as personality assessment, evaluations of knowledge and abilities, and the measurement of attitudes and perceptions. Though some surveys are ostensibly made mandatory by organizational leadership, many surveys are voluntary such that the recipient has the option to answer all or a portion of the items. For voluntary organizational surveys, a successful response that yields complete data from a questionnaire recipient is the vehicle for many organizational interventions and often the route to periodic, systemic evaluations of organizational functioning. Thus, there is a practicality in identifying ways in which survey practices can be improved or optimized.

A survey effort in an organization is comprised of five general phases (Edwards & Thomas, 1993; Rogelberg, Church, Waclawski, & Stanton, 2002). The first phase involves identifying the objectives and appropriateness of a survey, and then developing a plan for conducting the chosen survey. In the second phase, the survey materials are chosen, reviewed, and finalized. In the third phase, the survey instrument is administered to the target recipients. In the fourth phase, the data collected from the survey instrument are analyzed, including verifying the responses and doing any necessary data cleaning. In the fifth and final phase, the results of the survey effort are communicated back to stakeholders. As such, the aims of a survey effort can only be realized if recipients consent to provide complete data, and do so in ways which are conceptually consistent with the type information provided by others. To this end, it can be argued that the administration phase is the crux of the success of
a survey effort, with all other phases of the survey process either dictated by or seeking to influence this crucial point of interaction between the survey sponsor and the recipient. It is no surprise, then, that maximizing survey response has been a research focus in organizational literature for decades.

Indeed, as stated by Tourangeau (2004), “surveys rest on a delicate and complicated relationship between those who conduct surveys and those who take part in them” (p. 776). Though the stages of conducting a survey may involve a variety of choices to be made by survey developers and stakeholders, the focus of many studies of survey response behavior concerns what happens when a survey recipient receives a questionnaire. The magnitude of the influence of survey characteristics and their importance over time warrants continued investigation, as empirical findings and technological advancements continue to change how organizations and researchers plan, collect, and analyze survey data. Accordingly, there is an ever-present need to understand from a broad perspective those factors that lead a recipient to answer or fail to answer a survey and the contemporary contexts in which these outcomes occur.

Though there are several extant meta-analyses on response rates in organizational research, as will be described below, the present study contributes to the literature in three important ways. First, this study conducts a quantitative review of published response rates and factors related to survey content, survey methodology, and the recipient characteristics in top tier journals in the fields of I/O psychology and management and compares which factors are most influential on rates of survey return. This comparison will be accomplished via
relative importance analysis (Johnson, 2000), which has not previously been applied to meta-analytic data on response rates. Second, this study expands previous reviews such as those by Roth and BeVier (1998), Baruch and Holtom (2008), and Anseel, Lievens, Schollaert, and Choragwicka (2010) both by focusing exclusively on more recent volumes in the literature (2000-2014) than has been done previously and by including a range of variables related to the use of response enhancing techniques in organizational research. Third, this review examines variability in response rate trends over the span of fifteen years via hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002), which also has not been previously applied to meta-analytic data on response rates in organizational surveys. In addition to allowing questions to be answered about variability in survey return over time, the HLM regression model can be used to explore what response enhancing techniques may account for variability in response rates both within and between years in the literature. Though previous reviews of response rates in organizational research have provided benchmarks for representative levels of survey return (e.g., Baruch, 1999; Baruch & Holtom, 2008; Cycyota & Harrison, 2006; Roth & BeVier, 1998), no detailed explorations are available that compare the degree to which different aspects of surveys, their administration, and target recipient characteristics account for unique variability in response rates when considered both comparatively as well as across time. Accordingly, a quantitative review of the influence of catalysts for driving response rates would enrich this gap in the existing knowledge concerning organizational surveys.

In sum, the results of this review should provide academic researchers and
practitioners with current, empirically-based guidelines which can be used to proactively
gauge the potential response rate when planning a survey data collection. Such information
can enable survey designers to make strategic, informed decisions about the likely rate of
return based on aspects of survey content, administration, and the recipients who will receive
an invitation to participate. Given that surveys are utilized to measure a wide range of job-
related constructs for a variety of purposes, it is critical to determine how effectively
response enhancing techniques may be in influencing survey return in contemporary
organizations.

Before outlining the potential antecedents to recipient behavior, we next turn to
defining survey response rates and their implications, followed by a review of how recipients
respond to a survey and a qualitative summary of previous meta-analyses in organizational
research.

**Defining Response Rates in Organizational Research**

Response rates have been the primary outcome of interest in many examinations of
survey response behavior in organizational science and related disciplines (e.g., Anseel, et
al., 2010; Baruch, 1999; Baruch & Holtom, 2008; Church, 1993; Cycyota & Harrison, 2006;
Fox, Crask, & Kim, 1988; Roth & BeVier, 1998; Yu & Cooper, 1983). A response rate can
be defined as “the number of complete interviews with reporting units divided by the number
of eligible reporting units in the sample” (American Association for Public Opinion Research
[AAPOR], 2011, p. 5). The ratio of returned surveys to distributed surveys has been seen as a
heuristic, albeit an imperfect one, for the relative quality of a data collection effort. With the
goal of understanding response behavior, past research focused on developing an understanding of the antecedents of survey response rates in organizational samples (e.g., Barr, Spitzmüller, & Stuebing, 2008; Newell, Rosenfeld, Harris, & Hildelang, 2004; Spitzmüller, Glenn, Barr, Rogelberg, & Patrick, 2006). The goal of such investigations was to explore which factors of survey content, methodology, and recipient characteristics significantly contributed to maximizing the rate of return for a data collection effort that utilizes surveys as a primary method of data collection.

Variability in the number of completed surveys has been omnipresent in the published literature, and response rates have historically been reported by researchers in organizational science often accompanied by speculative assumptions as to why the rate of return was higher or lower than expected. For instance, Carter (1947) reported a 22% response rate to a survey of 2,000 university employees, surmising that low interest in any forms distributed by campus mail was the culprit; in contrast, Britt and Morgan (1946) yielded a response rate of 57% in a survey of 1,710 military psychologists, though the authors used follow-up reminders over the course of several months. By the time of early meta-analyses such as Heberlein and Baumgartner (1978), Eichner and Habermehl (1981) and Goyder (1982), many of the contributing factors to response rates for mailed questionnaires were beginning to come into focus in social science research.

Several relatively recent meta-analyses have sought to provide benchmarks for researchers and practitioners in organizational science, given the variability observed in response rates and antecedents identified in primary study designs. Among oft-used
benchmarks, Baruch (1999) estimated an average response rate of 55.6% across studies published in several management journals over three decades, and a similar review by Baruch and Holtom (2008) found comparable response rates in more recent research. Other quantitative reviews have found comparable numbers; Anseel et al. (2010) reported an average response rate of 52.3%, and Roth and BeVier (1998) reported 57% in their meta-analysis. However, Cycyota and Harrison (2006) found that response rates can depend on the recipients—the authors’ quantitative summary of survey return for executive samples suggested that a lower rate of survey return is likely. As such, beneficial information on response rates continues to be an area of concern for consumers of survey data as a heuristic to gauge the relative effectiveness of a data collection methodology.

The historical attention paid to response rates in the research literature is not unwarranted. Maximizing survey return whenever possible is of interest due to the implications for survey research and practice, and there are a variety of reasons for survey sponsors to concern themselves with response rates. Without an adequate sample size, fewer data points due to low response rates can limit the statistical power needed to perform analyses of interest (Rogelberg & Stanton, 2007). This may subsequently require an organization to incur greater costs in soliciting additional respondents who will provide complete data (Newell et al., 2004). Low response rates may also damage the credibility of survey data in the perception of organizational decision makers, stakeholders, and journal reviewers, regardless of the actual legitimacy of any inferences made from the data (e.g., Campion, 1993; Luong & Rogelberg, 1998). Moreover, if consumers of survey data are not
aware of current trends in response rates and what may or may not constitute a survey effort with a satisfactory rate of return, the conclusions attributed to such data may be dismissed despite a survey sponsor utilizing best practices for data collection. In other words, to the extent that response rates are dynamic over time, and may be driven by a variety of methodological techniques and survey recipient characteristics, consumers of survey data benefit from continued examinations of response rates to inform their appraisals of survey research. For example, a stakeholder in an organization being presented with results from a web-based survey of executives may conclude a response rate of 35% indicates a poorly-executed survey if Baruch’s (1999) general response rate of 55.6% is his or her benchmark, even though Cycoya and Harrison’s (2006) finding of an average response rate of 32% for executive-level employees suggests the response rate may be adequate or at least typical given the survey recipient sample. Even further, taking into account a meta-analysis conducted by Manfreda, Bosnjak, Berzelak, Haas and Vehovar (2008) which concluded that the online medium resulted in an 11% lower response rate on average when compared to other media, it may be that the 35% response rate is in fact the outcome of a well-executed survey effort given the sample and methods.

One notable concern with low response rates pertains to the potential for nonresponse bias, which is defined as differences between individuals responding to a survey and those who did not complete the survey on variables relevant to the purpose of the survey effort (Rogelberg & Luong, 1998). This bias may take the form of range restriction, where the sample appears to be more homogenous than the population due to selection effects.
Alternatively, non-arbitrary differences between respondents and nonrespondents may produce a systematic bias in the mean scores obtained from a sample of recipients (e.g., Lynn, 2008; Taris & Schreurs, 2007). When nonresponse systematically distorts data in the preceding manners, it can lead to an erroneous estimation of population parameters and well as faulty conclusions regarding true relationships between variables (Allen, Stanley, Williams, & Ross, 2007; Newman, 2009). As such, there is reason for concern regarding the extent to which missing data causes sample statistics to vary from the underlying population parameters (Newman & Sin, 2009; Olson, 2006). However, popular concerns over response rates rest on the assumption that an acceptable response rate serves as a proxy for a sample’s representativeness of the target population. In reality, nonresponse only affects the quality of survey data when it functions to bias the results of statistical analyses and/or introduce ancillary measurement error (Rogelberg & Stanton, 2007). Further, information about the response rate does not serve as a direct indicator of nonresponse error, though it is a crucial first step in assessing the extent of and potential reasons for such error (AAPOR, 2011; Lynn, 2008).

