The Compromise Effect in Post-Purchase Consumption of Complementary Products: A Meta-Analysis of Experimental Studies

Masters Thesis

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List of Abbreviations

C	Control group
CI_{95}	95% confidence interval
ES	Effect size
FM	Fixed-effect model
H_0	Null hypothesis
MA	Meta-analysis
MAD	Mean absolute deviation
mTurk	Amazon Mechanical Turk
PI_{95}	95% prediction interval
RM	Random-effects model
RQ	Research question
S	Estimated standard deviation
σ	Standard deviation of the population
SE	Standard error
SG	Subgroup
SMD	Standardized mean difference
T	Treatment group
T1	Treatment 1 group
T2	Treatment 2 group
θ	True effect size
UMD	Unstandardized mean difference
Y	Observed effect

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Abstract

Marketing research increasingly uses the method meta-analysis to integrate the results of the growing number of studies. This thesis applies this approach to the field of consumer behavior, which has most frequently published meta-analyses in marketing. The methodological foundation regarding the meta-analyses conducted on the compromise effect and post-purchase consumption are presented. The compromise effect is an important and variously demonstrated context effect. The thesis investigates how a compromise decision influences the choice of complementary products and how these two choices made are evaluated. 18 meta-analyses summarize the results of 15 studies conducted by this chair. They apply distinct effect sizes and both fixed-effect and random-effects models. Participants, who compromise, tend to select more complementary products, spend more money and take less time for this decision. Respondents are less satisfied and confident with their compromise choice and find it more difficult to make it. Participants, who compromise, are less satisfied and confident with their decision on additional products and perceive this choice as more difficult in the studies. The findings indicate implications for practitioners and future research.

Keywords: meta-analysis, fixed-effect and random-effects model, compromise effect, consumer behavior

Introduction

The influence of contextual factors on consumer behavior has been frequently investigated in marketing literature (Lichters et al. 2016, p. 184). The compromise effect is one of the most important context effects (Kivetz, Netzer, and Srinivasan 2004, p. 238). It states that the “market share” (Simonson 1989, p. 159) of an option increases if it is displayed as middle or compromise option in a set of alternatives. The relevance of this effect is undeniable for marketing strategies like branding or the positioning of products and its impact on sales (Neumann, Böckenholt, and Sinha 2016, p. 195). This thesis aims at addressing how a purchase decision of a product made under a compromise effect further influences the post-purchase consumption of its complementary products. The research questions include whether people, who compromise, behave differently in terms of how many additional products they select, how much money they spend and how much time they need for this decision. Moreover, the thesis examines how people evaluate the compromise choice and the decision of complementary products in terms of satisfaction, confidence and difficulty.

To answer these questions, 18 meta-analyses based on up to 15 experimental studies are conducted. In the marketing field, the method meta-analysis is increasingly applied for “integrating the findings” (Glass 1976, p. 3) across various individual studies (Grewal, Puccinelli, and Monroe 2018, p. 9). The methodological foundations required for these meta-analyses are presented in detail.

Consequently, the thesis starts presenting the method meta-analysis before specifying the research questions. Furthermore, the underlying experimental studies are described and the empirical results of the numerous meta-analyses are reported and interpreted. A discussion finally sums up the key findings, shows managerial implications and identifies limitations and interesting further research directions.

Methodological Foundation of the Meta-Analysis

1.1 Introduction to Meta-Analysis

The method meta-analysis (MA) was introduced by Gene V. Glass in the mid of the seventies and is a "statistical analysis of a large collection of analysis results from individual studies for the purpose of integrating the findings" (Glass 1976, p. 3). Its aim is to "accumulate knowledge" (Grewal, Puccinelli, and Monroe 2018, p. 9) regarding a specific research question or field. It summarizes the outcome of various studies by computing a "numerical measure" (Eisend 2015, p. 27) regarding the link of two research variables and presents the magnitude and the significance of this effect. The MA further examines both consistency and differences across studies and analyzes potential sources of heterogeneity (Churchill Jr. and Peter 1984, p. 360; Grewal, Puccinelli, and Monroe 2018, p. 9; McShane and Böckenholt 2017, p. 1048). It helps to synthesize the outcome of a growing number of publications and summarizes the current state of research (Grewal, Puccinelli, and Monroe 2018, p. 23; Palmatier, Houston, and Hulland 2017, p. 2). It allows "empirical generalization" (Hanssens 2018, p. 6) based on the amount of underlying studies and derives further theoretical and practical implications. It has a broad field of application like medicine, health, social and business sciences (Hartung 2008, p. 2; Johnson, Mullen, and Salas 1995, p. 94). According to the review paper of Grewal, Puccinelli, and Monroe (2018) on seventy-four MAs in highly-ranked marketing journals, MAs are constantly used in marketing since 1985, with an increase in application from 2000 on. The consumer behavior, product management, communication and sales most frequently use MAs.

The method "vote-counting" marks the beginning of synthesizing studies. A common effect is derived by comparing the sum of positive and negative significant study results (Hedges and Olkin 1980, p. 359). Low sample sizes and low underlying effects, however, reduce power substantially (Hedges and Olkin 1980, p. 359).

Based on the work by Glass (1976), Schmidt and Hunter (1977) and Rosenthal (1978), various MAs approaches have evolved (Grewal, Puccinelli, and Monroe 2018, p. 11; Hall and Brannick 2002, p. 377). The procedure by Hedges and his colleagues (Hedges 1981, 1982; Hedges and Olkin 1985; Hedges and Vevea 1998) and the so-called Hunter-Schmidt method (Schmidt and Hunter 2015) are applied most (Ellis 2010, p. 109; Hall and Brannick 2002, p. 377). Aguinis et al. (2011) show, that the choice of a specific approach does not substantially impact the magnitude of the effect size. In line with the majority of MAs in marketing, the thesis uses "standard recommended meta-analytic techniques" (Grewal, Puccinelli, and Monroe 2018, p. 12), which are presented by the book of Borenstein et al. (2010) referring to the approach by Hedges and his colleagues.

Several steps structure the procedure of a MA. After specifying the research questions and variables, the appropriate effect size and the model to integrate, i.e. fixed-effect or random-effects model, are chosen (Grewal, Puccinelli, and Monroe 2018, p. 20). In case of too high diversity and unavailability of data for the calculation of the effect sizes, p-values of the primary studies are used (Borenstein et al. 2010, p. 326). Effect sizes are preferred since p-values only investigate whether "the effect is probably not zero" (Borenstein et al. 2010, p. 325). Next, the collection of all relevant publications on the research objective, ranging from journal articles to dissertations and manuscripts, follows (Lipsey and Wilson 2001, p. 25). The coding of the data based on a coding scheme involves capturing all study characteristics, which may cause variation between studies like the year, authors and the research design, and summarizing the necessary data to calculate the effect sizes (Grewal, Puccinelli, and Monroe 2018, p. 15; Schulze, Holling, and Böhning 2003, p. 12). The quality of the studies are evaluated regarding how the studies fit the research objective and how adequate the techniques applied are (Cooper 2010, p. 85). Finally, the integration of the studies leads to a common effect (Hartung 2008, p. 8). The heterogeneity of the data is assessed by subgroup analysis or meta-regression. A sensitivity analysis checks the robustness of the findings regarding methodological assumptions (Cooper 2010, p. 106). Guidelines like the meta-analysis reporting standards (MARS) capture how to present results in an understandable way (Cooper 2010, p. 219).

In the following, all methodological consideration relevant for this thesis are presented.

Effect Size of Individual Studies

Definition and overview. The effect size (ES) determines "the strength of a relationship or the magnitude of a difference between variables" (Peterson, Albaum, and Beltramini 1985, p. 97) or groups in the underlying population (Borenstein et al. 2010, p. 17; Fern and Monroe 1996, p. 90). It measures "the degree to which the null hypothesis is false" (Cohen 1977, pp. 9–10). ESs are calculated on study level and then integrated across trials (see 2.3) (Fern and Monroe 1996, p. 90; Grewal, Puccinelli, and Monroe 2018, p. 11). The ES is chosen according to the research objective, the availability of data, the comparability and interpretability across all trials (Borenstein et al. 2010, p. 18). Various ESs exist: means, odds or risk ratios in case of binary data and correlations for correlational data (Borenstein et al. 2010, p. 19; Ellis 2010, p. 13). As this thesis compares the means of a treatment group (T) and a control group (C) based on separate samples, ESs based on means of independent groups are selected. Various forms, i.e. the unstandardized mean difference (UMD) and different types of the standardized mean difference (SMD), are required to account for distinct scale characteristics of the research variables across studies and to compare results based on different ESs as part of a sensitivity analysis. The individual ESs are directly computed from primary data. Methods to estimate ESs from test statistics like t- or F-values are described in Borenstein et al. (2010).

The variances of the ESs are an essential component for the integration of the ESs. Their calculation depends on whether the standard deviations of the underlying populations (σ) of T and C are equal, i.e. $\sigma_T = \sigma_C = \sigma$ (Grissom and Kim 2005, p. 53). The Levene-test investigates the frequently violated assumption of homogeneity of variance and indicates whether this equation is met by the data, as equal variances imply same standard deviations of the two populations (Grissom and Kim 2005, p. 53). If the test is statistically significant, the null hypothesis (H_0) of equal population variances, i.e. $\sigma^2_T = \sigma^2_C = \sigma^2$, is rejected and the two populations have unequal variances and so different standard deviations (Bühl 2016, p. 284).

The following sections use the notation and the formulas which are derived from basis literature, especially Borenstein et al. (2010), Hartung and Knapp (2003) and Schulze (2004).

Unstandardized mean difference. The UMD is used if all studies share the same scale (Borenstein et al. 2010, p. 21). The population mean difference (Δ) is based on the population means of T (μ_T) and C (μ_C) and is estimated by D, using sample mean T ($\bar{M}_T$) and C ($\bar{M}_C$)

$$\Delta = \mu_T - \mu_C$$

$$D = \bar{M}_T - \bar{M}_C$$

(Borenstein et al. 2010, pp. 21–22). As $\bar{M}_C$ is subtracted from $\bar{M}_T$, the sign of D indicates whether the treatment has a positive effect, if $\bar{M}_T > \bar{M}_C$, or negative effect, if $\bar{M}_T < \bar{M}_C$ (Grissom and Kim 2005, p. 53). The variance of the ES (V_D) is calculated based on the Levene-test result. If H_0 of homogenous variances is rejected and thus the standard deviations differ, V_D with the standard deviations of T (S_T) and C (S_C) and sample size of T (n_T) and C (n_C) is

$$V_D = \frac{S_T^2}{n_T} + \frac{S_C^2}{n_C}$$

(Borenstein et al. 2010, p. 22). Otherwise, V_D uses the pooled standard deviation (S_{pooled}) (Grissom and Kim 2005, p. 60; Hedges 1981, p. 110). The standard error (SE_D) equals the square root of V_D (Borenstein et al. 2010, p. 22).

$$V_D = \frac{n_T + n_C}{n_T\, n_C} * S^2_{pooled} \text{ with}$$

$$S_{pooled} = \sqrt{\frac{(n_T - 1)\, S_T^2 + (n_C - 1)\, S_C^2}{n_T + n_C - 2}}$$

Standardized mean difference. The SMD is applied if studies contain different scales to measure a research variable (Grissom and Kim 2005, p. 49). It standardizes the mean difference of T and C by dividing it by a standard deviation so that the SMD can be compared across trials (Glass 1977, p. 371). It is a “measure of overlap between distributions” (Borenstein et al. 2010, p. 26). Depending on variance heterogeneity, either the SMD Glass’ d or Hedges’ g is required.

Glass’ d (Δ_{Glass}), developed by Gene V. Glass, is needed if studies reveal heteroscedasticity (Glass 1977, p. 370). It only uses the standard deviation of C to standardize and is estimated by d based on the respective sample values

$$\Delta_{Glass} = \frac{\mu_T - \mu_C}{\sigma_C}$$

$$d = \frac{\bar{M}_T - \bar{M}_C}{S_C}$$

(Glass 1977, p. 370). The ES Glass’ d indicates the difference between T and C in terms of standard deviation of C (Glass 1977, p. 371). The variance (V_d) is

$$V_d = \sqrt{\frac{(n_T + n_C)}{n_T\, n_C} + \frac{d^2}{2(n_T - 1)}}$$

(Hartung 2008, p. 15). If heterogeneity is not the case, the usage of S_{pooled} for standardization is appropriate. S_{pooled}, presented above, is preferred over S_c in Glass’ d as it considers both samples (Hedges 1981, p. 109). S_{pooled} is a “less biased and a less variable estimator of σ” (Grissom and Kim 2005, p. 53). This ES is called Hedges’ g (g_{pop}) and is estimated by g

$$g_{pop} = \frac{\mu_T - \mu_C}{\sigma}$$

$$g = \frac{\bar{M}_T - \bar{M}_C}{S_{pooled}}$$

(Grissom and Kim 2005, p. 54; Hedges 1981, p. 110). However, the ES tends to be overestimated – the smaller the sample size and the higher the value of the ES of the population are (Grissom and Kim 2005, p. 54; Hedges 1981, p. 112). So, g is adjusted (g_{adj}) by multiplying it with the approximation of a correction term with degrees of freedom (df) of $n_T + n_C - 2$

$$g_{adj} = g * (1 - \frac{3}{4\,df - 1})$$

(Grissom and Kim 2005, p. 54; Hedges 1981, p. 114) This is of concern if the sample size is very small and is negligible otherwise since the approximation of the correction term is nearly one with a high sample size (Grissom and Kim 2005, p. 54; Hedges 1981, p. 114; Schmidt and Hunter 2015, p. 362). The usage of g_{adj} is more adequate but does not tremendously influence the result (Schmidt and Hunter 2015, p. 362). $V_{g_{adj}}$ and $SE_{g_{adj}}$ are

$$V_{g_{adj}} = \frac{n_T + n_C}{n_T\, n_C} + \frac{g^2}{2\,(n_T + n_C - 3.94)}$$

$$SE_{g_{adj}} = \sqrt{V_{g_{adj}}}$$

(Hedges and Olkin 1985, p. 80).

