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# Meta-analysis selection bias in marketing research

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ABSTRACT

The tendency of meta-analytic authors to select particular studies is called selection bias. Selection bias can affect the strength of the meta-analytic estimate and the attention that scholars devote to the results. This research is, in effect, a meta-analysis of the effect sizes reported or calculated from 94 meta-analysis studies of various topics in marketing research. The analysis reveals that estimates depend on the publication status of the included studies. The greater the percentage of studies that were published in academic journals vs. non-published studies, the greater is the size of the meta-effects, and the more published studies from leading journals the meta-analysis includes, the stronger the effect size. The meta-analytic effect size is a mediator for the influence of both the ratio of unpublished studies and the ratio of studies from leading journals on the probability of a meta-analysis to be published in a leading journal, which increases the number of citations to a meta-analysis. The findings of this study have several implications for meta-analysts, editors, reviewers and the marketing community on how to conduct and read current and future meta-analysis in marketing research.



## 1. Introduction

It is a well-known problem that preferential publication of significant and strong results over non-significant and weak results leads to a literature that provides a false impression regarding the size of the effect in question. There is strong evidence from several fields of science that this "publication bias" exists (Dickersin, 2005). By including published and unpublished studies in their quantitative review, meta-analysts try to mitigate the problem that the publication status of a study (i.e., whether the study is published or unpublished) is related to the effect size estimate in the study. The efforts to include studies of various publication statuses and the tendency of meta-analytic authors to select particular studies—whether intentionally or not—are called selection biases (Ferguson & Brannick, 2012). The current study identifies and examines selection bias in 94 meta-analyses in marketing research and its consequences for academia.

Selection bias arises from the selection decision of a meta-analyst, whereas publication bias is based on the decision of authors and editors to submit and to publish a manuscript, which precedes the selection decision of the meta-analyst. Although it is a different kind of bias, a selection bias might have similar consequences as a publication bias because certain studies are more likely to be selected than other ones, which influences the strength of the meta-analytic estimate and the attention scholars pay to the results. These consequences are of importance for both practitioners and scientists. Biased estimation of effects can lead to wrong decisions of practitioners and cause harm because inefficient measures are chosen. Biased findings can steer future research endeavors and achievements of academics in the wrong direction, lead to wastage (i.e., unnecessary work), and harm the pursuit of scientific truth (Knight, 2003). A thorough investigation of a selection bias is essential to evaluate the true value of meta-analytic findings.

This study contributes to the literature in several ways. First, the study contributes to the research about meta-analyses by examining for the first time the selection bias of meta-analysts and its consequences for academia. Second, the study contributes to our general knowledge about publication bias, which is related to the selection bias. The findings indicate not only that whether a study is published influences the size of an effect (which has been the focus of prior research on publication bias) but also that where (i.e., journal outlet) the study is published can bias the findings reported in the study. Third, the study provides details about the existence and extent of selection bias in the field of marketing. These insights provide implications for marketing researchers on how they should conduct, review, and read current and future meta-analyses.

## 2. Background and hypotheses

To avoid publication bias, scholars recommend that meta-analysts make a purposeful attempt to collect both published and unpublished studies (e.g., Borenstein, Hedges, Higgins, & Rothstein, 2009). Unpublished studies are produced by academic institutions that

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are not controlled by publishers, such as working papers or unpublished doctoral theses (Hopewell, Clarke, & Mallett, 2005).

Meta-analysts have better access to published studies, as a representative sample of unpublished studies does not exist (Ferguson & Brannick, 2012; Kepes, Banks, McDaniel, & Whetzel, 2012). While other scientific fields such as medicine have developed registers that help scientists to track unpublished research, this has not been done in marketing research. It is, therefore, easier and more likely for a meta-analyst in marketing to access and to include primarily published studies compared to unpublished studies. However, even among published studies, those that are published in leading journals are more easily accessible (e.g., the meta-analyst's academic institution might not have a subscription to non-leading journals).

Meta-analyses vary in the percentage of included studies that have differing publication statuses, which at least partly depends on the efforts a meta-analyst exerts into searching and retrieving the studies (Banks & McDaniel, 2011). For instance, there is meta-analysis that puts much effort into retrieving unpublished studies. Other meta-analyses are based on systematic issue-by-issue searches of particular journals, usually the leading journals in the field as well as topic-related journals. Such issue-by-issue searches increase the likelihood that relevant studies from the searched journals are included. Studies from other journals that are searched by other means (e.g., a keyword search in electronic databases) might be overlooked because effect size estimates worthy of inclusion might not be detected this way (e.g., the relevant effects might not be mentioned in the abstract of the study that is searched for the occurrence of keywords). Furthermore, the number of citations to a study makes it easier to identify a study when searching references of previously found studies, which consequently favors studies published in leading journals that have high citation rates.

The selective sampling of studies can produce an incorrect estimate of the true effect (Renkewitz, Fuchs, & Fiedler, 2011). It is difficult to determine the exact nature of the selection bias, because we do not know the true effect of the relationship that is investigated in a meta-analysis. Whether the findings in top journals are upward biased or the findings in lesser journals or of unpublished studies are downward biased can only be inferred from the empirical distribution of meta-analytic effect sizes (Egger & Smith, 1998).

### *2.1. The influence of whether and where a study is published on meta-analytic effect sizes*

In marketing research, it has been shown that the percentage of significant results reported in journal articles has increased over the years, particularly in the leading journals (Hubbard & Armstrong, 1992). Several studies in medicine and psychology have surveyed reviewers, editors, and authors and found that studies with results rejecting the null hypothesis are more likely to be published (e.g., Coursol & Wagner, 1986; Dickersin, Chan, Chalmers, Sacks, & Smith, 1987; Greenwald, 1975). In order to investigate the reasons for the lack of insignificant results in publications, several cohort studies have examined the process from study initiation to dissemination of results by following studies approved by research ethics boards (e.g., Cooper, DeNeve, & Charlton, 1997; Dickersin, 1997; Easterbrook, Berlin, Gopalan, & Methews, 1991; Olson et al., 2002). They found that the majority of researchers do not submit manuscripts with non-significant results. In addition to the self-selection of authors, the editorial staff is responsible for a publication bias because studies are more likely to be rejected due to the lack of an incremental contribution to the literature.

The publication bias suggests that the publication status is related to the effect size (e.g., Egger, Smith, Schneider, & Minder, 1997; Rust, Lehman, & Farley, 1990). Meta-analytic authors' tendency to select published studies more than unpublished studies aggravates the publication bias problem (Renkewitz et al., 2011). The more unpublished studies that are included, the weaker the meta-analytic effect size will be.