Indeed, researchers and practitioners have ample reasons to seek a more in-depth understanding of what potentially influences response rates. As such, we now turn to describing what may impel an individual survey recipient to respond to a request for survey data.

**Existing Models of the Response Process**

Considering the nontrivial consequences of low response rates described above, it is
vital to understand the factors that contribute to higher observed response rates in survey efforts. The logical entry point for understanding the comparative impact of antecedents to recipient behavior is to examine existing perspectives on how and why individuals respond to surveys and the items contained therein.

From a cognitive perspective, the survey response process entails the expenditure of effort required to comprehend an item, consider one’s own attitude or judgment in reaction to the item stem, conceptually map that attitude or judgment onto the continuum of provided response options, and decide on the most accurate response (e.g., Furse & Stewart, 1984; Tourangeau & Rasinski, 1988). Expanding on the idea of survey response as a decision-making process, Helgeson, Voss, and Terpening (2002) posited that a recipient makes a hierarchical series of judgments as he or she moves through the process of completing a survey. In Helgeson et al.’s (2002) conceptualization of response behavior, the basic steps in the survey process are attention, intention, completion, and return. Attention involves the cognitive cost of attending to a survey and survey material; intention is the probability that a response behavior will occur despite constraints; completion is the behavioral act of expending the effort and energy to answer items that appear on the survey instrument; return occurs when the recipient fulfills the objective of the data collection effort by submitting his or her responses to the researcher or survey sponsor. Within completion at the survey level, there is a further layer of contributing factors at the item level; Cannell Miller, and Oksenberg (1981) detailed a question-answering process whereby a recipient must first comprehend the question and then make a series of subsequent decisions and evaluations to
provide his or her response. Such models suggest that the cognitive processes underlying a recipient’s progress through a survey are determined by a combination of both recipient factors, such as perceptions and attitudes, and environmental factors external to the recipient, such as elements of the survey design. According to Helgeson et al. (2002), these factors have a cumulative effect on recipient behavior via a variety of cost/benefit evaluations concerning the ultimate valence of participating in the survey.

Alternately, Rogelberg and colleagues (2000, 2003, and 2006) developed a model of response behavior which outlined several attitudinal and trait-based predictors of survey return, mediated by behavioral intentions (see Figure 1). Of note in this model is the array of variables posited to lead to the behavioral intention to return a survey, such as technological constraints, anonymity beliefs, and attitudes towards surveys in general and survey topics. Rogelberg, Spitzmüller, Little, and Reeve (2006) provided a test of this model of response behavior and successfully accounted for 6% of the variance in response behavior and roughly 20% of the variance in response intentions. Notably, the Rogelberg et al. model provides evidence that aspects of a survey’s administration and content do have a statistically significant predictive linkage to the outcome of survey return.

Lastly, Peytchev (2009) proposed a model to explain participation in web surveys and the relationships of respondent factors, page and question characteristics, and survey design to nonresponse. The author presents these broad categories of predictors as influencing three key recipient decision points: the decision to start a survey, the decision to continue responding to a survey, and decisions to answer individual items. Notably, page and question
characteristics such as the length of a survey and the types of items are not posited to influence the decision to start a survey. Peytchev also makes the point that some factors related to survey recipients may not always be controllable by a researcher, whereas the design and administrative mechanics of a survey are managed by the researcher and malleable to the needs and requirements of a survey effort or sponsor. Even though this model focuses on nonresponse outcomes within a single modality, it is still an informative framework for considering the precursors to survey response behavior in general.

**Previous Meta-Analyses of Survey Response Behavior**

Quantitative inquiries into the relationships proposed by conceptual models depend on data and descriptions commonly reported in extant research, and the method sections of primary studies become crucial sources of such information. As noted by the APA Working Group on Journal Article Reporting Standards, without “complete reporting of methods and results, the utility of studies for purposes of research synthesis and meta-analysis is diminished” (APA, 2008, p. 840). Therefore, the frameworks of past meta-analyses can inform what variables are likely to be reported reliably enough in order to test hypotheses related to the antecedents to survey return.

As response rates have been of interest to researchers across a range of academic disciplines that utilize survey data collection techniques, a number of quantitative reviews (i.e., meta-analyses) of response rates in surveys have been conducted (e.g., Anseel et al., 2010; Baruch, 1999; Baruch & Holtom, 2008; Church, 1993; Cook, Heath, & Thompson, 2000; Cycyota & Harrison, 2006; Fox et al., 1988; Goyder, 1982; Heberlein & Baumgartner,
1978; Hopkins & Gullickson, 1992; Manfreda et al., 2008; Roth & BeVier, 1998; Sheehan, 2001; Shih & Fan, 2008; Van Horn, Green, & Martinussen, 2009; Yammarino, Skinner, & Childers, 1991; Yu & Cooper, 1983). Table 1 presents an overview of previous meta-analyses of response behavior and the antecedents that were tested by those authors, along with the interval of time included in the analysis and how many primary studies were included. Of note is that the majority of the existing meta-analyses were conducted prior to the widespread proliferation of web-based surveys and the differences in survey administration borne of Internet technology compared to paper questionnaires. Several of these reviews pertaining specifically to organizational surveys and response rates in various samplings of empirical literature are described below.

Roth and BeVier (1998) summarized 251 studies in volumes for the years 1990 through 1994 from 6 organizationally-relevant journals. Although hypothesizing several relationships between research procedures and response rates, their main findings were that advanced notification and follow-up reminders, in addition to the use of ID numbers instead of names, were associated with higher response rates. In addition, the salience of a survey topic had a positive effect on response rates. The authors noted that some of their expected findings may not have materialized due to large amounts of missing data and low variance for some of their study variables.

Baruch (1999) meta-analyzed 175 studies published in 5 organizationally-relevant journals during the years of 1975, 1985, and 1995. The focus of this review was mainly to provide a benchmark for response rates in organizational survey research, as well as to assess
the trends in response rates across time by sampling across decades. Results showed that response rates demonstrated variability across journals, and response rates tended to consistently be poorer for studies that surveyed individuals in upper management positions. In addition, data suggested that response rates decreased across each sampled decade. However, as pointed out by the author, reporting of response rates in primary studies has also become more common with time, so there is some likelihood that low response rates were simply omitted in older research. Lastly, the review was primarily a descriptive treatment of response rates, such that it sought only to describe average response rates as opposed to predicting what may cause response rates to vary. As such, Baruch (1999) called for more research that enabled a greater comprehension of the reasons for low response rates.

Though Roth and BeVier (1998) and Baruch (1999) have often been cited (87 and 232 citations, respectively, as of November 2014 in the PsycINFO database) as benchmarks of response rates in organizational research, neither of these reviews were conducted prior to the proliferation of web-based surveys. In this sense, the sophistication of contemporary survey technology may have impacts on response behavior not considered in these previous reviews. In an effort to address this concern, as well as to provide an updated benchmark of unit response, Baruch and Holtom (2008) expanded upon Baruch (1999) to include 463 studies in volumes from 2000 and 2005 from 17 organizationally-relevant journals. The main findings were that response rates appear to be stable across the time period the study considered.

Anseel et al. (2010) examined 1,761 articles from a variety of journals in the I/O,
management, and marketing that were published between 1995 and 2008. The results of this study suggested that response enhancing techniques such as advance notice, personalization, or institutional sponsorship were significantly and positively associated with unit response rates, whereas techniques such as follow-ups were significantly and negatively associated with unit response. The authors then conducted a multiple regression that demonstrated that variables such as the use of identification numbers and institutional sponsorship explained 20% of the variance in response rates. Anseel et al. (2010) also concluded that there has been no appreciable decline in average response rates since 1995.

Previous quantitative summaries of organizational research portray the treatment of response behavior as a topic that requires rigorous and strategic methodological attention. Because of the vintage of many existing reviews, questions arise as to how advancements such as web-based surveys and the prevalence of reporting of response rates in journals may limit the applicability of previous examinations of recipient behavior. There is a need not only to provide a more unified and contemporary analysis of response behavior in empirical organizational research, but there is also a need to update the answers to questions about the comparative worth of the drivers of response rates and their trends over time.

A Conceptual Model of Response Behavior in Organizational Survey Research

To consider the variety of ways that aspects of survey delivery and recipient characteristics may influence individuals’ propensity to respond to organizational surveys, an inductive model is proposed that takes into account common survey features and sample characteristics in the prediction of recipient behavior. The model found in Figure 2 is
proposed as an empirically-testable model of the antecedents to survey return. An adaptation of meta-analytic methodology will be employed to test this model, effectively allowing comparisons of the precursors to response rates across a broad sampling of primary studies in organizational research. It should be noted that to test the model in Figure 2 experimentally would necessitate a prohibitive number of conditions as well as a formidable sample size to provide adequate information to explore how survey features and recipient characteristics influence response rates. Therefore, the framework outlined here describes cross-study phenomena with the intention to utilize a meta-analytic strategy that facilitates hypothesis testing at the level of primary studies. Though this model is not intended to be exhaustive in including all possible antecedents of survey behavior, it is adapted from the model proposed by Peytchev (2009) and draws from the framework of Rogelberg and colleagues (2000, 2003, 2006) in addition to themes common to previous meta-analyses of response behavior. As suggested above, many factors have been identified by researchers as being integral components to the success of survey efforts; the proposed model seeks to organize these factors into coherent conceptual categories to permit a review of the antecedents of response behavior using different statistical means than has previously been employed. In doing so, this study seeks to extend and update previous reviews wherever applicable, offering new insights for practitioners and researchers into drivers of survey response in the process.