The formula of the 95% confidence interval (CI_{95}) for the ES per study holds for both UMD and SMD with $\alpha = 0.05$ and Z as (1-α/2)-quantile of the standard normal distribution

$$CI_{95} = ES \pm Z * \sqrt{V_{ES}}$$

(Borenstein et al. 2010, p. 52).

Fixed-Effect and Random-Effects Model

The integration of individual trials results in a summary or pooled effect with higher accuracy and “statistical power” (McShane and Böckenholt 2017, p. 1048) compared to the individual findings of the studies. The summary effect is computed either by the fixed-effect model (FM) or random-effects model (RM) (Grewal, Puccinelli, and Monroe 2018, p. 20). The formulas presented in the following are applicable for any ES.

The FM implies that every study i out of all included studies k has the identical underlying population or true effect size (θ), i.e. $\theta_1 = \ldots = \theta_k = \theta$, due to uniform influencing factors (Borenstein et al. 2010, p. 64). The observed effects (Y_i) deviate from θ due to sampling error (ε_i) that stems “from different person sampling” (Schulze 2004, p. 35) (Borenstein et al. 2010,

p. 64). The summary effect (M) is a weighted mean of Y_i over all studies and weighting factor (W_i) per study i is the inverse of its within-study variance (V_{Y_i}) (Borenstein et al. 2010, p. 65)

$$M = \frac{\sum_{i=1}^{k} W_i Y_i}{\sum_{i=1}^{k} W_i}$$

$$W_i = \frac{1}{V_{Y_i}}.$$

This "minimize(s) the variance of the pooled estimate" (Schulze 2004, p. 36) by giving more weight to more accurate Y_i as the quotient rises with smaller V_{Y_i}. The variance of M (V_M) is computed "as the reciprocal of the sum of the weights" (Borenstein et al. 2010, p. 66) and the standard error (SE_M) as the square root of V_M

$$V_M = \frac{1}{\sum_{i=1}^{k} W_i}.$$

In contrast, the RM assumes that the true effect size per study i (θ_i) varies across studies (Hedges 1983, p. 389). The parameter θ_i result from "a super-population of effects with mean" (Hartung and Knapp 2003, p. 56) μ and with a between-study variance (τ^2) (Hedges 1983, p. 391). The true effect sizes θ_i of the trials incorporated reflect "a random sample" (Borenstein et al. 2010, p. 61) and follow a normal distribution. The variation of Y_i is based on ε_i per study i and the between-study variance τ^2 (Borenstein et al. 2010, p. 71). The weighting factor W_i^* of the estimated summary effect (M^*) includes the within-study variance V_{Y_i} per study, like in the FM, and the estimated between-study variance of τ^2 (T^2)

$$M^* = \frac{\sum_{i=1}^{k} W_i^* Y_i}{\sum_{i=1}^{k} W_i^*}$$

$$W_i^* = \frac{1}{V_{Y_i} + T^2}$$

(Borenstein et al. 2010, p. 73). The computation of T^2 is explained in section 2.4 in detail. The measures of the RM are all marked with *. The weights of the RM are "more balanced" (Borenstein et al. 2010, p. 85) since the consideration of T^2 increases the proportional importance of W_i^* of small trials and decreases W_i^* for larger studies. V_M^*, with SE_M^* as its square root, is calculated as

$$V_M^* = \frac{1}{\sum_{i=1}^{k} W_i^*}\ .$$

The 95% prediction interval (PI_{95}) presents the "distribution of true effect sizes" (Borenstein et al. 2010, p. 133) with α = 0.05, df = k - 2 and value t as

$$PI_{95} = M^* \pm t_{df}^{\alpha} * \sqrt{T^2 + V_{M^*}}\ .$$

The formula of the CI_{95} and of the test of significance of the pooled effect hold for both FM and RM. The CI_{95} uses α = 0.05 and Z as the (1-α/2)-quantile of the standard normal distribution. It reveals how precise M and M* are (Borenstein et al. 2010, p. 5). The CI_{95} of the RM is wider as it includes within- and between-study variance (Borenstein et al. 2010, p. 85).

$$CI_{95} = M \pm Z * \sqrt{V_M} \ \text{ or } \ CI_{95} = M^* \pm Z * \sqrt{V_{M^*}}.$$

A significance test for the H_0 of zero true effect is essential. The FM sets H_0: θ = 0 and the test of the RM considers H_0: μ = 0, i.e. that the mean of all true effect sizes θ_i (μ) is zero (Borenstein et al. 2010, p. 330; Schulze 2004, p. 40). The test is based on a Z-value, which is checked against "a crucial value from the standard normal distribution" (Schulze 2004, p. 37). The two-sided p-value is computed with the cumulative standard normal distribution Φ(Z) (Borenstein et al. 2010, p. 298)

$$Z = \frac{M}{SE_M} \ \text{ or } \ Z^* = \frac{M^*}{SE_{M^*}}$$

$$p = 2(1 - (\Phi(|Z|)) \ \text{ or } \ p^* = 2(1 - \left(\Phi\left(|Z^*|\right)\right).$$

FM and RM differ in terms of the conclusions they allow and in their applicability (Grewal, Puccinelli, and Monroe 2018, p. 20). The findings of a RM can be transferred to the population, which the included studies form a sample of (Hedges 1983, p. 389). Thus, the results are generalizable while the outcome of the FM is restricted to the studies included in the MA (Hedges and Vevea 1998, p. 488). A FM is feasible if the included trials are "functionally identical" (Borenstein et al. 2010, p. 83) and if the same parameters have an impact on the individual effect sizes. McShane and Böckenholt (2017) suggest, however, that heterogeneity even plays a role in MAs with very similar studies. Thus, the usability of this model is restricted due to the specific and rarely fulfilled assumptions (Schulze 2004, p. 35). In contrast, the RM considers other factors than sampling error alone and assumes that the true effect sizes differ between studies (Hedges 1983, p. 389; Schmidt and Hunter 2015, p. 366). A test of significance is useful to examine whether heterogeneity across studies exists (see section 2.4 for details). The test, however, should not be conducted in advance to indicate a specific model (Hedges and Vevea 1998, p. 500). Accordingly, the choice should be based on the understanding of the characteristics of the underlying data and the test result should encourage this decision (Hedges and Vevea 1998, p. 500). However, in case that the test is significant, i.e. the H_0 of equal true effect sizes across studies is rejected, a FM is inappropriate (Grewal, Puccinelli, and Monroe 2018, p. 20). The choice of a RM is preferred due to the limited applicability of the FM and due to the fact that the FM is a subtype of the RM as an RM with a between-study variance of zero mathematically becomes a FM (Schmidt and Hunter 2015, p. 222).

Measurement and Interpretation of Heterogeneity

In line with the RM, numerous influencing factors next to the sampling error exist, which cause variation of the effects, e.g. "methodological characteristics" (Grewal, Puccinelli, and Monroe 2018, p. 10) like sample source, data collection method or variable measurement.

The test for homogeneity, firstly described by Hedges (1982), examines the presence of heterogeneity. It addresses the H_0 whether the same true effect size underlies all incorporated trials, i.e. H_0: $\theta_1=\ldots=\theta_k=\theta$, or accordingly the between-study variance (τ^2) equals zero (Hedges

1982, p. 493; Pigott 2012, p. 56). If H_0 holds, the parameter Q closely follows a χ^2-distribution with df=k-1 (Borenstein et al. 2010, p. 112; Cochran 1954, p. 114; Hedges 1982, p. 493)

$$Q = \sum_{i=1}^{k} W_i(Y_i - M)^2.$$

Q captures the total variation, which is observed from study to study, and df represents the anticipated magnitude of Q if the total variation only stems from sampling error (Borenstein et al. 2010, p. 109). W_i and M are calculated as presented in section 2.3. A significant outcome results in the rejection of H_0 and indicates that distinct true effect sizes underlie the trials (Hedges 1982, p. 493). An insignificant test does not imply homogeneity since the power of the test may be decreased due to a low amount of trials and high inaccuracy of the studies included (Borenstein et al. 2010, p. 113; Hedges 1982, p. 493).

Following measures examine how large heterogeneity is. As important component of the RM, τ^2 describes the variance between the individual studies and captures how the true underlying ES varies across studies. It is measured as T^2 based on the DerSimonian and Laird method or "method of moments" with df = k -1 as

$$T^2 = \frac{Q - df}{C} \text{ with}$$

$$C = \sum_{i=1}^{k} W_i - \frac{\sum_{i=1}^{k} W_i^2}{\sum_{i=1}^{k} W_i}$$

(Borenstein et al. 2010, p. 114; DerSimonian and Laird 1986, p. 182). A negative value of T^2, which is possible if Q-df is negative, is changed to zero (Borenstein et al. 2010, p. 114).

The parameter I^2 based on the work by Higgins and Thompson (2002) and Higgins et al. (2003) captures the share of the variation which results from heterogeneity and not from sampling error (Grewal, Puccinelli, and Monroe 2018, p. 21). It is a relative value between 0% and 100% and is changed to zero if the parameter is negative (Higgins et al. 2003, p. 558). Its advantage is its independence of the number of studies included (Higgins et al. 2003, p. 557)

$$I^2 = 100\% * \frac{Q - df}{Q}.$$

The degree of I^2 is divided into “low” with 25%, “moderate” with 50% and “high” beginning with 75% (Higgins et al. 2003, p. 557). I^2 is an indicator of how consistent the studies are (Higgins et al. 2003, p. 558). A large value of I^2 requests a more detailed analysis of the underlying reasons for the heterogeneity in terms of a subgroup analysis or meta-regression (Borenstein et al. 2010, p. 122; Higgins et al. 2003, p. 559). In contrast to the subgroup analysis, the meta-regression analysis accounts for various factors at once (Grewal, Puccinelli, and Monroe 2018, p. 21). Various subgroup analyses are conducted in the course of this thesis. Based on a moderator, the studies are assigned to distinct subgroups (SG) and a mean effect size is computed per individual SG (Borenstein et al. 2010, p. 149). The subgroup analysis applies the RM as well and uses the same parameters and procedures for M* and W_i* per SG like previously for all studies together. As according to Borenstein et al. (2010) a number of less than five studies per SG can decrease the precision of T^2, a pooled parameter (T_{within}^2) is calculated based on the sum of the individual measures Q, df and C per SG j with m as the total number of SGs

$$T^2_{within} = \frac{\sum_{j=1}^{m} Q_j - \sum_{j=1}^{m} df_j}{\sum_{j=1}^{m} C_j}.$$

Otherwise, T^2 is computed individually per SG j (Borenstein et al. 2010, p. 164). If the moderator has an influence, the distinct SGs reveal smaller heterogeneity, i.e. a lower value of I^2 compared to the overall heterogeneity, and the differences between the mean effect sizes of the SGs are statistically significant (Borenstein et al. 2010, p. 119; Grewal, Puccinelli, and Monroe 2018, p. 22). The “Q-test for heterogeneity” (Borenstein et al. 2010, p. 178) already presented above examines whether the estimated mean effect size per SGs are statistically significant. The SGs are treated as if they were individual studies and – instead of the individual ES and its variance – the mean effect size and the according variance per SG are used as input (Borenstein et al. 2010, p. 170).

Finally, a sensitivity analysis examines the robustness of the findings regarding underlying methodological assumptions and investigates whether the results are consistent (Cooper 2010, p. 106). The analysis contrasts the results based on distinct ES measures. It further investigates the influence of single studies on the overall effect by excluding every study and recalculating the summary effect.

Definitions and Research Questions

The compromise effect was firstly shown by Simonson (1989) and describes that the choice of an alternative is more likely when it becomes the middle or compromise option "with intermediate attribute values relative to the choice set" (Dhar and Simonson 2003, p. 147) (Simonson 1989, p. 161). Extremeness aversion of the customers induces this behavior – in case a customer is uncertain regarding the preferences of "different combinations of attribute values" (Simonson 1989, p. 158) (Simonson and Tversky 1992, p. 282; Tversky and Simonson 1993, p. 1183). The choice of the middle option is "easier to justify and less likely to be criticized" (Simonson 1989, p. 168). Neumann, Böckenholt, and Sinha (2016) show the robustness of this consumer behavior in their meta-analysis based on 72 distinct studies. Many more publications demonstrate this effect in various contexts and conditions (Kivetz, Netzer, and Srinivasan 2004, p. 238; Lichters et al. 2016, p. 184).