To date, publication bias studies have focused on the relationship between publication status and effect size by examining whether a study was published. Another plausible, yet barely investigated approach is to search for variations in the quality of publication outlets and their relationship with effect sizes. The underlying idea is that the size of the effect denotes the explanatory potential and, by this, the usefulness of a theory (Aguinis, Dalton, Bosco, Pierce, & Dalton, 2011). The more variance in the dependent variable that is explained, the more useful the underlying theory is thought to be. Combs (2010, p. 11) explains this as follows: “A theory might find support, but its explanatory power—that is, the effect size observed—is so weak that further efforts to develop the theory might not be warranted. … Small effects also raise questions about managerial relevance. … If managers begin to act on theories that are supported by small effects, they are not likely to notice positive results even when they occur.”

Because the standards of methodological rigor and theory development that are considered acceptable in leading journals are higher than in non-leading journals (e.g., Lehmann, 2005; Varadarajan, 2003) and because effect sizes signal a theory's usefulness and the rigorous application of methods, the editors and reviewers of leading journals are more likely to select studies with strong effect sizes, thus suppressing weak results. Also authors, who have strong findings or who are more careful and thorough in their work and better control for confounding factors and thus find stronger findings, might be more likely to select these findings for a submission to a leading journal. In other words, censorship due to authors, editors, or reviewers in marketing research is related to the size of effects reported in the studies (Rust et al., 1990).

**H1.** The ratio of studies published in leading journals in a meta-analysis is positively related to the meta-analytic effect size.

### *2.2. Consequences of selection bias on publication of and citations to a meta-analysis*

Strong and significant effects are considered as important and attract more attention by scholars than weak or non-significant effects. The importance of research findings is evaluated in academia in at least two measurable ways: first, by the gatekeepers of publication outlets (editors and reviewers), who decide which findings are worthy of being published, and second, by scholars who indicate the importance of the findings by citing these studies.

Tierney, Clarke, and Stewart (2000) have shown that meta-analyses of individual cancer patient data with significant and impressive results tend to be published in journals with higher impact factors. While the importance of the effect size is rather obvious in medical science, because it indicates how successful treatments and interventions are, studies in business research are more concerned with the mere significance of an empirical finding (Ellis, 2010). We suggest that effect sizes in meta-analyses in marketing research influence their publication success, because they indicate a relative contribution. The magnitude of a meta-analytically derived effect size denotes explanatory potential of theories: theories that explain a larger portion of the variance in relevant outcomes are more useful than those that explain a small portion (Aguinis et al., 2010; Bacharach, 1989). The theoretical relevance increases the likelihood of authors to submit their meta-analysis papers to a top journal and it influences the decision of editors and reviewers to support these papers during the review process. Because we assume that the meta-analytic effect size depends on the publication status of the studies included in the meta-analysis, we formulate the following mediation hypothesis that describes the consequences of selection bias on the probability of a meta-analysis to be published in a leading journal.

**H2.** The meta-analytic effect size is a mediator for (a) the ratio of unpublished studies and (b) the ratio of studies published in leading journals included in a meta-analysis on the probability that the meta-analysis is published in a leading journal.

Scholars rely on strong effects to use for groundwork in their own research. If meta-analyses are cited based on their effect size, then they are cited according to their relative merit, that is, the ability to explain outcomes of interest (Aguinis et al., 2011). Because meta-analyses do not only focus on the significance of the meta-analytic effect but also on its size, citations are driven by the meta-analytic effect size beyond its mere significance: the stronger the effect, the more likely scholars will refer to the finding and cite it in their own work.

Previous research has shown that journals publishing statistically significant results compared to those publishing null results had on average a higher impact factor, that is, are cited more by scholars (Easterbrook et al., 1991). Meta-analyses that are published in leading journals lead to more citations because these journal vehicles have a higher impact factor. By this, the meta-analytic effect size does not only influence citations directly (i.e., independent on where the meta-analysis is published), it also influences the publication probability of a meta-analysis in a leading journal (Hypothesis H2), which in turn drives citations to the meta-analysis. Therefore, we expect a mediating path next to the direct effect of the meta-analytic effect size on citations.

**H3.** (a) The meta-analytic effect size increases citations to a meta-analysis. (b) The probability that a meta-analysis is published in a leading journal is a mediator for the relationship between the meta-analytic effect size and citations to a meta-analysis.

Fig. 1 summarizes the relationship between the variables investigated in our study.

## 3. Method

### 3.1. Document retrieval

We restrict our search for meta-analyses in marketing research to journals that are currently listed in the social science citation index. To locate meta-analyses in marketing research published by the end of 2012, we searched every marketing journal (see Appendix). The journals that were categorized as marketing journals followed the comprehensive journal classification provided by Harzing's list (Harzing, 2012). We further include meta-analyses on marketing topics from other business journals that publish marketing studies (e.g., *Journal of Applied Psychology* and *Journal of International Business Studies*) and that we found by keyword searches, such as “marketing,” “consumer,” and “meta-analysis,” in EBSCO and Google Scholar.

We define a meta-analysis as the following (see also Richard, Bond, & Stokes-Zoota, 2003): the meta-analysis must report a numerical measure of a relationship between two variables (e.g., correlation or mean difference). The meta-analysis had to systematically summarize evidence of this effect collected within two or more primary scholarly studies (i.e., studies by academic scholars) by two or more researchers or research teams. This definition results in a number of exclusions. We exclude review studies that do not report numerical measures for a relationship between two variables, such as vote-counting studies. We further exclude studies that compile descriptive results such as the mean survey response rates (e.g., Yu & Cooper, 1983), content analytic percentages (e.g., Abernethy & Franke, 1996), occurrence of analytical approaches (e.g., Dekimpe & Hanssens, 1995), or reliability and validity coefficients (e.g., Homburg, Klarmann, Reimann, & Schilke, 2012). We exclude two review studies that use only databases other than scholarly journals (Lodish, Abraham, Kalmenson, et al., 1995; Lodish, Abraham, Livelsberger, et al., 1995), because it is not possible to decide on a corresponding number of studies nor their publication status. We further exclude studies that meta-analyzed meta-analytic results (e.g., Peterson, 2001). If the meta-analytic data were published in more than one journal article, we refer to the article that was published first. Based on this procedure, we identified 115 meta-analyses in the marketing area.