The outcome of interest in the model concerns the endpoint of response behavior; specifically, the criterion of rate of survey return, calculated as the ratio of respondents to recipients. As shown in Figure 2, three general categories of antecedents to response rates are
proposed: survey content, survey methodology, and recipient characteristics. The model assumes that although many of these antecedents are mutually exclusive (e.g., a sponsor cannot simultaneously use and not use incentives for the same recipient) any survey effort will inevitably include an assortment of these factors. In addition, it mirrors the distinction made by Peytchev (2009) that several antecedents, such as those related to recipient demographics, are unable to be controlled by the survey sponsor, whereas others, such as survey length or the use of incentives, are directly under the charge of the survey sponsor and/or researcher. Hypotheses will be distinguished within each conceptual category concerning specific predictors identified by past meta-analytic reviews related to survey response. A summary of study hypotheses concerning response behavior outcomes, including the direction of expected relationships, is presented in Table 2.

Next, we will turn to elucidating the three general categories of antecedents, beginning with factors related to the content of a survey.

**Survey Content**

**Salience.** Multiple aspects of survey content can be influential in determining recipient behavior, such as topic salience and item sensitivity of the survey for an individual. Salience can be interpreted as the importance or relevance of a survey’s content to a recipient, such that the items ask questions that are of interest to the recipient and related to the recipient’s current circumstances (Heberlein & Baumgartner, 1978). For instance, a survey concerning a past organizational intervention might be less salient to an employee responding to the survey than if the focus of the survey was on a current intervention which
would affect the employee’s wellbeing. Similarly, issues personally important to recipients or relevant to their particular occupations are likely to be more salient, which in turn should encourage unit response.

Groves, Singer, and Corning (2000) described a theory of participation in household interviews that included salience as a determinant of compliance with a survey request. Moreover, the authors stated that salience was a construct that could be inferred from characteristics of the survey and their likely valence for a group of recipients, such that greater importance or relevance of a survey’s content to recipients was likely to influence response behavior. In this regard, the more directly relevant to recipients that a survey is, the greater the likelihood of survey cooperation. Past meta-analyses of response behavior such as Anseel et al. (2010), Cycyota and Harrison (2006), Roth and BeVier (1998), and Sheehan and McMillan (1999) concluded that issue salience was related to higher unit response rates. Heberlein and Baumgartner (1978) found that salience had more influence on observed response rates than methodological characteristics in the primary studies they considered. Accordingly, the more a recipient sees a survey as being pertinent to him- or herself, the more likely he or she should be to return the survey. Thus, the following hypothesis is proposed:

Hypothesis 1: Topic salience in a survey effort will have a positive, non-zero relationship with rates of survey response.

Sensitivity. The sensitivity of a survey topic can also influence a recipient’s willingness to provide substantive answers to a survey. A sensitive survey topic can be
conceptualized as including three components: the intrusiveness of the item content, the threat of potential consequences for responding to the item, and the social undesirability of a recipient’s answer to the item (Tourangeau & Yan, 2007). As the items contained in a survey are perceived to be increasingly sensitive, a recipient may feel more apprehensive about providing information to the survey sponsor and fail to return his or her survey data.

A study by Rasinski, Willis, Baldwin, Yeh, and Lee (1999) suggested that for sensitive survey topics, reluctance to provide answers to all or part of the survey may be motivated by a concern that the confidentiality afforded to recipients does not cover the potential risks of providing meaningful answers to sensitive items. Moreover, although providing an incentive or using some other administrative means of combating low response rates (e.g., Dillman, Smyth, & Christian, 2009) may yield acceptable response rates for surveys on sensitive topics, it is plausible that a higher rate of response would have been obtained if the incentive had accompanied a less sensitive survey. Only two previous meta-analyses have examined the impact of sensitive survey items on response rate (Cook et al., 2000; Edwards et al., 2002). Neither found an effect for the inclusion of sensitive questions on a survey, although in both cases a dichotomous dummy variable was used to code primary studies and arguably oversimplifies item sensitivity. Despite the lack of a finding in these two meta-analyses, a recent review by McCluskey and Topping (2011) urged survey sponsors to carefully consider the sensitivity of item content and the appropriateness of such items to the target recipients to mitigate unnecessary negative effects on response rates. As the current study seeks to extend the treatment of sensitivity in summaries of recipient
behavior beyond a binary concept, and given survey recipients’ likely reluctance to answer sensitive items, the following hypothesis is proposed:

Hypothesis 2: Topic sensitivity will have a negative, non-zero relationship with rates of survey response.

Though the salience or sensitivity of a survey topic may influence a recipient’s decision to return a survey, features related to survey content omit the influence of the mechanics of survey administration. We now turn to outlining the potential for factors related to survey methods to influence response rates.

**Survey Methodology**

The procedural and social characteristics of a survey’s methodology, such as the survey medium, anonymity or confidentiality assurances, and overall survey length, have received repeated scrutiny in past research to gauge the likely impact on response rates (e.g., Cook et al., 2000; Edwards et al., 2002; Heberlein & Baumgartner, 1978; Roth & BeVier, 1998; Shih & Fan, 2008). In most cases, the use of such response enhancing techniques functions to effectively draw in members of a group of recipients that may not be highly committed to the survey initiative, thereby encouraging more recipients to respond to a survey. Though aspects of survey methodology may not be as conspicuous to some recipients as the topic of a survey, differences in administration methods across studies may contain enough variability to account for differences in observed response rates. In addition, methodological differences between studies have largely been the focus of several past reviews of response rates (e.g., Armstrong & Lusk, 1987; Church, 1993; Fox et al., 1988;
Salutation Specificity. Personalizing the salutation on a survey solicitation, such as addressing the recipient by name, has been suggested as a way to encourage survey return (e.g., Dillman et al., 2009; Rogelberg & Luong, 1998). However, while the personalization of a survey request can affect rates of participation in a portion of survey efforts, such that a personalized salutation may increase response rates (e.g., Bosnjak, Tuten, & Wittmann, 2005; Cook et al., 2000; Heerwegh, Vanhove, Matthijs & Loosveldt, 2005), this is not always the case (e.g., Worthen & Valcarce, 1985).

Personalization plays an integral part of Dillman and colleagues’ (2000; 2009) tailored design method for surveys, with the assumption that the more important a recipient is led to believe he or she is to the survey effort, the more that recipient feels the benefit of responding outweighs the cost in time and effort. As databases of information become increasingly easy to link together and computerized tools facilitate personalizing contact with recipients, this practice may have fewer implementation barriers in organizations compared to the past. The majority of existing meta-analyses (e.g., Anseel et al., 2010; Cycyota & Harrison, 2006; Edwards et al., 2002; Fox et al., 1988; Yu & Cooper, 1983) have found a significant effect for this methodological device in encouraging unit response. Accordingly, the following hypothesis is proposed:

Hypothesis 3: Personalization of survey salutations will have a positive, non-zero relationship with rates of survey response.

Identification Likelihood. Some survey efforts collect names, social security
numbers, and/or other personally identifying information from recipients. This may occur in order to hold people accountable for their responses or for methodological reasons, such as when there is a need to link recipients’ data to ratings provided on another survey or to information stored in a Human Resource Information Systems database. The likelihood that a recipient can be identified by a survey sponsor has been posited as a factor that may influence response behaviors (e.g., Rogelberg et al., 2006; Thompson, Surface, Martin, & Sanders, 2003). Past research supports this view, suggesting that requiring recipients to identify themselves can exacerbate low response rates. For instance, meta-analyses by Anseel et al. (2010) and Roth and BeVier (1998) found that the use of identification numbers to maintain confidentiality significantly increased unit response.

With respect to assurances made to recipients in informed consent procedures, there is a spectrum of situational constraints and researcher norms that can lead to variegated promises of confidentiality or anonymity (Sobal, 1984). As such, the effectiveness of privacy assurances may not be the same across surveys, as recipients may see their likelihood of being identified differently under assorted conditions. Certainly, there are ways to track recipients without necessarily asking them to report their names, which may be less detrimental to response rates. Dillman (2000) maintained that the use of a number in place of the recipient’s name, for instance, increased response rates compared to conditions where a name was requested. In effect, identification falls along a continuum from full identification (name or other personal information provided), partial identification (non-personal identification number or other non-personal identifier), to anonymity, and the degree to
which a recipient’s identity is known has likely ramifications for response behavior. It should be noted that when anonymity has been treated as a binary variable in previous meta-analyses, there has not been a demonstrable effect on the rate of return for surveys (e.g., Cook et al., 2000; Yammarino et al., 1991; Yu & Cooper, 1983). Accordingly, the current study will consider privacy as a continuum in an attempt to better capture the range of conditions under which recipients are implored to participate in a survey effort.

Obviously, there are survey practices independent of informed consent protocols and requests for identification that may give some recipients reason to see their identity as being partially known to the survey sponsor, such as the presence of multiple items seeking demographic information (Edwards & Thomas, 1993). As noted by Rogelberg et al. (2006), recipients that question the privacy afforded by a survey may be reluctant to provide answers to items that could reflect poorly on them or otherwise instigate some form of reprisal. Particularly when completing a survey is voluntary on the part of the recipient, provisions for privacy should encourage response. Thus, the following hypothesis is proposed:

Hypothesis 4: Identification likelihood will have a negative, non-zero relationship with rates of survey response.