The focus of this thesis goes beyond the objective of the studies on the compromise effect as it especially investigates the influence of a product choice made under the compromise effect on the post-purchase consumption of complementary products. The thesis covers various research questions (RQ) and aims at gaining a first insight regarding these effects. In terms of the choice of complementary products, the sum of items chosen, the amount of money and the time spent on selecting additional products are examined. The complementarity of a product includes that the decrease of the price of one product results in the sales growth of a second product (Shocker, Bayus, and Kim 2004, p. 28). This implies that the products are utilized together in order to fulfill a certain customer's need (Walters 1991, p. 18).

Further RQs refer to the evaluation of the product decisions: choice satisfaction, confidence and difficulty are examined for both the compromise decision and the choice of complementary products.

The specific RQs of this thesis are presented in Table 1 (insert Table 1 about here). For each research variable, the RQs distinguish between two options, A and B, which are presented as compromise option in the treatment conditions in the primary studies. The experimental design of the primary studies is presented in more detail in section 4.1. The RQs are:

Does a product choice made under the compromise effect influence

(1) the sum of complementary products in case of option B (RQ1.1) and option A (RQ1.2) as compromise option?

(2) the amount of money spent on choosing complementary products in case of option B (RQ2.1) and option A (RQ2.2) as compromise option?

(3) the amount of time spent on choosing complementary products in case of option B (RQ3.1) and option A (RQ3.2) as compromise option?

Does a product choice made under the compromise effect influence

(4) the satisfaction with this choice in case of option B (RQ4.1) and option A (RQ4.2) as compromise option?

(5) the confidence in this choice in case of option B (RQ5.1) and option A (RQ5.2) as compromise option?

(6) the difficulty to make this decision in case of option B (RQ6.1) and option A (RQ6.2) as compromise option?

Does a product choice made under the compromise effect influence

(7) the satisfaction with the choice of complementary products in case of option B (RQ7.1) and option A (RQ7.2) as compromise option?

(8) the confidence in the choice of complementary products in case of option B (RQ8.1) and option A (RQ8.2) as compromise option?

(9) the difficulty to make the decision on complementary products in case of option B (RQ9.1) and option A (RQ9.2) as compromise option?

Conceptual Foundation for the Empirical Analysis

Overview and Coding of the Experimental Studies

The bases for the MAs form 15 studies conducted by this chair. The studies involve a between-study design with participants, who are randomly assigned to either a control condition or to one of the two treatment groups. They form independent groups (Koschate 2008, p. 116).

In these studies, participants are firstly asked to make a purchase decision on a specific product, named choice 1. Respondents can select from different alternatives of a product. These options differ on two attributes, which involve a trade-off. For example, distinct camera types ranging from a cheap and low-quality to an expensive, top-quality camera are presented. The two treatment conditions show three distinct alternatives to choose from and thus create a situation in which the participant might compromise, i.e. select the middle option. Treatment 1 group (T1) sees options A, B and C with B as middle option and Treatment 2 group (T2) is exposed to alternatives A', A and B with A as compromise. The control group (C) only includes A and B. The respondents, who select the compromise option B in T1 or alternative A in T2 are compared to the respective participants selecting A and B in C. The difference between T1 and T2 is that alternative A is compromise option in T2 and the lower extreme in T1, while option B is the middle option in T2 and the upper extreme in T1.

Secondly, participants make a choice on complementary products, called choice 2. In anticipation of a prospective situation, in which they would utilize the product of choice 1, they are asked whether they would consider buying one or more of 10 additional products. Accordingly, 10 distinct complementary items are displayed, which are derived from the recommendations on Amazon for the product in choice 1.

Thirdly, respondents are asked to evaluate both choice 1 and 2 regarding satisfaction, confidence and difficulty.

The chair conducted a total of ten study runs. In each run, respondents see two or three different products and thus make two or three choices 1 and 2, i.e. they make choice 1 and 2 regarding a first product like a laptop with additional items and a second product like a camera with complementary camera products. As an unrelated filler task separates these different products in the study, the answers are considered to be independent. After excluding the preliminary study runs 1.a and 2.a and test run 7 on a differing research focus, a sum of 15 different trials are used for the MA.

To use the studies in a MA, the coding of all studies regarding their characteristics and the relevant data is necessary (Lipsey and Wilson 2001, p. 85). Every test gets a unique study ID. The trials share almost the same survey and procedure but differ in terms of the type of products displayed and the sample source as presented in Table 2 (insert Table 2 about here). Studies involve choices on durables like a camera, consumables like a toothbrush and services as a gym membership. Test 1 to 7 use students of the University of Mannheim and study 8 to 15 apply the qualified workforce called Amazon Mechanical Turk (US only) (mTurk).

Furthermore, the basic data, from which all MA parameters are derived, is calculated. This includes the mean, the standard deviation and the sample size per each research variable, group and study. Pivot tables in Excel compute the data for MA1 to MA6 and STATA computes the remaining values. In MA5 and MA6 on the time spent on choice 2, the primary data requires an adjustment. The group means of a few tests stand out with very high values ranging from 25.062 in test 2 to 40.445 seconds in test 9 in MA6. These figures result from only a few participants with values ranging from 142.217 seconds to about 11 minutes. As the time tracking finally ends with the submission of the page of the survey, a participant might report these long durations in case of distraction or interruption. Four high values are identified in study 7 in MA5 and test 2, 8 and 9 in MA6 and are excluded. These so called "outliers" also comply with the criteria of the detection method described by Wilcox (2010, p. 33), which uses the median absolute deviation (MAD). It indicates an observation X as outlier if following equation holds, with $\bar{X}$ as mean

$$|X - \bar{X}| > 2 * \frac{MAD}{0.6745}.$$

Conceptual Procedure of the Meta-Analyses

The objective of this thesis is to combine the findings of the 15 experimental studies outlined above and address the RQs by 18 MAs. Table 1 also gives an overview of all MAs regarding the specific RQs. The number of incorporated studies varies since not all variables are covered by every test. This section outlines the general procedure and assumptions underlying the MAs. It is based on the methodological foundation of MAs presented above. All MAs are programed in Excel. The Excel Add-in "MetaXL" is used to compute key measures and figures (Barendregt and Doi n.d., p. 10). MetaXL, however, only considers the formula of the variance of the UMD according to variance heterogeneity. The Excel file further includes the output of the Levene-tests from STATA.

For every MA, a forest plot and a table condense the findings. A forest plot is a graph that displays the individual ESs per study, the CIs and the summary effect (Borenstein et al.

2010, p. 366). To enable a general overview per research variable, the figures contain the MAs for both options of comparison A and B.

Every MA starts with the choice of a suitable ES and its calculation depending on two criteria. Firstly, either a UMD or SMD depending on whether the scale of the research variable is identical across trials is selected. Secondly, the presence of heteroscedasticity influences the choice of the formula for the variance of UMD and the type of SMD. The values of the Levene-tests are based on the sample means (Bühl 2016, p. 284). If the Levene-tests report heteroscedasticity, the variance of the UMD requires the formula based on variance heterogeneity (see 2.2.2) and the SMD Glass' d is appropriate. Otherwise, the other variance formula and the adjusted Hedges' g are applied. When one test out of the MAs on the same research variable shows heteroscedasticity, both MAs align their ES choice. A RM is generally assumed since it is the preferred model as discussed in section 2.3. Alpha is 0.05 for all MAs.

Afterwards, the MAs compute and interpret heterogeneity measures. In case of high heterogeneity, which is reflected by a high I^2, a subgroup analysis evaluates both content-related and methodological influencing factors on the ESs. So, the impact of the type of product and the sample source is assessed. According to the product displayed in the study, tests 1, 3 and 6 form the subgroup "consumable", studies 2, 4, 8 to 16 the group "durable" and finally tests 5 and 7 "service" (see Table 2). Consumables are products that are consumed during usage whereas durables are products which are used over a longer period of time (Sander 2011, p. 364). Services are immaterial goods, which cannot be stored and which are provided in close contact between provider and receiver (Sander 2011, p. 364). Due to the few studies per group, the measure T^2_{within} is applied; otherwise T^2 is calculated per group separately (see 2.4). Despite the low number of trials per subgroup, the analysis gives a first insight into the effects.

In the end, the sensitivity of the results is investigated regarding following issues, if required. Firstly, MetaXL is used to compute how the outcome changes if every individual study is excluded from the calculation of the summary effect. For MA13 to 16 the values are calculated in Excel as MetaXL does not support the required formula as described above. Secondly, different ES measures are applied. If a UMD is appropriate, its result is contrasted with the finding based on either Glass' d or Hedges' g depending on the occurrence of heteroscedasticity. If a MA initially applies Glass' d, the MA is also performed with Hedges' g to compare both results as the results might deviate since the standard deviations used for standardization in the denominator might vary (Fern and Monroe 1996, p. 90). Thirdly, the results based on both sample sources, i.e. students and mTurk, are contrasted.

Empirical Analysis and Results

Meta-Analyses of Aspects of Post-Purchase Consumption

Sum of complementary products. MA1 and MA2 address how a compromise choice affects the number of complementary products chosen. MA1 targets RQ1.1 with option B as compromise comparing T1 and C and MA2 focuses on RQ 1.2 with T2 and C regarding middle option A. The "sum of complementary products" reflects the total amount of chosen items. The research variable sums up diverse complementary products, e.g. camera items or laptop items depending on the product in choice 1, across studies. Thus, a SMD is needed. Glass' d is used since the Levene-tests detect heteroscedasticity in following studies: tests 3 ($F = 9.313$, $p < 0.01$), 5 ($F = 17.003$, $p < 0.001$) and 11 ($F = 4.838$, $p < 0.05$) in MA1 and trials 3 ($F = 8.052$, $p < 0.01$), 4 ($F = 6.805$, $p < 0.05$), 5 ($F = 4.460$, $p < 0.05$), 6 ($F = 9.980$, $p < 0.01$) and in MA2 test15 ($F = 8.419$, $p < 0.01$). Glass' d is measured in standard deviation of C since the difference between the means of T and C are divided by the standard deviation of C. Figure 1 concludes the results of MA1 and MA2, which are presented in the following (insert Figure 1 about here).

MA1 displays a positive, nonsignificant summary effect of 0.095 (CI_{95}: -0.158, 0.348; $p > 0.05$) and MA2 reveals a significant pooled effect of 0.405 (CI_{95}: 0.194, 0.615, $p < 0.001$). Regardless of the type of compromise option, A or B, participants select more complementary items after choosing a compromise option in choice 1. The effect is higher and even significant for respondents who compromise on option A. The PI_{95} in MA 1 shows that the underlying true effect size widely varies from -0.846 to 1.036. The PI_{95} in MA2 ranges from -0.300 to 1.109.

In both MAs, the test for homogeneity is significant (MA1: $Q = 54.160$, $df = 14$, $p < 0.001$, MA2: $Q = 33.711$, $df = 14$, $p < 0.01$) and demonstrates that the true effect size differs across studies. The high value of I^2 in MA1 ($I^2 = 74.2\%$) and a moderate/high value in MA2 ($I^2 = 58.5\%$) show that the total variation between studies is based on differences in the ESs across studies and not on sampling error (Higgins et al. 2003, p. 559).

The impact of the product type as possible sources of this heterogeneity is analyzed using a subgroup analysis. In MA1, the summary effects per SG are: durable with -0.048 (CI_{95}: -0.317, 0221, $p > 0.05$), consumable with 0.472 (CI_{95}: -0.093, 1.038, $p > 0.05$) and service 0.516 (CI_{95}: -0.174, 1.205, $p > 0.05$). Interestingly, the data for durables are more consistent, indicated by the insignificance of the test for homogeneity and a reduction of I^2 from 74.2% to 33.2% ($Q = 13.480$, $p > 0.05$). The pooled effect of -0.048 within this SG is near zero and even slightly negative, which contradicts the direction of the summary effect of 0.095 across all studies. Accordingly, participants, who compromise, might not select more complementary products if the products are durables. In contrast, the pooled effects of consumables and services are higher and more similar to each other. However, the I^2 for both SG becomes even higher and the test for homogeneity is still significant (consumable: $Q = 11.481$, $p < 0.01$, $I^2 = 82.6\%$; service: $Q = 13.963$, $p < 0.001$, $I^2 = 92.8\%$). However, the findings are limited since the wide CI_{95}s of the summary effects reveal low precision of the pooled effects (CI_{95} consumable: -0.093, 1.038; CI_{95} service: -0.174, 1.205) and the number of studies per SG is very low – SG consumable including 3 studies and SG service with 2 trials. The comparison of the pooled effects across all SGs further reveals that the dispersion of the outcomes does not result from differences in the SG across the distinct product types but from sampling error. This finding is based on the insignificant test for homogeneity across SGs ($Q = 4.232$, $df = 2$, $p > 0.05$). Consequently, the product type does not explain the heterogeneity and does not lead to distinct effects across SGs. However, this finding is to be considered with caution as the test might erroneously be insignificant due to low power as described above (see section 2.4).