### 3.2. Coding

Most meta-analyses provide a single meta-analytic effect size that equals an average of all effect sizes that were provided in the primary studies that were included in the meta-analysis. Because we measure all variables in our models (see Table 1) on the meta-analysis level (that is, the variables vary between meta-analyses), we code for each meta-analysis one mean effect size that integrates all individual effect sizes in the meta-analysis. If the individual effect sizes in a meta-analysis were combined to subgroups of meta-analytic effect sizes rather than into a single meta-analytic effect size (such as, for instance, the effect of humor in advertising on attitudes, intentions, and behavior), the mean effect size was computed by averaging these meta-analytic effect sizes (weighted by the number of underlying individual effect sizes). Most of the meta-analyses in marketing use the correlation coefficient as meta-analytic effect size and therefore we chose the correlation coefficient as the mean effect size, and absolute values were coded because we are interested in the size of the effect, not its direction.

If the meta-analysis applied an effect size metric different from correlation coefficients, we transformed effect sizes to correlation coefficients according to common re-computation methods (e.g., Lipsey & Wilson, 2001). We used the raw mean effect size because this measure was provided in most cases. If the sample size weighted mean or variance-weighted mean was provided, we used this measure because we did not find any difference between raw mean and weighted mean values in meta-analyses that provided both estimates ($t = .19$, $p = .85$). Some meta-analyses provided attenuated effect sizes only. Attenuation-corrected estimates are bigger than raw means ($t = 4.97$, $p < .001$) and weighted means ($t = 4.70$, $p < .001$) because they correct for measurement errors of estimates. The ratio of non-corrected means to attenuation-corrected means that we found in the meta-analyses that provided both estimates is .87. This value is used to correct the estimates from meta-analyses that provide attenuation-corrected estimates only (i.e., we multiply the attenuation-corrected estimates by .87).

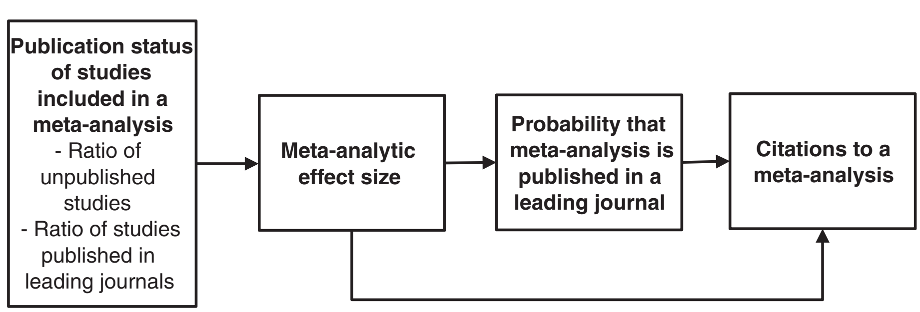


**Fig. 1.** Relationship between variables investigated.

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**Table 1**
Variables used in the analysis.

| Variable (symbol) | Description and coding | Function | Explanation of function | Data characteristics |
|---|---|---|---|---|
| Effect size (ES) | Meta-analytic correlation. | DV/M/IV | Hypotheses H1, H2a, H2b, H3a, and H3b | Min. = .01, max. = .71, mean = .27, SD = .15 |
| Ratio unpublished studies (RU) | Percentage of unpublished studies (the studies that are not controlled by publishers, such as unpublished dissertations and working papers), among all studies (unpublished and published, that is, the studies controlled by publishers that underwent a peer-review procedure, such as journal articles and peer-reviewed proceedings). | IV | Hypotheses H2a | Min. = 0, max = .5, mean = .06, SD = .10 |
| Ratio studies in leading journals (RL) | Percentage of studies in leading marketing journals (*Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, and *Marketing Science*) among studies in all SSCI-listed marketing journals. | IV | Hypotheses H1 and H2b | Min. = 0, max. = 1, mean .39, SD = .29 |
| Journal outlet (JO) | Dummy variable indicating whether the meta-analysis was published in one of the four leading marketing journals: *Journal of Consumer Research*, *Journal of Marketing*, *Journal of Marketing Research*, and *Marketing Science*. | DV/M | Hypotheses H2a, H2b, and H3b | 0 = other journal (71)<br>1 = leading journal (23) |
| Citations average (CA) | The average number of citations a meta-analysis receives per year, as provided by the SSCI database. The average citation is computed as the number of citations divided by the years since publication. | DV | Hypotheses H3a and H3b | Min. = 0, max. = 52, mean = 5.16, SD = 7.28 |
| Subject area | Following the classification of meta-analyses provided by Cano, Carrillat, and Jaramillo (2004), the meta-analyses were categorized in eight different fields: *advertising*, *channels*, *consumer behavior*, *methods*, *new product development*, *pricing*, *sales*, and *strategy*. One meta-analysis can belong to more than one field. | Control | Differences in effect size and publication success due to subject area. | Eight dummy variables (frequencies): Advertising (15), channels (7), consumer behavior (40), methods (7), new product development (11), pricing (8), sales (9), strategy (9) |
| Meta-analysis type | Meta-analyses focus either on the determination of an effect size (type 1), examine moderators of an effect (type 2), or examine an entire conceptual framework, often by means of structural equation models (type 3). | Control | Differences in importance of effect size and its consequences: the importance of the effect size is most obvious in type 1 meta-analyses. | Type 2: 0 = other (28), 1 = moderator meta-analysis (66) and Type 3: 0 = other (84), 1 = meta-analytic structural equation model (10) |
| Method type | Dummy variable that indicates whether the studies included in the meta-analysis are mainly based on experiments or surveys/field studies. | Control | Differences in effect size (and its consequences) due to different controls of confounding effects in experimental studies versus field studies. | 0 = mainly experimental (34)<br>1 = mainly surveys/field studies (60) |
| Year | The average publication year of the studies that are included in a meta-analysis. | Control | Differences in effect size and its outcomes due to changes over time, such as methodological advances. | Min. = 1950, max. = 2006, mean = 1987, SD = 10.03 |
| Number of effect sizes | The number of effect sizes that are included in the meta-analysis. | Control | Differences in the maturity of a field can influence effect sizes and publication success. | Min. = 11, max. = 3195, mean = 315.77, SD = 495.63 |
| Time frame | Measures the time frame between the oldest and most recent study that was included in the meta-analysis. | Control | Differences in the maturity of a field can influence effect sizes and publication success. | Min. = 5, max. = 80, mean = 26.33, SE = 12.73 |

Notes: IV = independent variable, DV = dependent variable, M = mediator.