**Number of Items.** The overall length of a survey instrument may significantly impact the likelihood of response as well, such that shorter surveys which demand fewer resources from the survey recipient are more likely to be returned (Rogelberg & Stanton, 2007). For instance, Yammarino et al. (1991) found that longer surveys (operationally defined as surveys longer than 4 pages) had a negative relationship with response rates. In
addition, Heberlein and Baumgartner (1978) found a significant relationship between the length of a questionnaire and the subsequent response rate after controlling for topic salience and the number of contacts, stating that there may be a 0.5% reduction in response rate per item. Similarly, a more recent review by Edwards, Roberts, Sandercock, and Frost (2004) found that the odds of a recipient returning a survey decreased significantly for longer questionnaires. A straightforward explanation is that more items require more total time to complete the survey, thereby requiring a larger expenditure of effort by the recipient.

However, a significant effect for survey length has not been consistently replicated. For example, quantitative reviews by Goyder (1982), Roth and BeVier (1998), and Yu and Cooper (1983) failed to find a significant effect for survey length. Cook et al. (2000) noted that a common issue with aggregating pertinent information about length is the inconsistency in format with which it is reported. To address this issue, Cook et al. decided on a page metric whereby 3 computer screens or 15 questions was coded as a single page when the number of pages was not otherwise available, though they failed to find a significant effect on response rates for survey length. Edwards et al. (2002), looking solely at mailed surveys, found a significant effect for the number of physical pages on response rates to health surveys. Indeed, as the differences between pages and the number of questions can be blurred between any two survey modalities (e.g., online surveys can be displayed on one scrollable screen compared to several pages of paper), the definition of survey length is nontrivial to predicting response rates. Moreover, as noted by Dillman (2000), “there is more to length than a simple count of pages… (putting) more questions into fewer pages to make a
questionnaire shorter is not likely to accomplish its intended purpose” (p. 306). In the current study, this variable will be treated as the total number of items reported in each primary article that meets inclusion criteria, as was done by Roth and BeVier (1998). Given the evidence that survey length does have an influence on response rates, the following hypothesis is proposed:

Hypothesis 5: The total number of survey items will have a negative, non-zero relationship with rates of survey response.

Advanced Notice/Follow-up Contacts. Two other common methods to increase response rates are the use of preliminary notifications and follow-up contacts, which are intended to notify, encourage, and remind individuals to complete and return survey materials (Bosnjak et al., 2005; Dillman et al., 2009; Rogelberg & Luong, 1998; Rogelberg & Stanton, 2007). With either strategy, the timeliness of contacts may be crucial to their effectiveness; according to Dillman et al. (2000, 2009), advanced notice contacts function best if they precede the participation request by several days to prime recipients, whereas follow-up contacts may be less likely to be seen as intrusive if they were at least two to three weeks after the initial request. The contacts between a survey sponsor and recipient in contemporary survey efforts can be made through a variety of methods, including “snail mail,” e-mail, or text messages on mobile devices (e.g., Mavletova, 2013; van Heerden, Norris, Tollman, Stein, & Richter, 2014).

Advanced notice of an upcoming survey has been shown to result in improved response rates in several past reviews (Edwards et al., 2002; Fox et al., 1988; Heberlein &
Baumgartner, 1978; Weathers et al., 1993; Yu & Cooper, 1983). In particular, Roth and BeVier (1998) found strong effects on unit response for preliminary notifications and follow-up contacts, such that advanced notice of an upcoming paper survey increased response rates by an average gain of 8% to 20%. In Yammarino et al.’s (1991) review, the effect of advanced notices of an upcoming survey on increasing response rates increased over time, and was not significantly related to the type of target recipients. While a recent review by Anseel et al. (2010) suggested that the gains in curbing low response rates via advanced notice may be slightly declining when considered over time, the overwhelming pattern in past reviews (including Anseel and colleagues) suggests that this tactic is effective in significantly increasing response rates. Therefore, the following hypothesis is proposed:

Hypothesis 6: The number of advanced survey notification will have a positive, non-zero relationship with rates of survey response.

Past reviews have identified follow-up reminders as a means to effectively increase response rates by providing recipients multiple opportunities and encouragement to complete a survey (Edwards et al., 2002; Fox et al., 1998; Sheehan, 2001; Yammarino et al., 1991; Yu & Cooper, 1983). Dillman (2000) advocated that “without follow-up contacts, response rates will usually be 20-40 percentage points lower than those normally attained, regardless of how interesting the questionnaire or impressive the mailout package” (p. 177). However, follow-ups may discourage some recipients from responding to a survey, as suggested by the lower response rates for reminders reported in reviews by Cycyota and Harrison (2006) and Baruch and Holtom (2008). Manfreda et al. (2008) posited that as computers are increasingly utilized
to deliver surveys, digital reminders may be seen by some recipients as intrusive and unwanted contact by the survey sponsor. In a meta-analysis of web and paper surveys, Shih and Fan (2008) found a positive effect for reminders in both media, postulating that the prevalence of spam email may have diminished the efficacy of follow-ups as surveys trended toward the web modality. Anseel et al. (2010) speculated that follow-up reminders may be an ad hoc tactic used more often by sponsors when response rates from an initial survey request are low, thereby creating somewhat of a methodological interdependency. Nonetheless, reminders have historically been recommended as a means through which to increase response rates, and the majority of quantitative reviews support their use. In addition, Fan and Yan (2010) stated that the number of contacts made by a survey sponsor to a recipient can be one of the most important factors in predicting response rates, based on their review of several past meta-analyses. Therefore, the following hypothesis is proposed:

Hypothesis 7: The number of follow-up contacts will have a positive, non-zero relationship with rates of survey response.

Survey Media. The medium through which an organizational survey is administered has garnered significant attention from both scientists and practitioners (e.g., Naus, Phillipp, & Samsi, 2009; Stanton, 1998; Thompson, Surface, Martin, & Sanders, 2003; Yost & Homer, 1998). There are a variety of possible delivery media available, including paper surveys, computer-based surveys (e.g., Internet, mobile platforms, CD-ROMs, networked intranet), person-to-person phone polls, computerized interactive voice response phone surveys, and interviews. In the current study the focus is on the comparison between paper
and web-delivered surveys, as has been the case in several recent meta-analyses of response behavior (Anseel et al., 2010; Baruch & Holtom, 2008; Groves & Peytcheva, 2008; Manfreda et al., 2008; Shih & Fan, 2008). Web-delivered surveys are also arguably the preferred survey format in many organizations, and can sometimes be easier to operationalize with email listservs compared to mailing copies paper questionnaires.

Past focus on survey administration media has been driven by questions about how responses may be affected by different formats, how these formats potentially affect what is being measured, and the investment of time and effort necessary to facilitate data collection (Presser et al., 2004). A topic of recurrent inquiry has been how different media may affect rates of return in a survey effort. The prevailing mode of thought in the literature suggests that computerized surveys will yield lower levels of response compared to paper surveys (Crawford, Couper, & Lamias, 2001; Cronk & West, 2002; Kaplowitz, Hadlock, & Levine, 2004), despite the fact that electronic surveys can be fully automated to reduce issues with the return and conversion of data for analysis (Fan & Yan, 2010). Indeed, Anseel et al. (2010) found support for their hypothesis that web-based surveys would yield higher response rates for non-managerial respondents. However, most meta-analytic results suggest that the relationship trends in the opposite direction.

Though Baruch and Holtom (2008) did not find significantly different levels of unit response across media in their review, meta-analyses by Manfreda et al. (2008) and Shih and Fan (2008) explicitly sought to compare mail and web-based surveys as the primary purpose of the research. Both reviews concluded that while there is variability in response rates
within media, electronic surveys have significantly worse response rates. Notably, the meta-analysis by Manfreda et al. (2008) found that the response rates were on average 11% lower for web-based surveys compared to other media. There are a number of technical failure points with online surveys that do not have a counterpart in paper surveys which may contribute to such observed differences. For example, a paper survey does not have to contend with a browser software crashing, or a broken hyperlink, or server downtime where the survey is hosted, or automated “spam” folders that may delete some or all attempted contacts from a survey sponsor. As Manfreda et al. (2008) concluded,

“In view of the fact that web surveys have undergone various changes in the last decade, primarily influenced by changes in technology (e.g. more sophisticated design options for conducting surveys on the web) and change at the societal level (e.g. broader segments of society have adopted the internet), it is to be expected that a cumulative meta-analysis approach will yield important information on the sufficiency and stability of results obtained over time.” (p. 99)

Lastly, a meta-analysis by Medway and Fulton (2012) on the impact of offering a web-based option for a mailed survey concluded that response rates were notably lower versus offering only a paper questionnaire. In other fields such as healthcare and marketing, response rates have historically been lower online compared to mailed surveys in general (e.g., Cho, Johnson, & VanGeest, 2013; Direct Marketing Association, 2010). In this respect, the bulk of empirical evidence suggests that there should be an effect on response rates for survey media in organizational surveys. As such, the following hypothesis is proposed:
Hypothesis 8: Survey medium will have a non-zero relationship with rates of survey response such that computer-based surveys will yield lower rates of survey response compared to paper surveys.