In contrast to MA1, the subgrouping by product type in MA2 leads to very similar summary effects across SGs including durable with 0.402 (CI_{95}: 0.135, 0.668, $p < 0.01$), consumable with 0.443 (CI_{95}: -0.147, 1.034, $p > 0.05$) and service with 0.370 (CI_{95}: -0.228, 0.967, $p > 0.05$). The pooled effect is significant for durables ($p < 0.01$). I^2 is reduced to 49.9% but the test for homogeneity is still significant ($p < 0.05$), which indicates that other factors explain heterogeneity across studies and the ESs are not consistent as reported by MA1. Accordingly, heterogeneity is not explained for the consumables: I^2 even increases to 85.3% with a significant test for homogeneity ($p < 0.01$). Contrary to the MA1, the ESs within SG service are more homogenous as the test for homogeneity is insignificant ($p > 0.05$) and an I^2 of 0.0% shows that any variance results from sampling error. The test for heterogeneity to compare the mean effects across all SGs is insignificant ($Q = 0.030$, $df = 2$, $p > 0.05$). It implies that the product type equally influences the SGs so that the underlying true ESs do not vary. However, the possibly low power of the test is to be considered. In conclusion, both subgroup analyses report contradictory findings regarding the SGs. They further indicate that the product type does not seem to influence the sum of complementary products.

Both sensitivity analyses show the robustness of the findings of the MAs. The sensitivity analysis of MA1 with a pooled effect of 0.095 reveals that the exclusion of any of the tests results in changes in the summary effect between 0.020 (CI_{95}: -0.200, 0.240) and 0.132 (CI_{95}:

-0.127, 0.391). The findings based on Glass' d are compatible with Hedges' g pooled effect of 0.061 (CI_{95}: -0.160, 0.281, $p > 0.05$). The summary effect based on mTurk with -0.043 (CI_{95}: -0.232, 0.146, $p > 0.05$) is almost zero in comparison to the studies based on students with a pooled effect of 0.302 (CI_{95}: -0.222, 0.826, p. > 0.05). Interestingly, the studies based on students are significantly heterogeneous (Q = 32,946, df = 6, $p < 0.001$) while the trials based on mTurk are more consistent (Q = 10.318, df = 7, $p > 0.05$). However, the effects do not significantly differ between the two groups (Q = 1.475, df = 1, $p > 0.05$). In MA2 with a summary effect of 0.405, the single exclusion of any of the tests leads to changes in the pooled effect between 0.347 (CI_{95}: 0.156, 0.537) and 0.450 (CI_{95}: 0.247, 0.653). The implications of the effect based on Hedges' g does not deviate from Glass' d with 0.343 (CI_{95}: 0.183, 0.503, $p < 0.001$). Referring to sample source students, the summary effect is 0.524 ($CI_{95:}$ 0.092, 0.956, $p < 0.05$) and regarding mTurk this value is 0.300 (CI_{95}: 0.122, 0.479, $p < 0.01$). As indicated by the insignificant test for heterogeneity, the findings might not differ (Q = 0.880, df = 1, $p > 0.05$). However, the trials using students are significantly heterogeneous (Q = 20.723, df = 6, $p < 0.01$), while mTurk-based studies are not (Q = 8.237, df = 7, $p > 0.05$).

In conclusion, regarding RQ1.1 and RQ1.2, participants, who compromise, select more additional products. This effect is lower for respondents compromising with option B and even significant for option A. The product type does not seem to account for differences in the effect. However, all results need be considered with caution due to the limited number of studies. Other sources of heterogeneity need to be considered in further analyses. All computed effects are robust regarding methodological assumptions. The usage of the RM allows the generalizability of the results to the study population, which the included trials form a sample of.

Amount of money spent on complementary products. MA3 and MA4 examine RQ2.1 and RQ2.2 on whether customers who compromise in choice 1 spend more or less money on complementary products. MA3 focuses on option B as compromise option and MA4 analyzes option A. The research variable sums up the prices of all items chosen per participant. Again, the prices are linked to the respective products, i.e. expensive camera items vs. cheaper toothbrush products. To make them comparable, a SMD is used. Glass' d is applied as the Levene-tests report heteroscedasticity for tests 3 ($F = 8.642$, $p < 0.01$), 5 ($F = 9.831$, $p < 0.01$) and 7 ($F = 6.737$, $p < 0.05$) in MA3 and studies 3 ($F = 7.061$, $p < 0.01$), 6 ($F = 7.520$, $p < 0.05$) and 9 ($F = 8.534$, $p < 0.01$) in MA4. Figure 2 presents the results (insert Figure 2 about here).

Both MAs reveal a positive effect of the compromise situation on the amount of money spent on complementary items. The effect of MA3 with option B as compromise option shows an insignificant summary effect of 0.081 (CI_{95}: -0.154, 0.316, $p > 0.05$). The PI_{95} of the true effect size ranges from -0.318 to 1.002. In contrast, MA4 shows that the participants compromising on option A spend significantly more money with a pooled effect of 0.342 (CI_{95}: 0.139, 0.544, $p < 0.01$). The PI_{95} of the true effect size is -0.300 to 0.975.

The test for homogeneity is significant in both MAs (MA3: $Q = 46.893$, $df = 14$, $p < 0.001$; MA4: $Q = 31.461$, $df = 14$, $p < 0.01$). The high value of I^2 in MA3 ($I^2 = 70.1$ %) and a high/moderate value in MA4 ($I^2 = 55.5\%$) show that the total variation between studies is based on differences in the ESs across studies. The impact of the product type as potential reason for this heterogeneity is investigated by a subgroup analysis (Higgins et al. 2003, p. 559).

In MA3, the slightly negative pooled effect of -0.049 (CI_{95}: -0.302, 0.203, $p > 0.05$) for durables differs from the other two SGs including consumables with a pooled effect of 0.499 (CI_{95}: -0.039, 1.037) and services with 0.378 (CI_{95}: -0.264, 1.020). The ESs for durables are more consistent since the test for homogeneity is insignificant ($Q = 15.646$, $df = 9$, $p > 0.05$) and I^2 is reduces to 42.5%. It becomes obvious that the studies in the other two SGs are very heterogenous. Both SGs show very wide CI_{95}s of their summary effect, I^2 even increases (SG consumable: $I^2 = 79.5\%$, SG service: $I^2 = 88.9\%$) and the test for homogeneity remains significant for both SGs ($p < 0.01$). Thus, the product type does not source heterogeneity, which is also supported by the insignificant test of heterogeneity to compare the SGs ($Q = 4.159$, $df = 2$, $p > 0.05$).

In contrast, to MA3, MA4 reveals more similar pooled effects per SG: durables with a pooled effect of 0.352 (CI_{95}: 0.101, .604, $p < 0.01$), consumables with a summary effect of 0.466 (CI_{95} -0.103, 1.035, $p > 0.05$) and services with 0.167 (CI_{95}: -0.395, 0.729, $p > 0.05$). The effect is, however, only significant for durables. Heterogeneity is an issue as well. An I^2 of 55.5% shows that only half of the variance is based on real differences between the studies. Subgrouping by product type does not lead to a decrease of heterogeneity for durables with an I^2 of 54.8% and a significant test for homogeneity ($Q = 19.891$ $df = 9$, $p < 0.05$). The same holds for consumables with an I^2 of 77.9% and a significant test for homogeneity ($Q = 9.069$, $df = 2$, $p < 0.05$). Both SGs are highly inconsistent and other influencing factors, which are not considered yet, play a role. In contrast, an I^2 of 0.0% and an insignificant test for homogeneity ($Q = 0.563$, $df = 2$, $p > 0.05$) in SG service indicate that only sampling error causes variation. The test on whether the underlying true effect sizes of the individual SGs are equal is insignificant ($Q = 0.563$, $df = 2$, $p > 0.05$). In line with MA3, the findings show that the product type probably does not lead to differences in the true effect sizes between SGs.

The sensitivity analysis for both MAs show that the methodological assumptions only lead to slight differences in the computed effects. In MA3 with a pooled effect of 0.081, the omission of single studies leads to a variation in the summary effect from 0.016 (CI_{95}: -0.191, 0.224) to 0.115 (CI_{95}: -0.125, 0.355). The result of Hedges' g is very similar with a pooled effect of 0.045 (CI_{95}: -0.161, 0.252, $p > 0.05$). The comparison of the mean effect sizes of students and mTurk is insignificant ($Q = 1.893$, $df = 1$, $p > 0.05$). In contrast to the mTurk trials, the studies with students are significantly heterogeneous ($Q = 24.607$, $df = 6$, $p < 0.001$).

In MA4, the results are robust as well with a significant summary effect of 0.342. The exclusion of any single study shows a pooled effect ranging from 0.288 (CI_{95}: 0.105, 0.471) to 0.385 (CI_{95}: 0.185, 0.585). Hedges' g reveals very similar results with a summary effect of 0.305 (CI_{95}: 0.125, 0.485, $p < 0.01$). A comparison of the estimated mean effect sizes between studies using students and mTurk as sample source is not significant ($Q = 0.544$ $df = 1$, $p > 0.05$). The pooled effect in both SGs are significant and vary only slightly: the estimated mean effect size using students is 0.441 (CI_{95}: 0.035, 0.846, $p < 0.05$) and the result based on mTurk is 0.269 (CI_{95}: 0.061, 0.477, $p < 0.05$). In line with previous findings, the studies using students are significantly heterogeneous ($Q = 18.536$, $df = 6$, $p < 0.01$).

With regard to RQ2.1 and 2.2, both MAs show that participants who compromise tend to spend more money on complementary products. This effect is only significant for MA4 with option A as middle option. The results on the role of the product type indicate that the underlying true effect sizes are not influenced by it. However, these findings are limited to the low number of studies included and need to be considered with caution. The findings are not sensitive to methodological assumptions. As the RM is applied, the results are generalizable to the large population from which the studies incorporated here form a sample of.

Amount of time spent on choosing complementary products. MA5 and MA6 focus on whether participants who compromise spend more or less time on the decision of the complementary items. MA5 addresses participants compromising on option B in T1 (RQ3.1) and MA6 examines respondents selecting option A as middle option in T2 (RQ3.2). The time is measured in seconds and covers the period of time that participants need for their decision on complementary products. The time tracking ends with the submission of the page. In total, 4 extreme values are excluded from primary data as described in section 4.1. The UMD is applied, since the variable is comparable across studies. The Levene-tests of trial 2 ($F = 4.091$, $p < 0.05$) and test 9 ($F = 5.627$, $p < 0.05$) in MA6 report heteroscedasticity and thus the variance of UMD is calculated accordingly (see 2.2.2). Tests 3 to 5 do not track time and are excluded.

Although the RM is preferred, the analysis of heterogeneity parameter reveals that it is not the suitable approach. In line with Borenstein et al. (2010), the choice between FM and RM should not be based on heterogeneity but rather on theoretical considerations. However, a misfit between the assumption and the results should lead to a reconsideration of the initial choice (Hedges and Vevea 1998, p. 500). In this case, a RM is expected as the studies are not identical and various influencing factors might have an impact. However, the heterogeneity parameters do not support this choice. Figure 3 concludes all results (insert Figure 3 about here).

Firstly, the MAs report an insignificant test for homogeneity (MA5: $Q = 3.999$, $df = 11$, $p > 0.05$; MA6: $Q = 9.045$, $df = 11$, $p > 0.05$). The insignificance does not mean that the ESs are homogeneous and thus the RM is inappropriate. The test can be low in power due to a small number of trials and a high variation of the individual ESs based on sampling error. However, further heterogeneity measures should be considered (Borenstein et al. 2010, p. 113).

Secondly, I^2 and T^2 are analyzed, which are independent of the number of trials included. They are equal to zero in both MAs. An I^2 of zero shows that all variation is based on sampling error and a search for the reasons for heterogeneity by a subgroup analysis becomes unnecessary. A between-study variance T^2 of zero mathematically reduces the RM to a FM.

Thirdly, the forest plots show that the variation of the ESs per study are in the range of the CI_{95}s. This means that the sampling error within the studies is the reason for the variation and not between-study variance. This further indicates that the FM is the appropriate model.

Finally, it is examined whether SMDs report the same results. The outcome based on Glass' d and Hedges' g are in line with the UMD. Regarding Glass' d, the test for homogeneity is also insignificant for both MAs (MA5: $Q = 4.446$, $df = 11$, $p > 0.05$, MA6: $Q = 11.083$, $df = 11$, $p > 0.05$). T^2 and I^2 are zero in MA5 and near zero in MA6 with T^2 of 0.001 and I^2 of 0.7%. Hedges' g also leads to an insignificant test for homogeneity (MA5: $Q = 4.317$, $df = 11$, $p > 0.05$; MA6: $Q = 7.815$, $df = 11$, $p > 0.05$) and reports a zero value for T^2 and I^2.

In conclusion, the assumption of the RM is rejected as the heterogeneity measures do not support this model. Consequently, a FM is applied to integrate the findings of the trials.

Based on the FM, both MAs present an insignificant and slightly negative summary effect. Participants, who compromise in choice 1, need minimally less time to decide on complementary products than participants in the control condition. The insignificant negative summary effect of -0.156 (CI_{95}: -1.756, 1.444, $p > 0.05$) in MA5 shows that participants compromising on option B need 0.156 seconds less. This effect is higher for MA6 with an insignificant pooled effect of -0.853 (CI_{95}: -2.409, 0.704, $p > 0.05$). However, the wide CIs imply low precision of the summary effect. According to the FM, these effects only hold for the studies of the MAs and cannot be generalized to other studies (Cooper 2010, p. 191). The FM also indicates that the studies are identical regarding the research variable time and share equal parameters that influence the trials (Borenstein et al. 2010, p. 63).