In addition to the effect size, several other dependent, independent and control variables were coded. Table 1 describes these variables and their coding, explains why they were considered (i.e., their function), and provides relevant data characteristics. Because these methodological variables, with the exception of the subject area, are based on codings that did not leave room for interpretation, these variables were double-coded by a second coder for only 25% of the meta-analyses (i.e., 29 meta-analyses), with a 100% agreement rate in codings. Subject area was double coded for all meta-analyses, and only two meta-analyses led to disagreements, which were resolved after discussion.

In the final analyses, only 94 meta-analyses were included. Twenty-one meta-analyses were excluded either because the list of manuscripts that were included in the meta-analysis could no longer be retrieved from the authors (eight meta-analyses) or because the meta-analysis does not provide sufficient information to compute a common effect size, because the effect size in the meta-analysis could not be readily transformed into a correlation coefficient (thirteen meta-analyses). That is the case for meta-analysis that apply elasticities (e.g., Kremer, Bijmolt, Leeflang, & Wieringa, 2008) or effect sizes that were created by the authors (e.g., Estelami, Lehmann, & Holden, 2001). Included and excluded meta-analyses do not differ in terms of the independent variables in Table 1, except for meta-analysis type 1 and number of effect sizes: the excluded meta-analyses had a higher percentage of moderator meta-analysis ($\chi^2 = 5.70$, $p = .017$) and a higher number of effect sizes ($t = 2.27$, $p = .025$). Both variables were not related to the dependent variables journal outlet or citations average among the excluded meta-analyses.

The 94 meta-analyses have included 4,677 primary studies (49.8 studies per meta-analysis) and 29,682 effect sizes (316 effect sizes per meta-analysis). From 60 meta-analyses that provided information on the underlying sample size of the primary studies, we receive an average of 55,001 subjects per meta-analysis. A list of all meta-analyses is provided in the appendix.

*3.3. Analytical procedure*

First, we run different kinds of regression models for each of the dependent variables:

$$\mathrm{ES_i} = \beta_1 + \sum_{i=2}^{16} \beta_i \mathrm{Control_i} + \beta_{17}\mathrm{RU_i} + \beta_{18}\mathrm{RL_i} + \mathrm{e_i} \tag{1}$$

$$\mathrm{JO_i} = \beta_1 + \sum_{i=2}^{16} \beta_i \mathrm{Control_i} + \beta_{17}\mathrm{RU_i} + \beta_{18}\mathrm{RL_i} + \beta_{19}\mathrm{ES_i} + \mathrm{e_i} \tag{2}$$

$$\mathrm{CA_i} = \beta_1 + \sum_{i=2}^{16} \beta_i \mathrm{Control_i} + \beta_{17}\mathrm{RU_i} + \beta_{18}\mathrm{RL_i} + \beta_{19}\mathrm{ES_i} + \beta_{20}\mathrm{JO_i} + \mathrm{e_i}. \tag{3}$$

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The dependent variable effect size (ES, as measured by the Fisher's z-transformed correlation) is a continuous variable and a linear regression is applied. The dependent variable journal outlet (JO) is dichotomous and we applied a logistic regression. For the variable citations average (CA), we apply a negative binomial regression, because the likelihood ratio test indicates significant overdispersion ($\chi^2 = 117.96$; $p < .001$). The analysis of the residuals of each model did not indicate any outlier problems nor did we find any other violations of the models.

To test mediation effects, we follow procedures for regression-based mediation tests (Zhao, Lynch, & Chen, 2010). We run three regression models (I to III) that include all control variables and that test: (I) the effect of the independent variable on the dependent variable (c-path), (II) the effect of the independent variable on the mediator variable (a-path), and (III) the effect of both the independent (c′-path) and the mediator variable (b-path) on the dependent variable. Mediation requires at a minimum that the a-path, the b-path and the indirect effect to be significant.

## 4. Results

### 4.1. Descriptive results

The mean meta-analytic correlation is .27 (SD = .17). Table 2 presents the correlation matrix of all variables.

### 4.2. Regression and mediation analysis

Table 3 presents the results of the regression models. The regression model (1) with effect size as the dependent variable shows that the ratio of unpublished studies reduces the meta-analytic effect size ($b = -.36$, $SE = .20$, $t = 1.85$, $p = .069$), supporting the publication bias. The ratio of studies in leading journals enhances the meta-analytic effect size ($b = .15$, $SE = .07$, $t = 2.19$, $p = .031$). The result supports Hypothesis H1.

Fig. 2 presents the results of the mediation analysis (i.e., a-path, b-path, c-path, and c′-path as retrieved from regression analysis). The first diagram shows that there is no direct effect of the ratio of unpublished studies on the probability that the meta-analysis is published in a leading journal. However, the indirect effect is significant as indicated by bootstrapping ($z = 2.66$, $p = .008$). The non-significant direct effect can be explained by the opposite sign of the indirect effects: the ratio of unpublished studies reduces the meta-analytic effect size that, in turn, increases the probability that the meta-analysis is published in a leading journal. The finding is consistent with the mediation effect that is suggested in Hypothesis H2a.

The second diagram shows that the direct effect of the ratio of studies in leading journals on the probability that the meta-analysis is published in a leading journal is significant. After adding the indirect path, the effect becomes non-significant. The indirect effect is marginally significant as indicated by bootstrapping ($z = 1.96$, $p = .097$). The finding is consistent with the pattern predicted by Hypothesis H2b.

The third diagram shows that the direct effect of the meta-analytic effect size on citations average is significant ($b = 1.87$, $SE = .67$, $t = 2.80$, $p = .005$), supporting Hypothesis H3a. After adding the mediating path, the effect is reduced but remains significant ($b = 1.49$, $SE = .27$, $t = 2.24$, $p = .025$). The indirect effect is significant as indicated by bootstrapping ($z = 2.75$, $p = .006$). The finding is consistent with the mediation effect that is suggested by Hypothesis H3b.

The regression results in Table 3 provide some additional findings related to the control variables that deserve attention. As for subject area, we find that meta-analyses dealing with issues related to advertising, channels, and consumer behavior are less likely to be published in leading journals. Meta-analyses dealing with topics related to new product development and strategy receive more citations than other meta-analyses.

As for method differences across meta-analyses, we find that meta-analyses that are mainly based on surveys and field studies receive more citations, but are less likely to be published in leading journals. Furthermore, the meta-analysis type does not influence the meta-analytic effect size, but meta-analyses that include moderators or structural equation models have a higher likelihood to be published in leading journals and receive more citations than meta-analyses that only present and discuss meta-analytic effect sizes.

As for the average publication year of the studies that are included in a meta-analysis, we did not find any influence on effect size, although we were expecting that more recent studies would apply more advanced methods and thus lead to stronger effects. We find a negative effect of the probability to be published in leading journals and on citations average that indicates that meta-analyses on more recent topics have lower publication success.