Incentives. The use of incentives has been championed as a way to motivate recipients to complete and subsequently return a survey instrument to a survey sponsor (e.g., Bosnjak et al., 2005; Dillman, 2000; Helgeson et al., 2002; Rogelberg & Luong, 1998; Rogelberg & Stanton, 2007; Rose, Sidle, & Griffith, 2007). Incentives can be monetary, such that they offer some form of cash or check to the survey recipient, or non-monetary, the latter of which Church (1993) defined as any extra item or token that would be considered above and beyond the normal procedure for most surveys. In several previous reviews of survey response rates, incentives have been shown to increase response rates (e.g., Fox et al., 1988; Yammarino et al., 1991; Yu & Cooper, 1983). The literature has many examples of primary studies that have demonstrated the utility of incentives on encouraging survey return; for example, Rose et al. (2007) conducted two large sample studies which showed that incentives, but not the size or novelty of the incentive, contributed to higher response rates. In meta-analytic results, Fox et al. (1988) found that a small monetary incentive did encourage recipients to complete a survey, though they noted there were diminishing returns with increasing the amount of the incentive in an attempt to increase response rates. Church (1993) found that incentives were effective in improving rate of return, regardless of whether they were monetary or non-monetary, although the incentives were less beneficial when they were contingent on recipients completing the survey compared to incentives being offered.
with the initial survey invitation. Further, Hopkins and Gullickson (1992) concluded that for incentives to be most effective, they need to be framed as a gratuity to the recipient and not as payment for returning data.

However, some recent reviews of the literature have not found a consistent relationship between the use of incentives and response rates (Baruch & Holtom, 2008; Cycyota & Harrison, 2006; Manfreda et al., 2008), and Anseel et al. (2010) found that incentives appeared to have a negative effect on unit response for employee and managerial samples. It should be noted, however, that in the above reviews, incentives were dichotomized as being present or absent; a similar coding approach used by Roth and BeVier (1998) found no significant effect for incentives on survey return. However, Church (1993) maintains that investigations into the effect of incentives should specify whether an incentive was monetary and the timing in the survey process where the incentive was offered; this approach will be followed in the current study. Nevertheless, the majority of experimental and applied research suggests that the use of incentives by a survey sponsor should lead to higher levels of response. Thus, the following hypothesis is proposed:

Hypothesis 9: Incentives will have a positive, non-zero relationship with rates of survey response.

As survey content and methodology have been discussed above, we now turn to outlining the potential for recipient characteristics to influence response rates.

Recipient Characteristics

While much attention has been paid to the external characteristics of a survey effort,
an equally important though often underemphasized factor in response behavior concerns the composition of the recipient sample. The type of target recipients and demographic characteristics of a given sample may be significantly related to observed response rates (Anseel et al., 2010). There is unequivocal agreement in the empirical literature that individual differences play a role in not only who responds to a survey, but how a person responds. Accordingly, a discussion of the gamut of antecedents to response rates would be incomplete without considering aspects of the individuals targeted by organizational data collection efforts. In the context of this meta-analysis, it should be noted that these characteristics are hypothesized to have an effect at the group level (i.e., across studies). The intention is to make inferences about the modal or most prevalent education level, target population, and job complexity of a sample of respondents reported in a primary study as these factors relate to response rates. In effect, the following hypotheses seek to examine the relationships between rates of return and the composition of a group of respondents considered in aggregate, consistent with past meta-analysis efforts (e.g., Baruch, 1999; Edwards et al., 2004; Shih & Fan, 2008; Yammarino et al., 1991).

**Education Level.** The level of a recipient’s education appears to relate to response behavior, as past research has demonstrated that recipients that fail to return a survey tend to have less education compared to respondents (Rogelberg & Luong, 1998). This effect has been demonstrated for mailed surveys (e.g., Gannon, Nothern, & Carroll, 1971) as well as for surveys administered on newer technologies such as mobile phones (e.g., Mavletova, 2013). Further, a study by Holbrook, Cho, and Johnson (2006) found that education level was
related to fewer difficulties comprehending a survey item or with mapping a judgment to response categories. Accordingly, past meta-analyses have reached similar conclusions when examining the influence of recipients’ education level on response rates across primary studies.

The quantitative review of response rates by Roth and BeVier (1998) suggested that the modal education level for a sample of recipients was a significant factor influencing response rates to a survey, such that a group of more educated recipients demonstrated higher observed response rates. In addition, Goyder (1982) found that education appeared to be a contributing factor to survey return when considered across studies. Thus, the following hypothesis is proposed:

Hypothesis 10: The modal education level of samples will have a positive, non-zero relationship with rates of survey response.

Target Population. A target population for a survey can be defined a number of ways, depending on the field of study, relevant sampling frame, or objective of the survey. Groves and Peytcheva (2008) describe a variety of potential target populations that are found often enough in aggregate to permit meta-analysis, such as a national population, specific occupational groups, customers and consumers, opinion panels, special interest groups, or—relevant to the current study—employees working in organizations.

The target population of recipients for a survey effort can have non-trivial implications both for the likely response rate and for the generalizations which a primary study researcher sought to make. This has not been ignored by researchers, and has been
reported consistently enough in primary studies to permit past meta-analysts to include it in their reviews (e.g., Anseel et al., 2010; Groves & Peytcheva, 2008; Heberlein & Baumgartner, 1978; Shih & Fan, 2008; Van Horn et al., 2009; Yammarino et al., 1991). Moreover, the source of a recipient sample has long been a concern in applied organizational research; early survey research such as Lawson (1949) focused on the response rates of different professions to a mail survey on gambling. Indeed, Dillman et al.’s (2009) recommendations for maximizing response rates include consideration of the types of recipients when determining appropriate response enhancing techniques.

Past meta-analyses have shown some agreement on the pattern of response rates depending on the sample of recipients. Heberlein and Baumgartner (1978) found that samples comprised of specific subgroups of students, organizational employees, and military personnel were more likely to return a survey compared to a sample from the general population. Anseel et al. (2010) found a significant effect for the type of recipient such that non-working and non-managerial recipients were most likely to return a survey compared to consumer, managerial, and executive groups, respectively. Shih and Fan (2008) noted that college samples tend to have better response rates than employee or general samples. Given the patterns in response rates determined by past reviews, the following hypothesis is proposed:

**Hypothesis 11**: Target population will have a non-zero relationship with rates of survey response such that university and non-managerial groups of survey recipients will have higher rates of survey response compared to professional and executive
groups of survey recipients.

**Job Complexity.** The complexity of a recipient’s job may also influence whether he or she completes a survey. Job complexity can be defined as “the extent to which a job entails autonomy or less routine and the extent to which it allows for decision latitude” (Shalley, Gibson, & Blum, 2009, p. 493). Given that jobs higher in complexity involve more multifaceted tasks that are difficult to perform (e.g., Morgeson & Humphrey, 2006), individuals who hold positions higher in complexity may have fewer opportunities to respond to a survey due to the regular demands of their occupation. Such an effect is only expected for primary studies examining applied field samples (i.e., experimental samples in academic settings are not expected to vary on job complexity, nor is such information probable to be reported), and a demonstrated relationship to response rates and its magnitude is of great utility to practitioners conducting surveys in contemporary organizations.

Past reviews on response rates appear to support the relationship between job complexity and response rates. For instance, meta-analyses by both Cycyota and Harrison (2006) and Baruch and Holtom (2008) found that individuals holding jobs with more stature in the target organization were particularly unlikely to complete and return a survey. It may also be that individuals with more complex jobs tend to have more power within the organization and therefore more opportunities outside of a survey effort to influence organizational decisions. For those lower in stature, survey input could be their primary opportunity for voice. As suggested by current theory about task complexity as well as past meta-analytic results, the following hypothesis is proposed:
Hypothesis 12: Job complexity will have a negative, non-zero relationship with rates of survey response.

**Unique Variance in Response Rates**

As there are a number of hypotheses concerning predictors of response rates, knowledge of which predictors account for the most variance in each of these outcomes would be of great value to researchers and practitioners designing surveys. In other words, which aspects of survey content, survey administration, and recipient characteristics are most important to predicting response rates? This study contributes to the literature on survey behavior by seeking to better understand how these predictors compare to each other, as they are often studied in isolation for reasons of experimental control or due to organizational constraints. However, that also means many variables tend to covary as sponsors deploy surveys based on accepted best practices at the time each study was designed. This review will evaluate predictors of response rates using an analytical approach that accounts for the dependence many variables have on each other in survey design, thereby allowing investigation of which factors demonstrate unique variance in predicting survey return.

Whether patterns of correlation between response enhancing techniques are due to trends, better technological controls, or use of frameworks such as Dillman et al.’s (2009) tailored response method, it is vital to understand the unique incremental and relative contributions of each of these predictors to the criterion of response rates.

The relative importance of the precursors to recipient behavior could better inform those conducting surveys where problems may arise with recipients and the survey context,
and aspects of survey content and methodology that might be effective in combating such issues. In situations where organizational or methodological constraints preclude an optimal survey effort, information concerning the importance of known antecedents to response would allow researchers and practitioners to prioritize, making informed decisions about investing time and resources in tactics to increase survey return. In other words, knowing which antecedents have the largest effects on response rates can point response facilitation efforts in the most fruitful directions. Therefore, the following research question is posed:

Research Question 1 What is the relative importance of predictors that account for variance in rates of survey response?

**Longitudinal Variability in Response Rates**

For a quantitative review of response rates, a question of interest to researchers and practitioners concerns the existence and directionality of trends over time. As suggested by Rogelberg and Stanton (2007), there are a number of factors that may contribute to declining response rates, such as respondent saturation due to ease of administration, or increased popularity of surveys with organizational decision-makers. Knowledge of increasing or decreasing response rates in general augments historical benchmarks for response rates such as those described earlier.