The sensitivity analysis shows the robustness of the findings in case of the exclusion of every single study. MA5 with a pooled effect of -0.156 shows a range of -0.018 (CI_{95}: -1.638, 1.675) to 0.137 (CI_{95}: -1.697, 1.953). The summary effects in MA6 with a pooled effect of -0.853 vary between -1.383 (CI_{95}: -3.025, 0.260) to -0.546 CI_{95}: -2.154, 1.063). The comparison of these results with findings based on SMDs shows that the SMDs lead to a smaller pooled effect of almost zero. Using Glass' d leads to a pooled effect of -0.002 (CI_{95}: -0.139, 0.136, $p > 0.05$) in MA5 and to a pooled effect of -0.011 (CI_{95}: -0.159, 0.137, $p > 0.05$) in MA6. It indicates that there is almost no difference regarding the time required to make a decision between participants, who compromise, and respondents, who make a choice without a compromise situation. These results are in line with Hedges' g with a pooled effect of -0.008 (CI_{95}: -0.145, 0.129, $p > 0.05$) in MA5 and a summary effect of -0.046 (CI_{95}: -0.192, 0.100, $p > 0.05$) in MA6.

To sum it up, the calculated effects are limited to the included trials due to the application of a FM and RQ3.1 and RQ3.2 are only answered for these studies. Regardless of the type of compromise option, participants who compromise require insignificantly and slightly less time on choosing complementary products.

Meta-Analyses of the Evaluation of the Compromise Choice

MA7 to 12 investigate whether participants evaluate a compromise choice differently than respondents who select this alternative without a compromise situation. RQs 4.1, 4.2, 5.1, 5.2, 6.1 and 6.2 include the satisfaction, the confidence and the difficulty regarding this decision for either compromise option B or A. In total, 12 trials form the bases for the MAs. Before each aspect is analyzed in detail, general considerations holding for all MAs are presented.

As the scales of the research variables are identical in all tests, an UMD is applied as ES. Research variables are measured on a five-point Likert scale with 1 = "not satisfied at all" and 5 = "completely satisfied" as well as 1 = "not confident at all" and 5 = "completely confident". Difficulty of the decision is captured by 1 = "not difficult at all" and 5 = "extremely difficult". Due to the heteroscedasticity contained in various tests, the according formula for the variance of UMD is used for all MAs (see 2.2.2) and Glass' d as SMD is applied as part of the sensitivity analysis. A RM is assumed for all MAs. Apart from MA11, all tests for homogeneity are insignificant, which means that the null hypothesis of homogeneous effects across studies cannot be rejected. This insignificance should not be taken, however, as an indicator for homogeneity as the test has limited power, if the variance within the studies is high and the amount of trials is low (Borenstein et al. 2010, p. 113). A subgroup analysis is not necessary, since all T^2 values are near zero and the I^2 figures are very small, which indicate low heterogeneity across studies. The studies based on mTurk are weighted more due to a lower within-study variance than the trials using students.

RQ4.1 and 4.2 aim at investigating the choice satisfaction and are targeted by MA7 and MA8, which are presented in Figure 4 (insert Figure 4 about here). The Levene-tests report heteroscedasticity in MA7 in test 2 ($F = 6.300$, $p < 0.05$) and in study 5 ($F = 4.492$, $p < 0.05$) and in test 9 of MA8 ($F = 4.978$, $p < 0.05$). Both MAs report a significant negative pooled effect. Consequently, participants, who make a compromise choice, are significantly less satisfied with their decision than respondent who chose this option in a set of two alternatives. The summary effect with compromise option B in MA7 is -0.250 (CI_{95}: -0.356, -0.144, $p < 0.001$) and the pooled effect in MA8 with middle option A -0.141 (CI_{95}: -0.267, -0.015, $p < 0.05$). In contrast to the initial considerations, the heterogeneity measures of MA7 reveal equal results for both FM and RM as T^2 is zero. The forest plot also implies that all studies share the exact same underlying true effect size as the individual ESs lie within the CI_{95}s. Thus, the FM is applied which means that the result of MA7 only holds for the studies investigated.

The sensitivity analysis shows the robustness of the results. In MA7 with a pooled effect of -0.250, the pooled effect varies between -0.288 (CI_{95}: -0.405, -0.172) and -0.215 (CI_{95}: -0.333, -0.098) if single studies are excluded. Glass' d also infers the same with a summary effect of -0.339 (CI_{95}: -0.478, -0.199, $p < 0.001$). The omission of single trials in MA8 with a pooled effect of -0.141 results in a range of pooled effects from -0.168 (CI_{95}: -0.290, -0.046) to -0.110 (CI_{95}: -0.232, 0.013). The ES Glass' d also leads to a significant negative summary effect of -0.190 (CI_{95}: -0.352, -0.029, $p < 0.05$).

MA9 and MA10 answer RQ5.1 and RQ5.2 on choice confidence, presented in Figure 5 (insert Figure 5 about here). The Levene-tests identify variance heterogeneity in test 9 ($F = 9.196$, $p < 0.05$), test 11 ($F = 7.550$, $p < 0.01$), test 13 ($F = 3.999$, $p < 0.05$) in MA10.

Irrespective of the compromise option A or B, respondents are significantly less satisfied with their decision if they compromise. Both MAs report significant negative pooled effects. The summary effect of MA9 is -0.366 (CI_{95}: -0.513, -0.219, $p < 0.001$) and of MA10 -0.339 (CI_{95}: -0.481, -0.197, $p < 0.001$). These results are not sensitive regarding single studies and the choice of the ES. In MA9, the exclusion of single studies leads to a range of the pooled effect from -0.399 (CI_{95}: -0.564, -0.235) to -0.319 (CI_{95}: -0.443, -0.194) and an effect of -0.435 (CI_{95}: -0.610, -0.260), $p < 0.001$) based on Glass' d. MA10 shows a range of -0.378 (CI_{95}: -0.517, -0.240) to -0.301 (CI_{95}: -0.446, -0.157) in case of omission of single studies and a pooled effect of -0.372 ($CI_{95:}$ -0.569, -0.174, $p < 0.001$) based on Glass' d.

RQ6.1 and RQ6.2 are about the difficulty of making the compromise choice, which are addressed by MA11 and MA12, and summarized in Figure 6 (insert Figure 6 about here). Regardless of the option, participants, who select the alternative as compromise option, evaluate the level of difficulty of this decision higher than people in the control condition. This effect is significant for MA12 showing alternative A as compromise option with a pooled effect of 0.355 (CI_{95}: 0.163, 0.546, $p < 0.001$). This inference does not change if single studies are excluded as the summary effect changes from 0.304 (CI_{95}: 0.144, 0.464) to 0.397 (CI_{95}: 0.213, 0.580). The result based on ES Glass' d, with a pooled effect of 0.275 (CI_{95}: 0.127 0.424, $p < 0.001$), is also in line with the outcome of UMD. In contrast, MA11 with compromise option B reports an insignificant pooled effect of 0.214 (CI_{95}: -0.014, 0.442, $p > 0.05$). Test 7 on "gym membership" stands out with a very negative ES of -1.243 as opposed to the remaining studies. A sensitivity analysis reveals that due to this study the test for homogeneity is significant ($Q = 22.281$, $df = 11$, $p < 0.05$). Moreover, the exclusion of this test would result in a higher pooled effect of 0.310 and also lead to a significant result (CI_{95}: 0.160, 0.461, $p < 0.001$). This result is in line with the summary effect based on Glass' d of 0.229 (CI_{95}: 0.034, 0.425, $p < 0.05$). Further research regarding services is required to either exclude this test as outlier or to further emphasize that influencing factors exist that cause this heterogeneity.

In conclusion, participants, who compromise, are significantly less satisfied with their decision. This finding is generalizable based on MA8 on option A as compromise. The FM used in MA7 restricts the outcome to the studies under investigation. Regardless of the type of compromise option A and B, respondents are further significantly less confident with their choice, if they select it as a compromise, in comparison to participants who choose these options in the control condition. Finally, participants who compromise find the decision more difficult than respondents in the dual option set. The outcome is only significant for option A. The findings are very consistent as indicated by heterogeneity measures.

Meta-Analyses of the Evaluation of the Choice of Complementary Products

The MAs 13 to 18 examine how participants evaluate their decisions of complementary products. RQ 7.1, 7.2, 8.1, 8.2, 9.1 and 9.2 address whether participants, who make a compromise decision in choice 1, evaluate choice 2 on complementary products differently regarding decision satisfaction, confidence and difficulty than respondents, who do not compromise in choice 1. Only 6 studies include these research variables. Due to the exclusion of various studies, the similarity among the tests is relatively high. Their product choices only cover the durables BBQ grill, camera and laptop and are completely based on mTurk data. A further issue is the small number of studies. The calculations of a RM based on a small number of studies result in an imprecise estimate of T^2 which leads to an inaccurate standard error of the summary effect and finally affects the CI of the pooled effect (Borenstein et al. 2010, p. 163). Borenstein et al. (2010) suggest the usage of the FM in this case as the FM is already applicable for two studies and reflects uncertainty of the summary effect by the CI_{95}. Therefore, all MAs apply an FM and the results are not generalizable and only hold for the included studies.

A UMD is required, as the research variables are measured by a 5-point Likert scale like in the previous MAs on the evaluation of choice 1. The heterogeneity measures do not contradict the assumption of a FM. All tests for homogeneity report an insignificant result and both T^2 and I^2 are equal or near zero which emphasizes the lack of between-study variance and the inappropriateness of a subgroup analysis. The forest plots clarify that the variation of the observed ESs depends on sampling error alone as the individual ES are within the range of the CI_{95}s, which further supports the usage of the FM. All findings are summarized in Figure 7 (insert Figure 7 about here).

MA13 and MA14 on RQ 7.1 and 7.2 on satisfaction with choice 2 show that participants, who compromise in choice 1, are significantly less satisfied with their decision on complementary products. MA13 reports a summary effect of -0.131 (CI_{95}: -0.247, 0.016, $p < 0.05$) and MA14 an effect of -0.150 (CI_{95}: -0.285, -0.015, $p < 0.05$). The variance of UMD is calculated according to the formula based on variance homogeneity as heterogeneity is not concluded in the Levene-tests. The findings of both MAs are very robust. The pooled effect of MA13 varies from -0.172 (CI_{95}: -0.305, -0.039) to -0.114 (CI_{95}: -0.249, 0.021) in case of the exclusion of every singly trial from the calculation of the results. The pooled effect of -0.179 (CI_{95}: -0.340, -0.019, $p < 0.05$) based on the standardized measure Hedges' g is in line with the findings. Regarding MA 14, the omission of individual studies results in a range of the summary effect from -0.184 (CI_{95}: -0.335, -0.033) to -0.089 (CI_{95}: -0.241, 0.063). Results with Hedges' g indicate the same outcome with a pooled effect of -0.184 (CI_{95}: -0.360, -0.008, $p < 0.05$).

The confidence of choice 2 included in RQ 8.1 and RQ8.2 is examined by MA15 and MA16. Participants, who make a compromise choice, are significantly less confident regarding their choice of complementary products. This inference is reflected by the negative summary effect of -0.157 (CI_{95}: -0.273, -0.040, $p < 0.01$) in MA15 and a pooled effect of -0.265 (CI_{95}: -0.406, -0.123, $p < 0.001$) in MA16. As the Levene-tests do not conclude variance heterogeneity among the studies, the variance of UMD is based on the formula, which does not account for variance heterogeneity. The sensitivity analyses show the consistency of the results. In MA15, the exclusion of single trials leads to a range of the pooled effect from -0.191 (CI_{95}: -0.324, -0.059) to -0.137 (CI_{95}: -0.277, 0.003). Hedges' g also leads to a significant negative summary effect of -0.209 (CI_{95}: -0.370, -0.048, $p < 0.05$). MA16 shows a range from -0.299 (CI_{95}: -0.463, -0.136) to -0.196 (CI_{95}: -0.356, -0.037) based on the omission of single studies. A pooled effect based on Hedges' g of -0.318 (CI_{95}: -0.495, -0.142, $p < 0.001$) supports the findings.

MA17 and MA18 regarding RQ9.1 and RQ9.2 conclude that participants, who compromise in choice 1, find it more difficult to make the decision on complementary products. While MA17 with compromise option B computes a nonsignificant summary effect of 0.093 (CI_{95}: -0.081, 0.267, $p > 0.05$), MA18 with option A as middle option shows a significant result with 0.321 (CI_{95}: 0.138, 0.504, $p < 0.01$). As the Levene-tests report variance heterogeneity in test 11 ($F = 7.689$, $p < 0.01$) and test 12 ($F = 6.921$, $p < 0.05$) in MA18, both MAs apply the variance UMD formula which considers this heterogeneity (see 2.2.2). The findings are not sensitive to methodological assumptions. The findings of MA17 vary from 0.057 (CI_{95}: -0.143, 0.258) to 0.139 (CI_{95}: -0.046, 0.324) if single studies are excluded. The application of Glass' d leads to a similar result of 0.088 (CI_{95}: -0.073, 0.249, $p > 0.05$). MA18 reports results varying from 0.281 (CI_{95}: 0.070, 0.492) to 0.371 (CI_{95}: 0.163, 0.579). A summary effect of 0.307 (CI_{95}: 0.128, 0.487, $p < 0.01$) based on Glass' d permits the same conclusion like the UMD.