As for the indicators related to the maturity of the field (number of effect sizes and time frame), we find that the number of effect sizes does not influence the dependent variables, but the time between the oldest and the most recent study that were included in the meta-analysis has a significant effect on the dependent variables. The longer the time frame, the more mature the field and the more established the research questions. At the same time, the less likely the meta-analysis gets published in a leading journal and the fewer citations the meta-analysis receives. This is in line with Rust et al. (1990) who argue that the more mature the field, the more suspiciously reviewers, who are often authors of previous studies, might look at results of additional studies. They might apply more rigorous standards in established research fields and are therefore less likely to accept a meta-analysis for inclusion in leading journals. In a similar way, readers might devote less attention to a meta-analysis once a research field is already fully established. There might be less activity and interest in this area and this lack of interest reduces the publication success.

### 4.3. Additional analysis

#### 4.3.1. Is variation in publication status indeed driven by the efforts of meta-analysts?

Our central assumption is that the ratio of unpublished studies and the ratio of studies that are published in leading journals in a meta-analysis depend largely on the efforts authors undertake in searching and retrieving studies. An alternative explanation might be that the availability of unpublished or published studies varies over the meta-analyses. To test whether our assumption holds, we additionally coded the methods section in each meta-analysis regarding the efforts authors undertake to retrieve studies with different publication statuses.

Efforts to retrieve unpublished studies go beyond searches that reveal published studies only (e.g., searching in databases with published articles only). Following suggestions in the literature (Hopewell et al., 2005), we distinguish between the following activities of meta-analysts to retrieve unpublished studies: (1) searching databases that include unpublished studies, (2) searching the Internet, (3) calls for unpublished studies (e.g., via ELMAR), (4) contacting authors, and (5) searching dissertations online. Out of 94 meta-analyses, 76 provide sufficient information on the study retrieval process. The number of activities mentioned to retrieve unpublished studies is positively related to the ratio of unpublished studies in the meta-analyses ($r = .60$, $p < .001$). If we replace the ratio of unpublished studies in regression model (1) with the number of activities to retrieve unpublished studies, we find support for our central assumption, because the number of activities reduces the effect size ($b = -.03$, $SE = .02$, $t = 1.83$, $p = .072$) (see Appendix Table A.4).

We decided to include the number of unpublished studies in our analysis because they are related to the efforts the authors invest in retrieving these studies. Because the percentage of unpublished studies is relatively low, an alternative measure would be one that simply

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**Table 2**
Correlation matrix.

| # | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Effect size (ES) | | | | | | | | | | | | | | | | | | | |
| 2 | Ratio unpublished studies (RU) | **−.30** | | | | | | | | | | | | | | | | | | |
| 3 | Ratio studies in leading journals (RL) | **.31** | **−.22** | | | | | | | | | | | | | | | | | |
| 4 | Journal outlet (JO) | **.32** | −.11 | **.39** | | | | | | | | | | | | | | | | |
| 5 | Citations average (CA) | **.29** | .03 | **.22** | **.45** | | | | | | | | | | | | | | | |
| | *Control variables* | | | | | | | | | | | | | | | | | | | |
| 6 | Subject area: advertising | .02 | −.06 | .12 | −.05 | −.14 | | | | | | | | | | | | | | |
| 7 | Subject area: channels | .09 | −.07 | .13 | −.07 | .02 | −.12 | | | | | | | | | | | | | |
| 8 | Subject area: consumer behavior | .05 | .09 | −.16 | **−.24** | −.07 | **−.32** | −.16 | | | | | | | | | | | | |
| 9 | Subject area: methods | −.05 | .16 | −.03 | .03 | −.07 | −.12 | −.08 | .01 | | | | | | | | | | | |
| 10 | Subject area: new product development | −.10 | −.10 | −.11 | .02 | .09 | −.16 | −.10 | **−.31** | −.10 | | | | | | | | | | |
| 11 | Subject area: pricing | .09 | −.09 | .15 | *.18* | −.01 | −.03 | −.09 | −.03 | −.09 | −.11 | | | | | | | | | |
| 12 | Subject area: sales | −.17 | .12 | .05 | .07 | −.03 | −.14 | −.09 | −.13 | −.09 | −.12 | −.10 | | | | | | | | |
| 13 | Subject area: strategy | .04 | −.09 | −.09 | .15 | **.21** | −.14 | −.09 | **−.28** | −.09 | −.01 | −.10 | −.11 | | | | | | | |
| 14 | Meta-analysis type 2 | −.12 | *.20* | −.05 | −.01 | .01 | −.03 | −.08 | .09 | .10 | .02 | .12 | −.18 | −.03 | | | | | | |
| 15 | Meta-analysis type 3 | .11 | −.11 | .06 | **.29** | .15 | .04 | .17 | −.23 | −.10 | −.02 | −.11 | **.24** | .01 | **−.53** | | | | | |
| 16 | Method type | .03 | −.14 | −.03 | .02 | .11 | **−.22** | **.21** | **−.43** | −.12 | **.27** | −.09 | .17 | **.25** | −.05 | .04 | | | | |
| 17 | Year | −.11 | .08 | **−.39** | **−.23** | −.08 | −.12 | −.04 | −.01 | .10 | *.18* | **−.30** | −.08 | **.31** | .06 | .10 | −.01 | | | |
| 18 | Number of effect sizes | .07 | −.09 | −.12 | .12 | −.01 | −.10 | −.08 | −.06 | .02 | .09 | .06 | −.02 | −.05 | .16 | .05 | .14 | −.11 | | |
| 19 | Time frame | −.14 | −.07 | .11 | −.12 | −.11 | .11 | .02 | .06 | −.16 | −.12 | .04 | **.24** | **−.30** | .06 | −.05 | .09 | **−.60** | .12 | |

Notes: Bold correlations are significant at $p < .05$, figures in italics are significant at $.05 \leq p < .01$ (two-sided tests). Correlations involving dummy variables are (point-)biserial correlations.

distinguishes whether unpublished studies were included or not. However, such measure does not as clearly relate to the efforts a meta-analyst invests in retrieval of unpublished studies. For instance, a meta-analyst who includes only one unpublished study out of 100 studies was probably putting less effort in study retrieval than a meta-analyst who includes one unpublished study out of ten. The dummy variable would indicate in both cases the same value for inclusion of unpublished studies. When including a dummy variable for unpublished studies in regression model 1, the effect is non-significant ($b = -.04$, $SE = .04$, $t = .99$, $p = .32$). This finding supports the idea that the selection bias is driven by meta-analysts' efforts during the study retrieval process and not just the fact whether unpublished studies were included, which can have different reasons.