However, past reviews do not show consensus on patterns of response rates. For instance, Baruch and Holtom (2008) explicitly sought to look at changes in response rates by selecting two specific years in the literature to consider (2000 and 2005). The authors then compared their findings with the past results of Baruch (1999), which considered specific
years from three previous decades (1975, 1985, and 1995). Despite Baruch’s (1999) conclusion that response rates have been declining, Baruch and Holtom (2008) did not find a significant difference in overall response rate trends in the time period considered. Alternately, Cycyota and Harrison (2006) found that response rates appeared to be declining for the 1992-2003 window included in the authors’ analysis. In both instances, however, the analyses used by the authors may not be optimum for exploring questions related to trends over time. Baruch and Holtom (2008) employed a $t$-test to compare mean response rates, and Cycyota and Harrison (2006) included year of publication as a variable in their main effects regression model. Ignoring a structural grouping in data when using regression—such as year of publication—can lead to underestimation of standard errors and put subsequent conclusions at risk of Type I error, as traditional regression techniques assume independence of observations.

The current study will utilize hierarchical linear modeling (HLM; Raudenbush & Bryk, 2002), an analytical approach that permits consideration of the amount of variance both within years and across years. As primary studies are nested within each publication year, this analytical approach recognizes the hierarchical nature of meta-analytic survey data. Given that the current study will be the first known application of HLM to data on response rates, a hypothesized relationship is difficult to presume based on the conflicting results of past quantitative reviews. As such, the following research question is proposed:

Research Question 2: Has there been significant variation in published rates of survey response?
Although there is benefit to knowing which antecedents of survey response account for unique variance (i.e., Research Question 1), no less important is information about whether the criterion-related validity of each predictor has changed over time. To answer this question, Anseel et al. (2010) examined regression coefficients for the interaction terms between each predictor in their model and the year of the primary study. Based on their analysis, the authors concluded that the effectiveness of advance notice, follow-up, and mailing paper versions of surveys as a means to enhance response rates has significantly declined over time whereas personalization has been increasingly effective. However, as with the previous research question, the approach taken by the authors to examine trends in predictors over time assumes error terms and their variances are stable across years, and therefore may not provide accurate estimations of the relationships between predictors and the criterion of response rates. It should be noted that the ability to test this question relies on a finding of variance in survey return between years of publication in Research Question 2. If there is not significant variance between years, then applying HLM will permit limited insight into the proposed relationships beyond the relative importance analysis conducted in Research Question 1.

As with the previous research question, it is not known whether the variance in study characteristics will account for response rates over time. For instance, as computer hardware, operating systems, and web software become increasingly sophisticated, it is difficult to hypothesize about how factors such as survey length or incentives may influence the variability in response rates in web-based surveys within a given year and across years.
Nevertheless, there is utility to both researchers and practitioners in knowing which factors are more likely to drive response rates in present day survey efforts, and similarly in knowing which factors have shown diminishing returns over time. As such, the following research question is posed:

Research Question 3: Has there been significant variation in response rates over time related to survey content, survey methodology, and recipient characteristics?

**Method**

**Study Search and Inclusion Criteria**

This study will employ the following strategy to identify published research for the purpose of meta-analysis. First, this meta-analysis will focus on empirical research reports published between 2000 and 2014 in the following journals: *Journal of Applied Psychology (JAP), Personnel Psychology (PP), Academy of Management Journal (AMJ), Journal of Management (JOM), Organizational Research Methods (ORM)*, and *Management Information Science Quarterly (MISQ)*. These journals were selected from lists of the top-ranked journals in the fields of applied psychology and management, according to *Journal Citation Reports* (Thomson Corporation, 2012). These outlets were chosen as they routinely and primarily publish empirical articles that report findings relevant to the study of I/O psychology and organizational science, and with the exception of MISQ all appear in Zickar and Highhouse’s (2001) list of top publication outlets in the field of I/O psychology. The time period of primary studies was chosen to constrain the data set to literature most likely to include web-based survey administration technology circa 2000 or later. The bulk of
previous meta-analyses included primary studies from the mid-1990’s or earlier, as summarized in Table 1, prior to widespread adoption of Internet access. Given the lifecycles of operating systems (e.g., Microsoft Windows XP was launched in 2001 and support ended in 2014), computer- or web-based surveys prior to this time period may not be analogous to the survey experience of an employee in present day organizations.

As with past meta-analyses of response rates, it is not be feasible to examine all published journals and unpublished manuscripts for information related to the hypotheses of this review. Accordingly, the top-ranked empirical journals selected present a cross-section of publications regarded as having especially high standards of rigor and likely to routinely report methodological information for each primary study. As such, these outlets serve as a normative indicator for organizational researchers as to what is methodologically acceptable (e.g., Cycoya & Harrison, 2006). To facilitate the identification of primary studies, literature searches will be conducted for each top-ranked journal using computerized databases of journal archives (e.g., PsycINFO, Business Source Premier, EBSCO Host). Keywords for the searches will include survey, questionnaire, instrument, self-report, and self-administered.

Of the following inclusion criteria, primary studies will have to meet criteria 1 through 3, and at least two criteria from 4 through 6 to be included in this meta-analysis:

1. Data in the primary study are collected through surveys or questionnaires;
2. Information regarding response rate or information that permits calculation of the rate of survey return is available;
3. The survey procedure must not have required mandatory response from
recipients, which fails to provide information regarding the variables affecting response rates (e.g., Cook et al., 2000);

4. Information concerning at least one of the variables identified as possible survey content predictors of response rates in the hypotheses is available;

5. Information detailing two or more aspects of the methods used for data collection (e.g., paper or web medium, use of advance notification and/or follow-up contacts, etc.) is available; and,

6. Information concerning one or more of the recipient characteristics (e.g., education, target population, etc.) of the observed sample is available.

The following types of primary research studies identified in the literature search will not be included: (a) studies that involved interviews, whether self-administered or conducted by an interviewer, or interviews executed through a technological medium; (b) studies failing to report information that permits an inference to be made about criterion 3 as stated above; (c) studies that use archival data; and, (d) studies where the primary level of analysis was not at the individual level (e.g., matched samples, dyads).

**Meta-Analytic Coding Scheme**

To address the hypotheses posited above, study characteristic codes will be adapted from various coding schemes such as those detailed in Heberlein and Baumgartner (1978), Yammarino et al. (1991), and Roth and BeVier (1998), as described below. It should be noted that in many previous meta-analyses of response behavior, dichotomous codes were often used to reflect the presence or absence of study features (e.g., Anseel et al., 2010; Cook
et al., 2000; Shih & Fan, 2008); the current study aims to employ ordinal codes whenever possible to facilitate a more granular analysis of response antecedents. In addition to the codes described below, the year of publication, final sample size, and average age of the respondents will be recorded.

Survey content characteristics coded will include topic salience and topic sensitivity. Topic salience, adapted from Heberlein and Baumgartner (1978), will be coded on a three-point scale of salient (important and of current interest to the recipient), possibly salient (important though not necessarily current), or nonsalient (neither important nor current). Topic sensitivity will also be coded on a three-point scale of sensitive (intrusive, overtly embarrassing), possibly sensitive (intrusive, not likely to be embarrassing), or nonsensitive (neither intrusive nor embarrassing) based on the definition of sensitivity by Tourangeau and Yan (2007) given previously.

Methodological characteristics coded will include salutation specificity, identification likelihood, the total number of items in the primary study survey, the total number of pre-notification contacts and follow-up contacts, the survey media, and the use of incentives. Salutation specificity will be coded as a dichotomous variable of no personalization or personalization of the recipient. Identification likelihood will be coded on a three-point scale of fully identified (name or other personal information required), partially identified (non-personal identifier assigned for the purpose of the survey), and anonymous. Survey length will be coded as the total number of items for all collected measures as reported by the authors of a primary study. The number of pre-notification and follow-up contacts will be
coded separately for both variables on a four-point scale of no contact, 1 contact, 2 contacts, or 3 or more contacts. The medium used to administer the survey will be coded to indicate the use of a mailed/paper survey or a computer-/web-based survey. Incentives will be coded to indicate the presence or absence of recipient incentives on receipt or return of the survey materials.

Recipient characteristics that will be coded include the modal educational level (high school diploma, some college, Bachelor’s degree, graduate degree; Roth & BeVier, 1998), the target population or source of the recipients (i.e., university population, professionals/employees, or general population; Shih & Fan, 2008), and job complexity. Job complexity will be coded on a three-point scale of low (i.e., hourly workers, clerical jobs), medium (lower- to mid-level managers), and high (executives, professions such as lawyer or physician); the code for job complexity will be based on the occupation held by the preponderance of the sample when available and appropriate (i.e., this variable will not be coded for academic samples). It should be noted that as these variables represent an aggregation of recipient characteristics in a given study and will not capture demographic diversity within a single sample, each variable noted above will be coded at the study level such that one code is assigned based on the most prevalent characteristic of participants in the same study.

For the criterion variable, response rate will be recorded when it is reported by the primary study authors or computed from information available in the method section for each primary study. In the case of the latter, the rate of survey return will be calculated so
resulting values are scaled in the direction of increasing response, by dividing the final number of usable surveys returned by the total number of recipients solicited.

A requirement of meta-analytic data sets is independence of data points, such that each study does not contribute more than one observation to aggregate data. In the case of articles that contain multiple waves of data collection or a “study 1—study 2” sequential hypothesis-testing design, only codes from the survey administration with the largest sample size will be used.