In conclusion, participants, who make a compromise choice first, are significantly less satisfied and confident regarding their choice of related complementary products and find this decision more difficult than respondents in the control condition, who make the choices without compromising. All findings are significant apart from the choice difficulty in case of option B as compromise alternative. These findings only hold for the studies under investigation as the FM is applied, which does not allow their generalization.

Discussion

Summary of the Main Findings

Participants, who make a compromise decision first, behave differently regarding the choice of complementary products than respondents, who do not compromise, as summarized in Table 3 (insert Table 3 about here). Participants, who compromise, select more additional items and spend more money on them. Both effects are significant and four times higher for participants, who compromise on option A, than for respondents compromising on option B. The product type does not seem to have an impact on these both aspects and other factors seem to account for the heterogeneity of the studies. Moreover, participants, who compromise in choice 1, spend insignificantly and slightly less time on selecting additional products than respondents without compromising. Based on a FM, the findings on time are restricted to the included studies.

Furthermore, the evaluation of the first product decision and the choice of complementary products varies between participants, who compromise, and respondents, who do not select the middle option in the first choice. Participants who compromise are significantly less satisfied and less confident with their decision. The finding, that they perceive it as more difficult to make this choice, is only significant for respondents who compromise on option A. Apart from the finding on satisfaction in case of option B, all results are generalizable since they are based on a RM. The results are very consistent across studies.

The findings of the evaluation of the decision on complementary products is very similar. Respondents who compromise report lower satisfaction and confidence and a higher difficulty concerning the choice of additional products. These findings are significant except for the difficulty regarding option B. The absolute magnitude of the summary effects is slightly lower for the second choice. However, in course of the analysis, the FM is identified as appropriate model which restricts the findings to the included studies.

Managerial Implications

The various meta-analyses in this thesis enable a first insight into the link between a compromise choice and the consumption of complementary products. An increase in the number of complementary items chosen and a higher spending is observed after a compromise choice on the initial product. The findings provide directions for practitioners in various ways. Firstly, marketers need to consider that a compromise choice is not only related to the initial product but also to the choice of complementary items. Consequently, pursuing a product positioning strategy, which encourages a compromise choice of a product, is also linked to the sales of its complementary items. Secondly, under the consideration of the compromise effect, a specific extension of the product range regarding complementary items might be beneficial. Thirdly, marketing measures like advertising, communication, product placement and pricing of the products might beneficially influence this effect. Especially in the online context, the specific presentation of a set of alternatives and complementary products in the form of recommendations might support this effect. However, the findings of this thesis can only give a first insight as they are limited in terms of methodological issues and investigated variables.

Limitations and Future Research

A critical evaluation of the conducted meta-analyses reveals that the inferences made are limited to the characteristics, the variables and the representativeness of the underlying studies (Rust, Lehmann, and Farley 1990, p. 220). A key issue is the low number of studies, which imposes challenges on the calculation of measures. Unprecise heterogeneity estimates leading to inaccurate confidence intervals of the summary effect imply that the findings need to be considered with caution (Borenstein et al. 2010, p. 363). A subgroup analysis with just two or three studies per group can only provide a first insight into the underlying effects. Especially, the required usage of the fixed-effect model in some analyses does not allow the generalization of these findings. The fact that the heterogeneity among studies cannot be fully explained in the course of the analyses reveals that further methods like a meta-regression analysis and other variables need to be considered. In contrast to the conducted subgroup analysis, a meta-regression analysis could consider various moderators in one analysis and thus could give deeper understanding of the variation across studies (Grewal, Puccinelli, and Monroe 2018, p. 22). Other variables like the composition of the choice set or the type of attributes presented might further lead to differences in the effects and explain heterogeneity (Neumann, Böckenholt, and Sinha 2016, p. 193). A meta-analytical structural-equation model could examine multiple relationships simultaneously (Grewal, Puccinelli, and Monroe 2018, p. 23).

The replication of the studies by further research is very important to increase the accuracy of the results and to create a wider base for empirical generalizations (Grewal, Puccinelli, and Monroe 2018, p. 19). Especially, additional studies including services and consumables are required to examine the effect of the product type in more detail. Furthermore, the MAs are limited to studies, which ask participants to anticipate a purchase decision. Further studies should investigate the research questions in real-life purchase situations and thus enable the comparison of the magnitude and significance of the effects with the current studies. Field experiments in stores or in an online context could indicate whether the effect differs across these settings. Other factors might also play a role in the investigated relationship, which are not addressed by the studies so far, like the influence of the degree of complementarity, which describes how customers perceive and evaluate “the necessity of one product for the performance or use of the second product“ (Samu, Krishnan, and Smith 1999, p. 59). Characteristics of the participants may also have an impact. Customers, named maximizers, who tend to maximize their value regarding the attributes on alternative, and thus are more likely to select the middle option in a three-choice, might behave differently in the choice of complementary products than satisfiers, who focus on only one attribute (Mao 2016, p. 66).

Tables

Table 1: Overview of Research Questions, Meta-Analyses and Underlying Studies

No. of research variable	Research variable	RQ	Option of comparison: Option B (T1 vs. C)	Option of comparison: Option A (T2 vs. C)	MA	Experimental studies included per MA (ID): 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Aspects of post-purchase consumption																				
1	Sum of complementary products	1.1	x		MA1	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		1.2		x	MA2															
2	Amount of money spent on complementary	2.1	x		MA3	X	X	X	X	X	X	X	X	X	X	X	X	X	X	X
		2.2		x	MA4															
3	Amount of time spent on choosing complementary	3.1	x		MA5	X	X				X	X	X	X	X	X	X	X	X	X
		3.2		x	MA6															
Evaluation of the compromise choice																				
4	Satisfaction with choice	4.1	x		MA7	X	X				X	X	X	X	X	X	X	X	X	X
		4.2		x	MA8															
5	Confidence in choice	5.1	x		MA9	X	X				X	X	X	X	X	X	X	X	X	X
		5.2		x	MA10															
6	Difficulty of choice	6.1	x		MA11	X	X				X	X	X	X	X	X	X	X	X	X
		6.2		x	MA12															
Evaluation of the choice of complementary products																				
7	Satisfaction with choice	7.1	x		MA13										X	X	X	X	X	X
		7.2		x	MA14															
8	Confidence in choice	8.1	x		MA15										X	X	X	X	X	X
		8.2		x	MA16															
9	Difficulty of choice	9.1	x		MA17										X	X	X	X	X	X
		9.2		x	MA18															

Note: C = Control group, ID = study identification number, MA = meta-analysis, No. = number, RQ = research question,
T1 = treatment 1 group, T2 = treatment 2 group
Experimental studies: X = research variable included in study

Table 2: Overview of the Experimental Studies

			Product information		Sample	
ID	**Study run**	**Study name**	**Product**	**Product type**	**Sample size**	**Sample source**
1	1b	1_Toothbrush	Toothbrush	Consumable	146	Students of University of Mannheim
2	1b	2_Camera	Camera	Durable	146	Students of University of Mannheim
3	2b	3_Shampoo	Shampoo	Consumable	268	Students of University of Mannheim
4	2b	4_Printer	Printer	Durable	268	Students of University of Mannheim
5	2b	5_Gym membership	Gym membership	Service	268	Students of University of Mannheim
6	3	6_Laundry detergent	Laundry detergent	Consumable	152	Students of University of Mannheim
7	3	7_Gym membership	Gym membership	Service	152	Students of University of Mannheim
8	4	8_BBQ grill	BBG grill	Durable	152	mTurk participants (US only)
9	4	9_Camera	Camera	Durable	152	mTurk participants (US only)
10	5a	10_BBQ grill	BBG grill	Durable	150	mTurk participants (US only)
11	5a	11_Camera	Camera	Durable	150	mTurk participants (US only)
12	5b	12_BBQ grill	BBG grill	Durable	363	mTurk participants (US only)
13	5b	13_Camera	Camera	Durable	363	mTurk participants (US only)
14	6	14_Laptop	Laptop	Durable	360	mTurk participants (US only)
15	6	15_Camera	Camera	Durable	360	mTurk participants (US only)

Note: ID = study identification number, mTurk = Amazon Mechanical Turk

Table 3: Overview of the Results of All Meta-Analyses

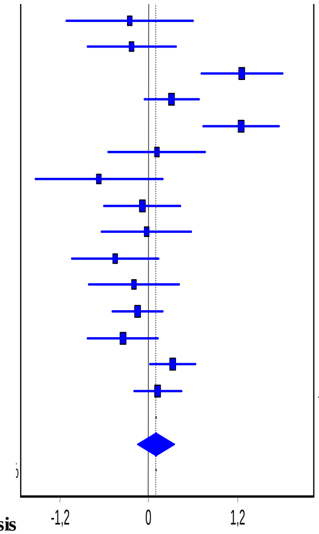
No. of research variable	Research variable	RQ	Option of comparison: Option B (T1 vs. C)	Option of comparison: Option A (T2 vs. C)	MA	Model	Effect size	Summary effect	CI_{95}
Aspects of post-purchase consumption									
1	Sum of complementary products	1.1	x		MA1	RM	Glass' d	0.095	(-0.158, 0.348)
		1.2		x	MA2	RM	Glass' d	0.405***	(0.194, 0.615)
2	Amount of money spent on complementary	2.1	x		MA3	RM	Glass' d	0.081	(-0.154, 0.316)
		2.2		x	MA4	RM	Glass' d	0.342**	(0.139, 0.544)
3	Amount of time spent on choosing complementary	3.1	x		MA5	FM	UMD	-0.156	(-1.756, 1.444)
		3.2		x	MA6	FM	UMD	-0.853	(-2.409, 0.704)
Evaluation of the compromise choice									
4	Satisfaction with choice	4.1	x		MA7	FM	UMD	-0.250***	(-0.356, -0.144)
		4.2		x	MA8	RM	UMD	-0.141*	(-0.267, -0.015)
5	Confidence in choice	5.1	x		MA9	RM	UMD	-0.366***	(-0.513, -0.219)
		5.2		x	MA10	RM	UMD	-0.339***	(-0.481, -0.197)
6	Difficulty of choice	6.1	x		MA11	RM	UMD	0.214	(-0.014, 0.442)
		6.2		x	MA12	RM	UMD	0.355***	(0.163, 0.546)
Evaluation of the choice of complementary products									
7	Satisfaction with choice	7.1	x		MA13	FM	UMD	-0.131*	(-0.247, -0.016)
		7.2		x	MA14	FM	UMD	-0.150*	(-0.285, -0.015)
8	Confidence in choice	8.1	x		MA15	FM	UMD	-0.157**	(-0.273, -0.040)
		8.2		x	MA16	FM	UMD	-0.265***	(-0.406, -0.123)
9	Difficulty of choice	9.1	x		MA17	FM	UMD	0.093	(-0.081, 0.267)
		9.2		x	MA18	FM	UMD	0.321**	(0.138, 0.504)

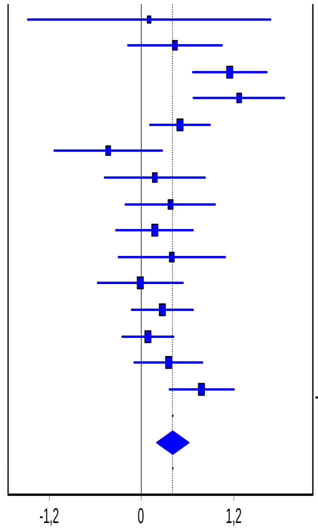
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

Note: C = Control group, CI_{95} = 95% confidence interval, FM = fixed-effect model, MA = meta-analysis, No. = number, RM = random-effects model, RQ = research question, T1 = treatment 1 group, T2 = treatment 2 group, UMD = unstandardized mean difference