The efforts made to retrieve studies from various journals can best be assessed by the issue-by-issue searches a meta-analyst performs. Only 28 meta-analyses provide information on the journals that were screened in an issue-by-issue search. The ratio of leading journals to all marketing journals that were systematically searched is positively related to the ratio of studies in leading journals that were eventually included in the meta-analysis ($r = .60$, $p < .001$). Due to the small sample size of only 28 meta-analyses, we run a regression model where we include only control variables that show a significant

**Table 3**
Model estimation results.

| Model | (1) | (2) | (3) |
|---|---|---|---|
| | Linear regression | Logit regression | Negative binomial regression |
| Dependent variable | Effect size | Journal outlet | Citations average |
| *Control variables* | | | |
| Subject area: advertising | .05 (.08) | −5.67 (3.11)* | −.24 (.44) |
| Subject area: channels | .03 (.09) | −5.83 (3.22)* | −.01 (.44) |
| Subject area: consumer behavior | .09 (.07) | −4.99 (2.59)* | .34 (.38) |
| Subject area: methods | −.01 (.08) | .82 (.2.23) | −.29 (.44) |
| Subject area: new product development | −.03 (.08) | 1.31 (1.95) | .73 (.43)* |
| Subject area: pricing | .01 (.07) | −1.03 (2.09) | −.30 (.40) |
| Subject area: sales | −.06 (.08) | 2.09 (2.33) | .07 (.42) |
| Subject area: strategy | .03 (.09) | 2.04 (2.07) | .98 (.46)** |
| Meta-analysis type 2 | −.01 (.05) | 5.55 (3.29)* | .56 (.28)** |
| Meta-analysis type 3 | .07 (.07) | 8.02 (3.73)** | .89 (.42)** |
| Method type | .05 (.05) | −3.33 (1.74)* | .44 (.26)* |
| Year | −.01 (.01) | −.28 (.11)** | −.04 (.16)*** |
| Number of effect sizes | .01 (.01) | .01 (.01) | −.01 (.01) |
| Time frame | −.01 (.01)** | −.14 (.07)* | −.02 (.01)* |
| *Main variables* | | | |
| Ratio unpublished studies (RU) | −.36 (.20)* | 2.69 (6.60) | 3.24 (.99)* |
| Ratio studies in leading journals (RL) | .15 (.07)** | 2.38 (2.39) | .30 (.39) |
| Effect size (ES) | | 12.69 (4.92)*** | 1.49 (.66)** |
| Journal outlet (JO) | | | .60 (.27)** |
| $R^2$/Pseudo $R^2$ | .27 | .62 | .13 |
| $Chi^2$ (df) | | 63.35 (17)*** | 64.17 (18)*** |
| F (df) | 1.79 (16,77)** | | |

Unstandardized coefficients and standard errors in brackets are provided.
*$p < .10$, **$p < .05$, and ***$p < .01$ (two-sided tests).

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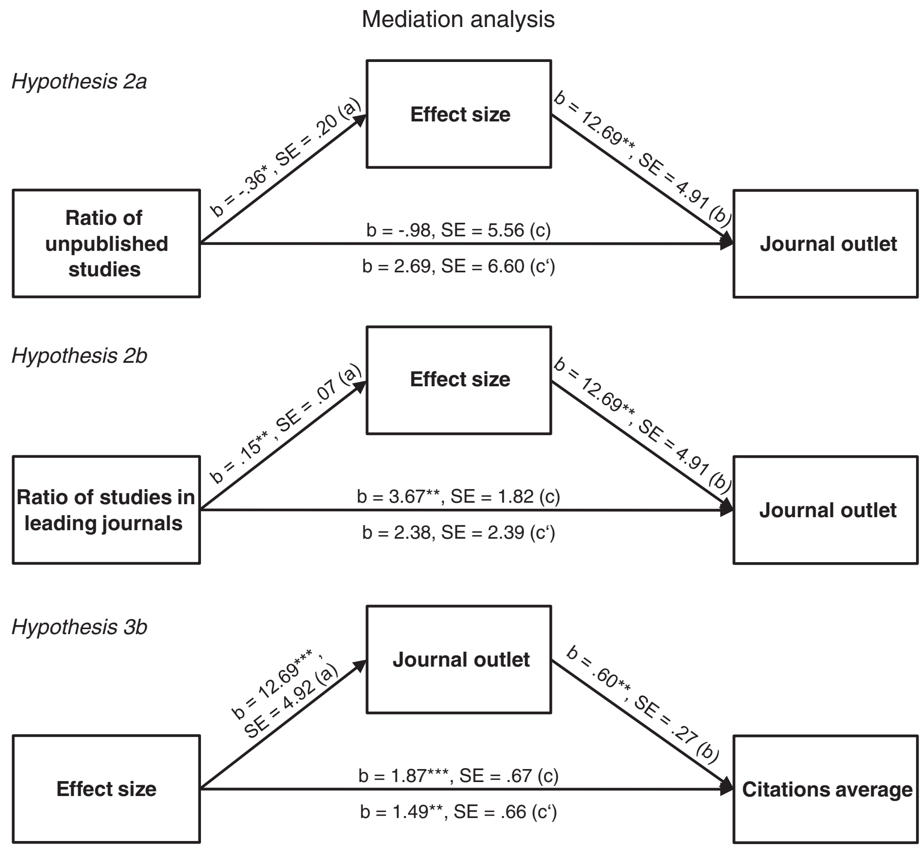


**Fig. 2.** Mediation analysis.

relationship with the main independent and dependent variables (see Appendix Table A.4). In line with our expectations, the ratio of leading journals that were systematically searched increases the effect size ($b = .27$, $SE = .15$, $t = 1.84$, $p = .078$). These results support our assumption that the efforts a meta-analyst undertakes to retrieve different types of studies is related to the percentage of the various studies being included in the meta-analysis, supporting a selection bias.

*4.3.2. Are effects in leading journals more likely reported due to size or due to statistical power?*

Hypothesis H1 suggests that the size of effect denotes its explanatory potential and is related to the likelihood to be published in a leading journal. An alternative line of reasoning would be that leading journals tend to publish high quality studies with rigorous methods that improve statistical power. Hence, when studies are selected on the basis of statistical significance (and not based on the size of the effect), leading journals would also include studies with relatively small effect sizes (significant due to the rigorous methods), which leads to predictions opposite to Hypothesis H1. Two major drivers of statistical power are sample size and reliability of measures. More reliable measures increase statistical power and so does sample size. That is, as sample size and reliability go up, p-values go down and smaller effects pass the significance threshold.