A summary table of the codes for all variables under examination is presented in Appendix A. Two raters will independently review and code primary studies following a frame-of-reference training to review the interpretation of rating scales. Codes will be recorded as missing values when a rater is unable to gauge the presence or absence of a predictor variable (Anseel et al., 2010; Cycyota & Harrison, 2006). The table in the appendix will serve as the guideline for rating primary studies from the identified primary studies and will be used by both raters. A random sample of 30 studies will be coded independently by the two raters, and inter-rater agreement statistics will be calculated $(r_{wg};$ James, Demaree, & Wolf, 1993) and presented as evidence of the stability of the codes. If inter-rater agreement is weak $(r_{wg} \leq 0.50;$ LeBreton & Senter, 2008), discrepancies will be discussed until the raters reach consensus on the interpretation of the codes, and a second random sample of 30 studies will be coded to confirm strong levels of inter-rater agreement $(r_{wg} > 0.70;$ LeBreton & Senter, 2008).
Proposed Analyses

In line with accepted meta-analytic methodology (e.g., Hunter & Schmidt, 2004) and past quantitative reviews (e.g., Anseel et al., 2010; Roth & BeVier, 1998), means, standard deviations, and zero-order correlations of the response rate criterion with coded study variables will be reported. For coded variables that are non-continuous (e.g., use of incentives, target population), ANOVAs and pertinent post-hoc analyses will be conducted to determine whether these variables significantly affect response rates considered at the group level.

Proposed Meta-Analytic Regression Analysis

To provide a test of the hypotheses, study variables coded on an ordinal scale will serve as input for a meta-analytic regression analysis (e.g., Huffcutt & Woehr, 1999; Judge & Piccolo, 2004; Riketta, 2008; Viswesvaran & Ones, 1995). Response rates will be regressed on study characteristics that are coded as continuous variables, akin to regressing an outcome variable on what would typically be designated as a meta-analytic moderator variable. The SAS Institute’s (2004) PROC REG program will be utilized for these computations.

The primary advantage of applying multiple regression to meta-analytic data is greater explanatory ability, compared to relying solely on bivariate meta-analytic coefficients. Moreover, the Type I error rate can be better controlled through the use of fewer tests, and unlike a bivariate test, the shared variance between predictors is accounted for in a regression model (Lou, Abrami, & d’Apollonia, 2001). A random effects model for meta-analysis will be employed, as outcomes of past meta-analyses on survey return suggest an
implicit heterogeneity in response rates depending on variables such as the target population (e.g., Cychota & Harrison, 2006). In addition, the random effects model has generally been shown to perform more accurately for meta-analytic data compared to fixed effects models in Monte Carlo studies related to meta-analysis (Kisamore & Brannick, 2007; Mason, Allam, & Brannick, 2007).

However, it should be noted that both the response rate criterion and the majority of the design and administration characteristic variables are data based on information reported in each primary study or codes generated by raters. Therefore, the regression analysis will conceptually treat studies as individuals, and characteristic variables as properties of those individual studies. In this sense, the sample of $k$ studies defines a sample of $n$ individual units from a larger population of studies. Further, this population of studies has been specifically defined by the literature search and inclusion criteria. To the extent that the information reported in each primary study is accurate and interrater agreement can be demonstrated for coded variables, this analysis can then be seen as a direct analogue to regression analysis on a sample of individuals. Moreover, the computations proposed do not involve correlations or slopes and intercepts, which may yield interpretive difficulties (Hunter & Schmidt, 2004). Therefore, analyses will be conducted and interpreted as if $k = n$ for a sample of individuals from a known population.

The use of regression analysis demands some attention to issues of statistical power. For a power of 0.80, Cohen’s (1988) convention for an effect size of .02, .15, and .35 for small, medium, and large effects, for a multiple regression in a meta-analytic context would
require a $k$ of 406, 66, and 36 studies, respectively. Green (1991) and Tabachnick and Fidell (2007) suggested a rule of thumb for the ratio of cases to independent variables of $N \geq (8 / f^2) + (m - 1)$ where the effect size $f^2 = .02, .15, \text{ and } .35$ for small, medium, and large effects when a small effect size is expected or reliability is a potential issue, and $m$ equals the number of independent variables in the regression analysis. Applied to the recommendation for $k$ values from Cohen’s power convention above, this would require a $k$ greater than 413, 66, and 36 studies for small, medium, and large effects, respectively. Tabachnick and Fidell (2007) also stated that as the number of cases increases, the likelihood that negligible variance may cause a statistic to depart significantly from zero also increases. Expecting missing data to be a potential issue for many variables, as it has been in past reviews on response rates (e.g., Anseel et al., 2010; Roth & BeVier, 1998), the regression analysis will likely have sufficient power to detect a medium-to-small effect size in respect to Research Question 1. Therefore, the meta-analytic sampling strategy in this study will follow common guidelines for considerations of sample size in multiple regression to permit adequate statistical power while remaining conservative enough to reduce the likelihood of Type II error.

Although not relevant for all applications of meta-analysis, there is precedent for using a regression approach with meta-analytic datasets (e.g., Colquitt, Conlon, Wesson, Porter, & Ng, 2001; Colquitt, LePine, & Noe, 2000; Judge & Piccolo, 2004; Kepes et al., 2013; Mason et al., 2007; Riketta, 2008). With respect to past meta-analyses of response rates, several reviews such as those by Anseel et al. (2010), Cook et al. (2000), Cyepyota and
Harrison (2006), and Roth and BeVier (1998) employed regression models to answer questions about trends over time and/or the contribution of different types of response enhancing techniques to explained variance in response rates. However, the unique variance attributable to each technique in predicting response rates can be difficult to interpret due to the fact that efforts to boost response rates often co-occur, and so the assumption of independent observations in multiple regression is violated. In the current study, the use of relative importance analysis will permit partitioning of shared variance between predictors of response rates, thereby facilitating “better conclusions about the relative meaning of multiple correlated predictors” (Tonidandel, LeBreton, & Johnson, 2011, p. 388) than has been available previously in similar meta-analyses.

With meta-analytic data there are often potential issues with multicollinearity among predictors for which relative importance analysis as described by Johnson (2000) is particularly suited to address. Relative importance was defined by Johnson and LeBreton (2004) as “the proportionate contribution each predictor makes to $R^2$, considering both its direct effect (i.e., its correlation with the criterion) and its effect when combined with the other variables in the regression equation” (p. 240). This analytical strategy provides a means with which to gauge the relationship between response rates and response enhancement techniques by providing more information as to the unique contribution of each predictor in the model. Relative importance analysis has been used in the organizational research domain in meta-analyses of relationships between cognitive ability and job performance (Lang, Kersting, Hülsheger, & Lang, 2010), emotional intelligence and job performance (O’Boyle,
Humphrey, Pollack, Hawver, & Story, 2011), and transformational leadership and follower performance (Wang, Oh, Courtright, & Colbert, 2011), but to date has not been utilized in a meta-analysis on determinants of survey response.

To investigate Research Question 1 examining unique variance in response rates, the potential predictors of rate of return as dictated by Hypotheses 1 through 12 will be compared via relative importance analysis (Johnson, 2000). This analysis will use the study-level data to provide a weighting scheme which indicates the predictor variables that account for greater or lesser proportions of the total explained variance in the regression model. The nominal variables for study characteristics related to salutation specificity (Hypothesis 3), administration medium (Hypothesis 8), and target population (Hypothesis 11) will be coded as dummy variables. This analytic strategy will regress the criterion of response rate on orthogonal transformations of the predictor variables to remove the effect of intercorrelations that may bias standardized regression weights. The resulting analysis provides coefficients that represent the contribution each predictor makes to variance in the criteria when the predictor is considered both uniquely and in the full regression model (Tonidandel & LeBreton, 2011). In the context of the current study, relative importance analysis provides a means to determine which antecedents carry the greatest explanatory power in predicting response outcomes in organizational surveys while effectively controlling for multicollinearity between the predictors. As many response enhancing techniques are likely to co-occur in survey designs based on the influence of past reviews on the effectiveness of such techniques (e.g., Baruch, 1999; Heberlein & Baumgartner, 1978; Roth & BeVier, 1998).
and on general recommendations such as those of Dillman et al. (2009), there is a strong likelihood of correlations between predictors of response rates.

**Proposed Multilevel Modeling Analysis**

To investigate Research Questions 2 and 3, a multilevel model will be fitted to the data through the use of HLM (Raudenbush & Bryk, 2002) to examine the variance in published response rates over time, and the extent to which study characteristics account for that variability within years and across years. HLM in meta-analysis can provide unique advantages over traditional meta-analysis (Van der Noorgate & Onghena, 2003). HLM incorporates analysis of random effects into the model calculations. As such, the total variation attributable to factors that can vary between studies, such as those coded for in the present research, can be disentangled from the variation between years and within years. As noted previously, this would represent the first use of HLM in meta-analytic research on response rates in published organizational literature.

There are several reasons for the appropriateness of utilizing HLM in the current study. First, the nested structure inherent in examining studies across time precludes an assumption of independent observations, and ignoring dependencies that exist in the data may result in significantly increased Type I error (Tabachnick & Fidell, 2007). Second, HLM has greater flexibility compared to other regression models with respect to missing data (Hox, 2010; Raudenbush & Bryk, 2002). Third, Raudenbush and Bryk (2002) described the random effects model for meta-analysis as a special case of a multilevel regression model, as study characteristics that are often part of meta-analytic coding frameworks inherently
represent second-level variables (i.e., characteristics across studies). Indeed, Hox (2010) noted that the formula for an unconditional model (also called an intercept-only, null, or empty model) in HLM is equivalent to the random effects model for meta-analysis as described by Hedges and Olkin (1985), and in practice the two computational approaches will produce convergent results. As Research Questions 2 and 3 in the current study seek to decompose the variability in survey return over time, a multilevel approach to study characteristics is suited to examining these trends that past reviews of response rates such as Anseel et al. (2010) have sought to do via examining regression coefficients with interaction terms between study characteristics and survey year in a hierarchical regression model.