Figures

Figure 1: Meta-Analyses 1 and 2 on Sum of Complementary Products





RM - Glass' d

Study ID	Study name	Meta-analysis 1: Option B Glass' d	CI_{95}	Weight	Meta-analysis 2: Option A Glass' d	CI_{95}	Weight
1	1_Toothbrush	-0.259	(-1.116, 0.598)	4.6%	0.101	(-1.477, 1.679)	1.6%
2	2_Camera	-0.231	(-0.833, 0.371)	6.2%	0.439	(-0.174, 1.051)	6.0%
3	3_Shampoo	1.259	(-0.548, 0.769)	6.6%	1.150	(-1.134, 0.274)	7.5%
4	4_Printer	0.311	(-1.534, 0.192)	7.9%	1.269	(-0.476, 0.829)	6.2%
5	5_Gym membership	1.248	(-0.606, 0.433)	6.8%	0.502	(-0.205, 0.959)	8.6%
6	6_Laundry detergent	0.110	(-0.548, 0.769)	5.8%	-0.430	(-1.134, 0.274)	5.2%
7	7_Gym membership	-0.671	(-1.534, 0.192)	4.5%	0.177	(-0.476, 0.829)	5.6%
8	8_BBQ grill	-0.086	(-0.606, 0.433)	6.8%	0.377	(-0.205, 0.959)	6.3%
9	9_Camera	-0.031	(-0.643, 0.580)	6.2%	0.173	(-0.330, 0.677)	7.2%
10	10_BBQ grill	-0.454	(-1.045, 0.136)	6.3%	0.397	(-0.296, 1.090)	5.3%
11	11_Camera	-0.197	(-0.811, 0.417)	6.1%	-0.009	(-0.565, 0.547)	6.6%
12	12_BBQ grill	-0.149	(-0.491, 0.194)	8.2%	0.274	(-0.124, 0.672)	8.5%
13	13_Camera	-0.351	(-0.828, 0.126)	7.2%	0.088	(-0.249, 0.426)	9.3%
14	14_Laptop	0.324	(0.014, 0.634)	8.4%	0.352	(-0.091, 0.796)	7.9%
15	15_Camera	0.123	(-0.201, 0.447)	8.3%	0.785	(0.363, 1.206)	8.2%
	Summary effect	**0.095**	**(-0.158, 0.348)**	**100%**	**0.405*** **	**(0.194, 0.615)**	**100%**

Heterogeneity and sensitivity analysis

Model - ES	MA 1: Summary effect	CI_{95}	Q	df	T^2	I^2	MA 2: Summary effect	CI_{95}	Q	df	T^2	I^2
RM - Glass' d	0.095	(-0.158, 0.348)	54.160***	14	0.173	74.2%	0.405***	(0.194, 0.615)	33.711**	14	0.095	58.5%
Subgroup analysis by product type												
Durable	-0.048	(-0.317, 0.221)	13.480	9	0.130	33.2%	0.402**	(0.135, 0.668)	17.978*	9	0.117	49.9%
Consumable	0.472	(-0.093, 1.038)	11.481**	2	0.130	82.6%	0.443	(-0.147, 1.034)	13.651**	2	0.117	85.3%
Service	0.516	(-0.174, 1.205)	13.963***	1	0.130	92.8%	0.370	(-0.228, 0.967)	0.704	1	0.117	0.0%
Test for heterogeneity			4.232	2					0.030	2		
Sample source												
Students	0.302	(-0.222, 0.826)	32.946***	6	0.395	81.8%	0.524*	(0.092, 0.956)	20.723**	6	0.224	71.0%
mTurk	-0.043	(-0.232, 0.146)	10.318	7	0.023	32.2%	0.300**	(0.122, 0.479)	8.237	7	0.010	15.0%
Test for heterogeneity			1.475	1					0.880	1		
RM - Hedges' g	0.061	(-0.160, 0.281)	42.570***	14	0.119	67.1%	0.343***	(0.183, 0.503)	20.948	14	0.031	33.2%

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

Note: CI_{95} = 95% confidence interval, ES = effect size, mTurk = Amazon mechancal Turk, RM = random-effects model,

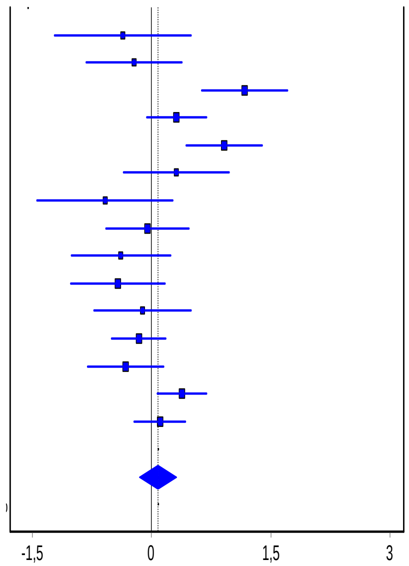
Forest plot (based on MetaXL): square = ES per study (size of square is proportional to weight of study), diamond = summary effect across all studies, horizontal lines = CI_{95} per study

Figure 2: Meta-Analyses 3 and 4 on Amount of Money Spent on Complementary Products

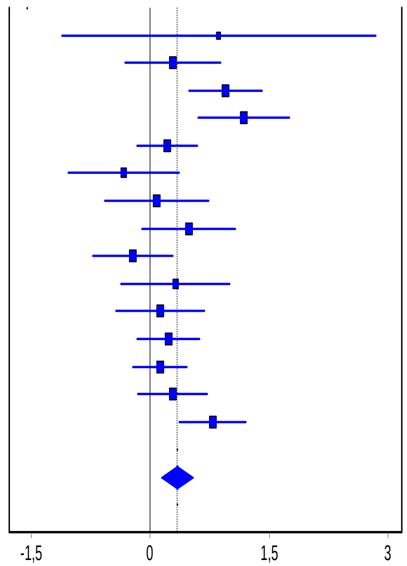
RM - Glass' d

Study ID	Study name	Meta-analysis 3: Option B Glass' d	CI95	Weight	Meta-analysis 4: Option A Glass' d	CI95	Weight
1	1_Toothbrush	-0.354	(-1.213, 0.505)	4.3%	0.866	(-1.111, 2.843)	1.0%
2	2_Camera	-0.215	(-0.816, 0.387)	6.1%	0.289	(-0.315, 0.893)	6.0%
3	3_Shampoo	1.173	(-0.346, 0.979)	6.6%	0.951	(-1.027, 0.371)	7.8%
4	4_Printer	0.319	(-1.437, 0.274)	8.1%	1.180	(-0.567, 0.736)	6.3%
5	5_Gym membership	0.917	(-0.567, 0.472)	7.2%	0.220	(-0.099, 1.08)	8.9%
6	6_Laundry detergent	0.317	(-0.346, 0.979)	5.6%	-0.328	(-1.027, 0.371)	5.1%
7	7_Gym membership	-0.582	(-1.437, 0.274)	4.3%	0.084	(-0.567, 0.736)	5.5%
8	8_BBQ grill	-0.048	(-0.567, 0.472)	6.8%	0.491	(-0.099, 1.080)	6.2%
9	9_Camera	-0.383	(-1.008, 0.241)	5.9%	-0.216	(-0.720, 0.289)	7.2%
10	10_BBQ grill	-0.420	(-1.010, 0.169)	6.2%	0.322	(-0.364, 1.008)	5.2%
11	11_Camera	-0.111	(-0.723, 0.501)	6.0%	0.130	(-0.428, 0.687)	6.5%
12	12_BBQ grill	-0.158	(-0.500, 0.185)	8.4%	0.231	(-0.165, 0.628)	8.6%
13	13_Camera	-0.322	(-0.798, 0.154)	7.2%	0.126	(-0.212, 0.464)	9.5%
14	14_Laptop	0.387	(0.076, 0.699)	8.6%	0.286	(-0.155, 0.726)	8.0%
15	15_Camera	0.107	(-0.217, 0.431)	8.5%	0.791	(0.369, 1.213)	8.3%
	Summary effect	**0.081**	**(-0.154, 0.316)**	**100%**	**0.342****	**(0.139, 0.544)**	**100%**

Forest plot (Meta-analysis 3: Option B):



Forest plot (Meta-analysis 4: Option A):



Heterogeneity and sensitivity analysis

Model - ES	Meta-analysis 3: Summary effect	CI95	Q	df	T²	I²	Meta-analysis 4: Summary effect	CI95	Q	df	T²	I²
RM - Glass' d	0.081	(-0.154, 0.316)	46.893***	14	0.140	70.1%	0.342**	(0.139, 0.544)	31.461**	14	0.083	55.5%
Subgroup analysis by product type												
Durable	-0.049	(-0.302, 0.203)	15.646	9	0.108	42.5%	0.352**	(0.101, 0.604)	19.891*	9	0.098	54.8%
Consumable	0.499	(-0.039, 1.037)	9.759**	2	0.108	79.5%	0.466	(-0.103, 1.035)	9.069*	2	0.098	77.9%
Service	0.378	(-0.264, 1.020)	8.977**	1	0.108	88.9%	0.167	(-0.395, 0.729)	0.125	1	0.098	0.0%
Test for heterogeneity			4.159	2					0.563	2		
Sample source												
Students	0.288	(-0.159, 0.735)	24.607***	6	0.264	75.6%	0.441*	(0.035, 0.846)	18.536**	6	0.184	67.6%
mTurk	-0.059	(-0.268, 0.151)	12.457	7	0.038	43.8%	0.269*	(0.061, 0.477)	10.964	7	0.032	36.2%
Test for heterogeneity			1.893	1					0.544	1		
RM - Hedges' g	0.045	(-0.161, 0.252)	37.202**	14	0.096	62.4%	0.305**	(0.125, 0.485)	26.126*	14	0.055	46.4%

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

Note: CI_{95} = 95% confidence interval, ES = effect size, mTurk = Amazon mechancal Turk, RM = random-effects model,

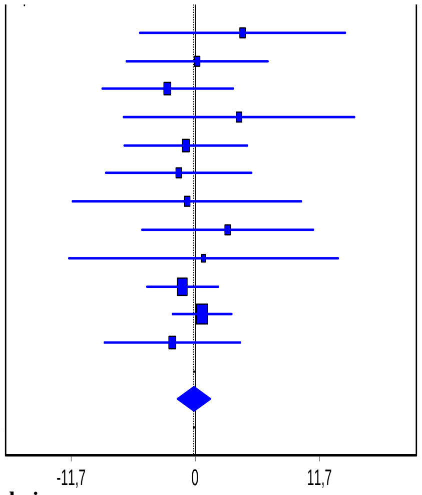
Forest plot (based on MetaXL): square = ES per study (size of square is proportional to weight of study), diamond = summary effect across all studies, horizontal lines = CI_{95} per study

Figure 3: Meta-Analyses 5 and 6 on Amount of Time Spent on Choosing Complementary Products

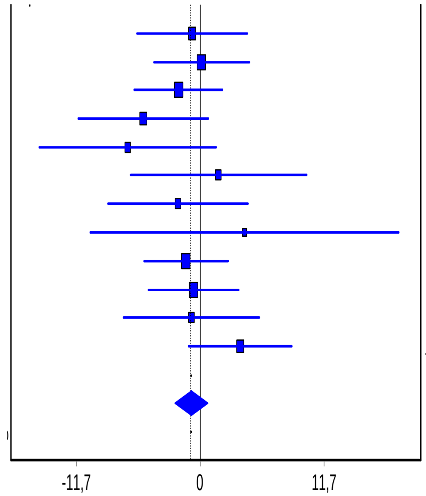
FM - UMD

		Meta-analysis 5: Option B			Meta-analysis 6: Option A		
Study ID	Study name	UMD	CI_{95}	Weight	UMD	CI_{95}	Weight
1	1_Toothbrush	4.466	(-5.172, 14.105)	2.8%	-0.752	(-5.955, 4.450)	8.9%
2	2_Camera	0.205	(-6.466, 6.877)	5.8%	0.163	(-4.312, 4.638)	12.1%
6	6_Laundry detergent	-2.584	(-8.769, 3.601)	6.7%	-2.023	(-6.203, 2.158)	13.9%
7	7_Gym membership	4.158	(-6.708, 15.024)	2.2%	-5.335	(-11.483, 0.814)	6.4%
8	8_BBQ grill	-0.848	(-6.652, 4.955)	7.6%	-6.786	(-15.138, 1.566)	3.5%
9	9_Camera	-1.536	(-8.377, 5.305)	5.5%	1.759	(-6.524, 10.043)	3.5%
10	10_BBQ grill	-0.749	(-11.525, 10.026)	2.2%	-2.089	(-8.687, 4.510)	5.6%
11	11_Camera	3.079	(-4.975, 11.133)	3.9%	4.178	(-10.365, 18.721)	1.1%
12	12_BBQ grill	0.769	(-11.902, 13.439)	1.6%	-1.313	(-5.262, 2.636)	15.5%
13	13_Camera	-1.171	(-4.554, 2.213)	22.4%	-0.599	(-4.854, 3.657)	13.4%
14	14_Laptop	0.659	(-2.119, 3.436)	33.2%	-0.785	(-7.201, 5.632)	5.9%
15	15_Camera	-2.138	(-8.541, 4.266)	6.2%	3.811	(-1.060, 8.682)	10.2%
	Summary effect	**-0.156**	**(-1.756, 1.444)**	**100%**	**-0.853**	**(-2.409, 0.704)**	**100%**

Forest plot (Meta-analysis 5: Option B)



Forest plot (Meta-analysis 6: Option A)