However, we did not find any relationship between the ratio of top journals included in a meta-analysis and the average sample size per effect size ($r = -.09$, $p = .797$, for $n = 11$ independent effect sizes; $r = -.19$, $p = .18$, for $n = 49$ dependent effect sizes). We did not find any relationship with the reliability of measures either, as indicated by the ratio of non-corrected means to attenuation-corrected means in a meta-analysis ($r = -.35$, $p = .18$, $n = 16$). Due to the small number of meta-analyses for these measures, we included these measures in model 1 only with the main variables (none of the control variables except for number of effect sizes was correlated with the additional variables). The results remained unchanged. The finding indicates that leading journals indeed report stronger effect sizes and not just effects with higher statistical power.

*4.3.3. Does this meta-meta-analysis itself have a selection bias?*

This study is restricted to meta-analyses that were published in journals that are listed in the SSCI database, because we are interested in investigating the citation outcomes of a meta-analysis. The selection of meta-analyses might have caused a selection bias itself, because the meta-analyses included in the study and in particular their findings might not be representative. That is, there might be additional meta-analyses that are not included in the SSCI database and that report meta-analytic effect sizes that are smaller than the ones reported in our study.

To check such a selection bias, we searched the literature for meta-analyses that were not (yet) published by 2012. We found nine meta-analyses that were either not published or published as extended abstracts only (see Appendix Table A.5). Although the unpublished meta-analyses tend to show smaller meta-analytic effect sizes than the published meta-analyses (.19 vs. .27), the difference is not significant ($t = 1.41$, $p = .16$) which can be due to the small number of only nine unpublished meta-analyses. More importantly, however, when applying regression model (1) to the extended sample of meta-analyses, the results remain stable: the ratio of unpublished studies reduces ($b = -.37$, $SE = .19$, $t = 1.97$, $p = .052$), and the ratio of studies in leading journals increases the effect size ($b = .15$, $SE = .07$, $t = 2.15$, $p = .034$). That is, the influence of a selection bias of the studies included in a meta-analysis does not depend on a possible selection bias of the meta-analyses that we choose for our study.

We further apply the trim and fill method that checks whether the meta-analyses in our sample provide meta-analytic effect sizes that follow the symmetry assumption of the funnel plot, that is, the graphical distribution of the meta-analytic effect sizes and their variances (Duval

& Tweedie, 2000). In case of a selection bias, this distribution would be asymmetrical and reveal that meta-analyses with small meta-analytic effect sizes are underrepresented. The trim and fill method shows that the distribution of meta-analytic effect sizes is symmetrical and does not show any gaps. The symmetry of the funnel plot indicates that we can assume that the mean value of the meta-analytic correlations of .27 is a good estimate of the true value and that an increasing ratio of unpublished studies leads to a downward bias of effect sizes, while an increasing ratio of published studies leads to an upward bias of effect sizes.

*4.3.4. Are the controls for subject area too coarse?*

Each meta-analysis covers a different topic and the eight subject areas we applied as control variables might be too coarse and inaccurate to capture substantive differences between the meta-analyses and their findings. While we cannot control for each meta-analytic topic, we applied a finer categorization as suggested by Stremersch, Verniers, and Verhoef (2007), who distinguish between 19 different subject areas. When using these finer categories of subject areas in our regression models, the findings still support our hypotheses and only the effect of the ratio of unpublished studies on the effect size (regression model 1) becomes weaker and significant only when assuming a one-sided test ($b = -.30$, $SE = .19$, $t = 1.54$, $p = .064$).

## 5. Discussion

The findings of this study show that whether and where a study that is included in a meta-analysis is published influence meta-analytic effect size estimates and that such a selection bias increases the probability of a meta-analysis to be published in leading marketing journals as well as the number of citations the meta-analysis receives.

First, this study contributes to research about meta-analyses by examining the selection bias of meta-analysts and its consequences for academia. The meta-analytic effect size influences both the attention and evaluation outcome of editors, reviewers, and academic readers, as indicated by the likelihood to be published in leading journals and the citations to these meta-analyses. Selection bias can drive meta-analytic effect sizes upward and fosters these publication outcomes when unpublished studies are neglected and studies in leading journals are preferred by the meta-analyst. Meta-analyses are cited at a significantly higher rate than primary-level studies (Aguinis et al., 2011), and therefore, the results are of particular importance as they indicate that these already high citations could be partly driven by selective sampling.

Second, the study contributes to our general knowledge about publication bias. The findings show not only that whether a study is published influences the size of an effect (which has been the focus of prior research on publication bias) but also that where the study is published (i.e., in leading journals) can bias the findings reported in the study. Notably, the results related to studies from leading journals are more indicative of a bias, because they reflect the final selection outcome of a review process. Unpublished studies, on the other hand, might be published at a later point and are consequently a less precise predictor of a selection bias.

Third, the study provides details about the existence and extent of selection bias in the field of marketing research. On average, a meta-analysis includes three unpublished studies. The regression coefficients show that increasing the number of unpublished studies by 25% (that is from three to four studies), would reduce the average meta-analytic correlation from .27 to .24. The percentage of studies from leading journals compared to studies from all journals listed in the SSCI is almost 40%. If this number would decrease to 20%, the effect size would decrease from .27 to .25. Both differences are significant ($p < .05$) for samples of 8000 subjects, respectively 4000 subjects and more. This sample size is not uncommon in meta-analyses; less than 15% or the 60 meta-analyses in our sample that provide information on the sample size are based on an overall sample that is smaller than 4000 subjects. Although the selection bias can affect the meta-analytic findings, the difference of .02 or .03 is small. That is, the effect of the bias has only a small impact on overall effect size, and this probably means in practice that what we currently hold to be "true" with respect to the conclusions drawn from existing published meta-analyses is actually still "true". Nevertheless, knowing the effect of a selection bias can help to achieve more accurate findings in meta-analyses.

### 5.1. Implications

To achieve more accurate findings in meta-analyses, editors, reviewers, and the academic community in marketing should (1) improve the reporting of a possible selection bias and (2) try to avoid a selection bias.