**Partitioning of variance.** To address Research Question 2 related to trends in response rates over time, an analysis will conducted on response rates to establish the presence of significant variability in the collected primary studies between and within their years of publication. A model with no predictors, referred to as a fully unconditional model, will be run to obtain estimates of within-year ($\sigma^2$) and between-year ($\tau_{00}$) variability in response rates. These estimates are then used to obtain an intraclass correlation coefficient (ICC) through the formula, $\rho_I = \tau_{00} / (\tau_{00} + \sigma^2)$, which indicates the proportion of variance between years. The proportion of within-year variance is then equivalent to $1 - \rho_I$. The $p$ values associated with $\rho_I$ and $1 - \rho_I$ give indication as to whether there is sufficient variability between- and within-years to warrant further analyses that would address Research Question 3 related to variability in predictors of response rates over time (Raudenbush & Bryk, 2002). Said another way, a hierarchical model to test the predictors at level 1 is not necessary if
there is not significant variance over time at level 2.

**Discussion**

To summarize, this study will test a conceptual model that considers the influence of aspects of survey research related to the content of a survey, the administration of a survey, and the characteristics of the target recipients on the outcome of response rates. The meta-analytic regression and HLM analysis that will be conducted offer a quantitative exploration of the use of surveys in published literature, seeking to provide a summative and comparative analysis of the contributors to survey return in contemporary organizational research over time. In addition, the relative importance and HLM analyses will be the first known application of these statistical techniques to a meta-analysis of survey response rates, providing potential insight into trends of survey return that have not been previously available in past reviews. Therefore, this study broadens both the understanding of response behavior in organizational research as well as the potential statistical applications possible with meta-analytic data sets of study methodology.

The investigation of response behavior in organizational research accomplished in this study appreciably expands the scope of previous reviews of response rates such as those conducted by Anseel et al. (2010), Baruch (1999), Baruch and Holtom (2008), Roth and BeVier (1998), and Yammarino et al. (1991). As noted by Newman (2009), data about response rates can be a deficient indicator of the quality of a study, particularly when isolated from other information about a survey effort. Nevertheless, it is often considered the “gold standard” for survey quality by non-technical consumers of self-report research. To this end,
it is vital to clarify the antecedents to response in contemporary organizational survey research and permit a better general understanding of the factors related to content, methodology, and recipients that may enable sponsors to positively influence the number of complete responses to a survey participation request.

In addition, this study will provide a summary for researchers and practitioners of the typical response rate for a survey effort based on trends observed in the current literature. This accomplishes the noteworthy aim of providing benchmarks as to the average response rate for survey data collection efforts in 21st century organizational research.

**Limitations**

While care was taken to encapsulate a broad spectrum of potential influences on response behavior, this study is not without limitations. Though the illustrative models of response behavior described above provide useful frameworks through which hypotheses relevant to response rates can be tested, no broad model necessarily provides a comprehensive summary of the antecedents of response rates. As survey methods continue to evolve, no single study will provide incontrovertible evidence that a given variable affects recipients’ behavior—the dynamic relationship of survey sponsor, survey administration, and survey recipient will continually call for empirical enquiry. There are other study characteristics that could be included in the conceptual model that will not be tested in the context of this study due to the scope or specificity of the variables and the information that can reliably be collected or coded from method sections of multiple primary studies. For example, Church (1993) commented that although an effort was made to include variables
such as survey length or topic salience in his meta-analysis, “many of the authors were too scant in their methodological descriptions to determine these details with any accuracy” (p. 66). In another illustrative instance, Kaplowitz, Lupi, Couper and Thorp (2012) found effects for survey invitation manipulations on response rates in a university population, but these effects differed between faculty, staff, and student respondents—distinctions in recipient groups that may be too granular to code reliably across university samples. Further, there are likely potential antecedents to survey return that are not reported or studied prevalently enough in the extant organizational literature to facilitate meta-analysis. As noted previously, attitudes are theorized to play a significant role in response behavior (e.g., Helgeson et al., 2002). However, it is conceptually difficult to aggregate measures of attitudes from primary studies into a meaningful, cross-study variable, due to inconsistencies in operationalizations of attitudes and the target of the attitude. For example, it would be inappropriate to combine measures of attitudes toward a survey topic with attitudes about the survey sponsor or employing organization as a predictor of response rates. Further, to utilize reported means of job satisfaction as a proxy for general attitudes, there would be a potential threat to internal validity when the target organization is not the sponsor of the survey. Therefore, the influence of attitudes on response behavior likely requires continued investigation on a study-by-study basis as applied researchers design and implement survey data collection efforts.

It should also be noted that some researchers have posed alternative taxonomies of response behavior that are not captured in the model proposed in the current study. In addition to outright intentional refusal, many employees may fail to complete and return
surveys for reasons such as neglect (Rogelberg & Luong, 1998; Viswesvaran, Barrick, & Ones, 1993). Groves and Couper (1998) distinguished three forms of nonresponse: nonresponse due to noncontact, nonresponse due to a refusal to cooperate, and nonresponse due to an inability to cooperate (it should be noted, however, that this nomenclature was intended to apply to household interview surveys, and therefore may not be entirely germane to organizational contexts.). Relatedly, Newman (2009) provided a quantifiable taxonomy for incomplete surveys: item-level nonresponse, where data are missing for only a few items, scale-level nonresponse, where data are missing for an entire measured construct, and unit nonresponse, where data were never provided by the survey recipient. While many of these distinctions cannot be directly assessed through meta-analytic techniques without access to primary study data, they bear mention as complementary conceptualizations of response behavior.

Another potential limitation concerns predicting the influence of recipient characteristics from primary studies on response rates in general. This study did not seek to make inferences about the populations underlying each primary study, or about the overarching population of individuals who may be the desired target of organizational surveys. Instead, the quantitative review conducted here specifically attempted to uncover relationships between the samples under study and the reported response rates for those samples. Appropriately, the level of analysis in this review was not individual survey recipients, but the level of a data collection effort as a whole (i.e., a primary study). Any demonstrated relationship between recipient characteristics and the criterion of response rates
functionally provides researchers and practitioners with information about what they can expect if sample characteristics are known or can be inferred.

Lastly, this meta-analysis only considered published research in top tier journals in the fields of applied psychology and management, which may be a criticism of the inclusion criteria for primary studies. Further, Baruch and Holtom (2008) found no significant difference in response rates between the top-tier and lower-tier journals included in their meta-analysis. Again, the goal of the research is not to examine the entire published and unpublished literature as is often done to address the “file drawer problem” (Rosenthal, 1979) common to meta-analyses of bivariate effect sizes, but to summarize response rates from survey research designs that have been deemed methodologically sound via the peer review process. As noted by Church (1993) in his meta-analysis on the use of incentives, the problem of unpublished data can be seen as less critical when the focus of a meta-analysis is methodological, as the significance of primary study results or type of effect size is less likely to bias meta-analytic results given that they are largely inconsequential to the methods employed in the research. As such, the sample of studies analyzed in the current research can be taken as likely to reflect the larger population of published organizational survey research that meets the inclusion criteria. Anseel et al. (2010) included lower tier journals in their meta-analysis, positing that “exclusive focus on top-tier journals may restrict the range of the observed response rates and may lead to upwardly biased estimates of response rates” (p. 339); however, the authors did not present results that would suggest this is in fact the case. Moreover, Baruch and Holtom (2008) found no significant difference in response rates
across 17 journals spanning first and second tier rankings which primarily published organizational research. Notably, according to Baruch and Holtom, the journals under investigation were not found to differ significantly in the average response rate, but did differ in the number of studies that reported such information in the “Methods” section of each individual study such that journals considered top tier were more likely to report richer detail on aspects of survey administration. To that end, the current study focuses on a selection of such outlets to provide a cumulative quantitative analysis of what may be considered the most methodologically rigorous survey efforts, as was the case in the meta-analysis by Baruch (1999).

**Future Research**

As technology, and computers in particular, continue to transform the business landscape, the methods through which employees are surveyed has increasingly been computer-based (Naglieri et al., 2004; Tourangeau, 2004). Accordingly, studies of survey methodology will likely require constant review and revisions to best practices. While advancements in paper production or pen design have little bearing on recipient behavior, browser interfaces and innovations in computer displays can have a non-arbitrary impact on how a recipient interprets the questions being asked. In essence, as online surveys have progressed in functionality and programming complexity, manifestations of low response rates may concurrently be subject to change. For example, early computer-administered surveys often presented a single item at a time, and respondents were required to provide an answer before the next item was presented (Rosenfeld, Booth-Kewley, & Edwards, 1993).
Continued research on response behavior is certainly warranted as web-based survey delivery practices continue to evolve with new technologies and delivery platforms such as mobile devices and social media frameworks.

Future research should also seek to better elucidate the relationship between individual differences such as personality and survey response behaviors. For instance, a study by Aviv, Zelenski, Rallo, and Larsen (2002) suggested that there may be a relationship between a recipient’s personality, particularly extraversion, and his or her likelihood of participating in a survey. Recently, Brüggen, Wetzels, de Ruyter, and Schillewaert (2011) created a measure that attempted to capture the motivational orientations underlying survey return. As such, the relationship of individual differences to response behavior would benefit from further investigation to identify the correlates of survey behavior and the profiles of those less likely to engage in survey response.