*5.1.1. Improve the reporting of a possible selection bias*

During the coding process for this study it became apparent that the documentation of meta-analysis methods in marketing research barely follows any standards and can be considered poor compared to reporting in other areas. For instance, 27.8% of the meta-analyses (32 out of 115) did not include the list of primary studies. In management research, Aguinis et al. (2011) report that only 7.6% of the meta-analyses did not provide such a list. Because methodological decisions in meta-analysis can influence meta-analytic outcomes (Wanous, Sullivan, & Malinak, 1989), it is important to provide as much information as possible on these decisions and to follow common reporting standards. Reporting standards have not been established in marketing research, but in neighboring fields such as psychology (APA, 2010) or economics (MAER Network, 2013). A successful example for such standards is found in medical science, where several scholars have developed the PRISMA statement (Moher, Liberati, Tetzlaff, Altman, & The PRISMA Group, 2009). The statement aims to help authors improve the reporting of meta-analyses by offering a flow diagram on the different phases of a meta-analysis and a checklist of 27 items pertaining to the content of meta-analysis. Many journals publishing health research nowadays refer to PRISMA in their instructions to authors. Among other things, the checklist includes items that advise meta-analysts how and what to report as related to the review protocol, study eligibility criteria, information sources, search procedure, and the study selection process. If journal editors adopt these guidelines in marketing research, they can support authors who are in the process of writing up a meta-analysis, and they can help reviewers, editors, and readers in evaluating the meta-analysis not just with respect to a possible selection bias. The major academic associations in marketing should support the installation of such guidelines by agreeing on a common standard that is adopted by all journals.

In addition, meta-analysts are well-advised to address the problem of selection bias by considering the influence the publication status has on the meta-analytic effect size. This can be accomplished by including moderator variables for publication status such as top journal vs. others or by using the impact factor of journals. Of the 115 meta-analyses we identified, only eight meta-analyses (7%) included a moderator variable that tests for differences of effect sizes across different publication outlets, with six out of eight meta-analyses providing significant differences that support the findings of our study.

*5.1.2. Avoiding a selection bias*

The main task to avoid a selection bias for the meta-analysts is a thorough systematic search of the literature. The findings of this study show that this is not done consistently in meta-analyses in marketing research. Too often, the literature search is limited to a few electronic databases. Rothstein (2012) provides an excellent overview and description of a rigorous and thorough literature search, that helps to minimize the potential for selection bias. With the increasing availability

**Table 4**
Recommendations.

| For whom? | Improve the reporting of a selection bias | Avoid a selection bias |
|---|---|---|
| Meta-analyst | Follow reporting standards when writing up a meta-analysis. Test for a possible selection bias by applying moderator variables of publication status. | Perform a rigorous and thorough literature search; try to access unpublished studies and studies that are more difficult to access (e.g., via Internet, postings, personal contact with authors). |
| Reviewers | Use reporting standards as template for evaluating meta-analyses; ask authors to report information according to these standards. | – |
| Editors | Install reporting standards for meta-analysis such as the PRISMA statement in medical science. | Publish empirical studies only when they are registered at inception. Install and support journals or journal sections that publish null results. |
| Academic associations (e.g., AMA, ACR) | Discuss and recommend a common reporting standard for research reviews and meta-analysis for all journals. | Install registers where researchers register their studies at their inception. Install journals or journal sections that publish null results. |

of unpublished work on the internet (e.g., via Google Scholar), the search process becomes less time-consuming and more efficient. In addition, the findings in our study suggest that postings in newsgroups and personal mails to researchers seem a fruitful way to access unpublished work. The effects of these efforts can be inferred from our findings: Performing only one additional research strategy reduces the average meta-analytic effect size from .27 to .26. Adding more non-leading journals to the issue-by-issue search such that the ratio of leading journals drops from an average of 50% to 25% would reduce the effect size from .27 to .25.

Another solution that requires a concerted effort of journal editors and academic associations in marketing is the installation of research registers and outlets for studies with null results. Research registers have been developed in medical science, where each research project is registered at its inception. Many top tier journals in the medical sciences do not publish studies unless their samples were registered prior to completion of the study (Laine et al., 2007). Such registers provide information about research projects that get published and that remain unpublished and allow a more systematic literature review for meta-analysis. To make sure that all research projects in marketing are registered at its inception, journal editors need to agree to publish studies only if they have been registered upfront. An additional option that makes it easier for meta-analysts to retrieve and include non-significant results and small effect sizes in their meta-analysis is the implementation of outlets (i.e., journals or journal sections) that publish studies with null results. Such non-significant results are not only informative for meta-analysts, they can help scholars in preventing them from investments in uninteresting research questions. Table 4 summarizes the recommendations for meta-analysts, reviewers, editors, and academic associations on how to improve the reporting of a selection bias and how to avoid such a bias.

### 5.2. Limitations and further research

One limitation refers to the concept of unpublished studies as it is commonly used in the meta-analytic literature: Unpublished studies are operationalized as studies that are available but not published. Beyond these studies, researchers might even refrain from writing up manuscripts for projects with non-significant results. As long as research registers have not been developed, such non-significant results might largely remain undetected, increasing both publication and selection bias. Such results can only be retrieved by addressing researchers directly, which has been done by a few meta-analysts in our study. Furthermore, some non-published studies will be published in a journal later, while some will never be published in a journal. However, even the later publication does not necessarily undermine the problem and the influence of publication status on effect sizes: it frequently occurs that only the significant and important findings will make it to the journal while the less important and non-significant findings do not get reported at all (Chan, Hróbjartsson, Haahr, Gotzsche, & Altman, 2004). The reasons are that authors decide not to include certain results when submitting a study to a journal or editors and reviewers ask to remove specific findings because they are deemed not interesting or simply to save journal space (Banks & McDaniel, 2011).

Another limitation is that we cannot fully determine the true value of the meta-analytic effect size, but a value that is based on an empirical distribution that itself underlies a sampling error. Hence, the figures we present are relative figures and they show how much the empirical effect size changes when different types of studies are included and how much the meta-analyst can influence this effect size by applying the suggested strategies.

### 5.3. Conclusions

This study examined the issue of selection bias in meta-analyses in marketing research by looking at meta-analytic effect sizes and their drivers and consequences. These effect sizes depend on whether and where a study included in a meta-analysis is published. The meta-analytic effect sizes steer the attention and the evaluation of a meta-analysis by other scholars. The main conclusion of the findings is that meta-analysts, reviewers, editors and the academic community should improve the reporting of a selection bias and—if possible—avoid such bias, because it is in the field's interest, like in any science, to concern itself with unbiased estimates and accurate findings. This helps to support the merit of meta-analyses that are both influential and important tools in research, because they develop empirical generalizations and summarize knowledge in an area.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ijresmar.2014.03.006. Estimation code for this article can be found online at http://www.runmycode.org. Interested scholars may contact either the corresponding author or IRJM's editorial office in order to request the dataset.

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