Heterogeneity and sensitivity analysis

	Meta-analysis 5: Option B						Meta-analysis 6: Option A					
	Summary		Heterogeneity measures				Summary		Heterogeneity measures			
Model and ES	**effect**	**CI_{95}**	**Q**	**df**	**T^2**	**I^2**	**effect**	**CI_{95}**	**Q**	**df**	**T^2**	**I^2**
FM - UMD	-0.156	(-1.756, 1.444)	3.999	11	0.000	0.0%	-0.853	(-2.409, 0.704)	9.045	11	0.000	0.0%
FM - Glass' d	-0.002	(-0.139, 0.136)	4.446	11	0.000	0.0%	-0.011	(-0.158, 0.136)	11.083	11	0.001	0.7%
FM - Hedges' g	-0.008	(-0.145, 0.129)	4.317	11	0.000	0.0%	-0.046	(-0.192, 0.100)	7.815	11	0.000	0.0%
RM - UMD	-0.156	(-1.756, 1.444)	3.999	11	0.000	0.0%	-0.853	(-2.409, 0.704)	9.045	11	0.000	0.0%
RM - Glass' d	-0.002	(-0.139, 0.136)	4.446	11	0.000	0.0%	-0.011	(-0.159, 0.137)	11.083	11	0.001	0.7%
RM - Hedges' g	-0.008	(-0.145, 0.129)	4.317	11	0.000	0.0%	-0.046	(-0.192, 0.100)	7.815	11	0.000	0.0%

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

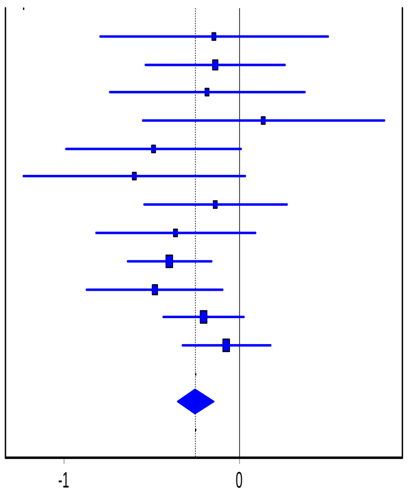
Note: CI_{95} = 95% confidence interval, ES = effect size, FM = fixed-effect model, RM = random-effects model, UMD = unstandardized mean difference

Forest plot (based on MetaXL): square = ES per study (size of square is proportional to weight of study), diamond = summary effect across all studies, horizontal lines = CI_{95} per study

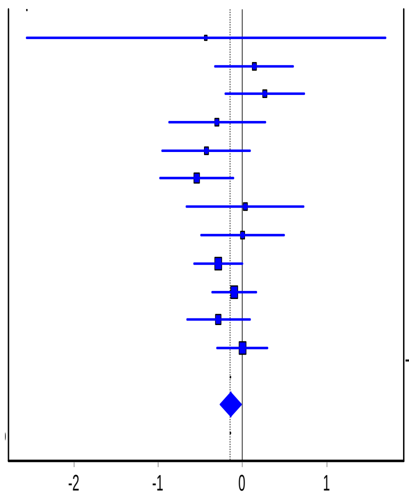
Figure 4: Meta-Analyses 7 and 8 on the Satisfaction with the Compromise Choice

		Meta-analysis 7: Option B (FM - UMD)			Meta-analysis 8: Option A (RM - UMD)		
Study ID	**Study name**	**UMD**	**CI$_{95}$**	**Weight**	**UMD**	**CI$_{95}$**	**Weight**
1	1_Toothbrush	-0.143	(-0.793, 0.508)	2.6%	-0.429	(-2.561, 1.704)	0.3%
2	2_Camera	-0.136	(-0.536, 0.263)	7.0%	0.141	(-0.324, 0.605)	6.8%
6	6_Laundry detergent	-0.181	(-0.738, 0.375)	3.6%	0.267	(-0.206, 0.741)	6.6%
7	7_Gym membership	0.139	(-0.550, 0.828)	2.4%	-0.300	(-0.873, 0.274)	4.6%
8	8_BBQ grill	-0.486	(-0.987, 0.014)	4.5%	-0.428	(-0.954, 0.099)	5.4%
9	9_Camera	-0.597	(-1.229, 0.034)	2.8%	-0.539	(-0.978, -0.099)	7.6%
10	10_BBQ grill	-0.135	(-0.543, 0.274)	6.7%	0.034	(-0.664, 0.733)	3.1%
11	11_Camera	-0.361	(-0.817, 0.095)	5.4%	0.006	(-0.489, 0.502)	6.1%
12	12_BBQ grill	-0.396	(-0.638, -0.155)	19.2%	-0.284	(-0.574, 0.006)	15.9%
13	13_Camera	-0.482	(-0.870, -0.093)	7.4%	-0.093	(-0.358, 0.173)	18.5%
14	14_Laptop	-0.202	(-0.434, 0.030)	20.8%	-0.281	(-0.658, 0.096)	10.0%
15	15_Camera	-0.073	(-0.325, 0.179)	17.6%	0.001	(-0.300, 0.301)	15.0%
	Summary effect	**-0.250*** **	**(-0.356, -0.144)**	**100%**	**-0.141***	**(-0.267, -0.015)**	**100%**

Forest plot (Meta-analysis 7):



Forest plot (Meta-analysis 8):



Heterogeneity and sensitivity analysis

	Meta-analysis 7		Heterogeneity measures				Meta-analysis 8		Heterogeneity measures			
Model and ES	**Summary effect**	**CI$_{95}$**	**Q**	**df**	**T²**	**I²**	**Summary effect**	**CI$_{95}$**	**Q**	**df**	**T²**	**I²**
FM - UMD	-0.250***	(-0.356, -0.144)	9.095	11	0.000	0.0%						
FM - Glass' d	-0.339***	(-0.478, -0.199)	10.844	11	0.000	0.0%						
RM - UMD	-0.250***	(-0.356, -0.144)	9.095	11	0.000	0.0%	-0.141*	(-0.267, -0.015)	11.951	11	0.004	8.0%
RM - Glass' d							-0.190*	(-0.352, -0.029)	12.620	11	0.010	12.8%

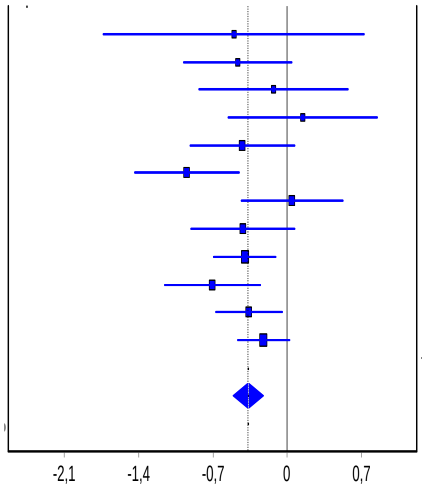
*** p < 0.001, ** p < 0.01, * p < 0.05; alpha = 0.05

Note: CI$_{95}$ = 95% confidence interval, ES = effect size, FM = fixed-effectts model, RM = random-effects model, UMD = unstandardized mean difference

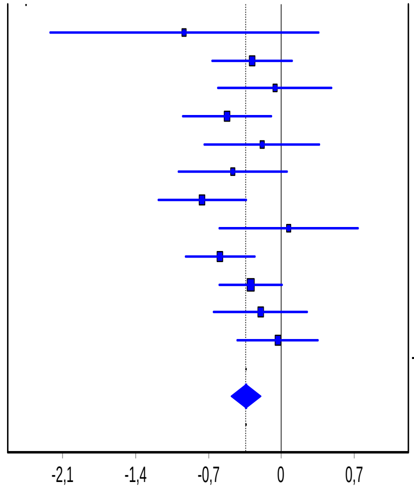
Forest plot (based on MetaXL): squares = ES per study (size of square is proportional to weight per study), diamond = summary effect across all studies, horizontal lines = CI$_{95}$ per study

Figure 5: Meta-Analyses 9 and 10 on the Confidence in the Compromise Choice

Meta-analysis 9: Option B — Forest plot



Meta-analysis 10: Option A — Forest plot



RM - UMD

		Meta-analysis 9: Option B			Meta-analysis 10: Option A		
Study ID	**Study name**	**UMD**	**CI_{95}**	**Weight**	**UMD**	**CI_{95}**	**Weight**
1	1_Toothbrush	-0.500	(-1.732, 0.732)	1.4%	-0.929	(-2.219, 0.362)	1.2%
2	2_Camera	-0.463	(-0.974, 0.047)	6.8%	-0.277	(-0.662, 0.108)	10.7%
6	6_Laundry detergent	-0.123	(-0.826, 0.580)	3.9%	-0.059	(-0.604, 0.487)	6.0%
7	7_Gym membership	0.153	(-0.549, 0.854)	3.9%	-0.518	(-0.946, -0.090)	9.1%
8	8_BBQ grill	-0.420	(-0.913, 0.073)	7.2%	-0.181	(-0.735, 0.373)	5.8%
9	9_Camera	-0.944	(-1.437, -0.452)	7.2%	-0.461	(-0.987, 0.064)	6.4%
10	10_BBQ grill	0.048	(-0.431, 0.527)	7.5%	-0.756	(-1.180, -0.331)	9.2%
11	11_Camera	-0.417	(-0.906, 0.072)	7.2%	0.072	(-0.596, 0.741)	4.2%
12	12_BBQ grill	-0.396	(-0.690, -0.101)	14.8%	-0.586	(-0.920, -0.251)	13.3%
13	13_Camera	-0.701	(-1.154, -0.248)	8.2%	-0.289	(-0.591, 0.013)	15.3%
14	14_Laptop	-0.358	(-0.672, -0.045)	13.7%	-0.196	(-0.646, 0.254)	8.3%
15	15_Camera	-0.218	(-0.462, 0.025)	18.2%	-0.031	(-0.418, 0.356)	10.6%
	Summary effect	**-0.366*****	**(-0.513, -0.219)**	**100%**	**-0.339*****	**(-0.481, -0.197)**	**100%**

Heterogeneity and sensitivity analysis

	Meta-analysis 9: Option B						Meta-analysis 10: Option A					
	Summary		**Heterogeneity measures**				**Summary**		**Heterogeneity measures**			
Model - ES	**effect**	**CI_{95}**	**Q**	**df**	**T^2**	**I^2**	**effect**	**CI_{95}**	**Q**	**df**	**T^2**	**I^2**
RM - UMD	-0.366***	(-0.513, -0.219)	14.532	11	0.015	24.3%	-0.339***	(-0.481, -0.197)	13.284	11	0.011	17.2%
RM - Glass' d	-0.435***	(-0.610, -0.260)	15.015	11	0.024	26.7%	-0.372***	(-0.569, -0.174)	17.079	11	0.040	35.6%

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

Note: CI_{95} = 95% confidence interval, ES = effect size, RM = random-effects model, UMD = unstandardized mean difference

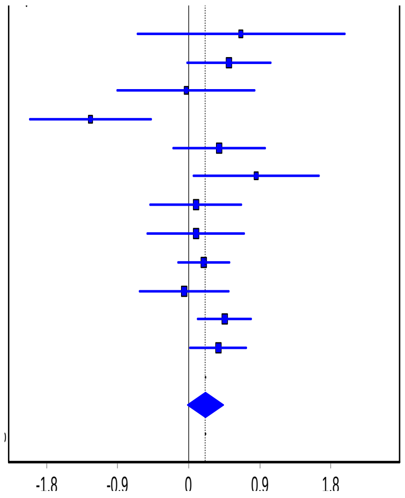
Forest plot (based on MetaXL): squares = ES per study (size of square is proportional to weight per study), diamond = summary effect across all studies, horizontal lines = CI_{95} per study

Figure 6: Meta-Analyses 11 and 12 on the Difficulty of the Compromise Choice

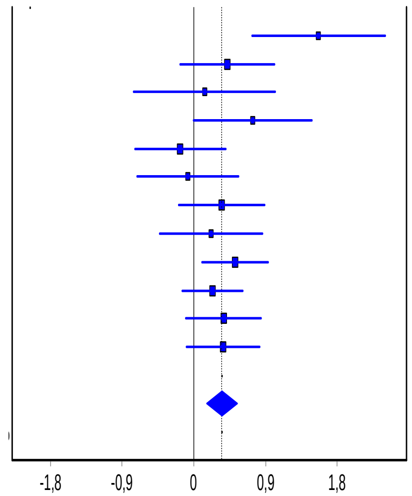
RM - UMD

Study ID	Study name	Meta-analysis 11: Option B UMD	CI95	Weight	Meta-analysis 12: Option A UMD	CI95	Weight
1	1_Toothbrush	0.667	(-0.647, 1.980)	2.6%	1.571	(0.731, 2.411)	4.4%
2	2_Camera	0.515	(-0.013, 1.044)	9.2%	0.424	(-0.169, 1.018)	7.7%
6	6_Laundry detergent	-0.029	(-0.901, 0.842)	5.0%	0.139	(-0.748, 1.026)	4.0%
7	7_Gym membership	-1.243	(-2.014, -0.473)	5.9%	0.745	(0.002, 1.489)	5.4%
8	8_BBQ grill	0.390	(-0.198, 0.978)	8.2%	-0.167	(-0.737, 0.404)	8.2%
9	9_Camera	0.861	(0.064, 1.658)	5.6%	-0.072	(-0.708, 0.564)	7.0%
10	10_BBQ grill	0.095	(-0.488, 0.677)	8.3%	0.353	(-0.184, 0.891)	8.9%
11	11_Camera	0.097	(-0.518, 0.713)	7.8%	0.219	(-0.426, 0.864)	6.8%
12	12_BBQ grill	0.195	(-0.135, 0.525)	13.2%	0.521	(0.104, 0.938)	12.4%
13	13_Camera	-0.053	(-0.622, 0.516)	8.5%	0.241	(-0.142, 0.623)	13.6%
14	14_Laptop	0.459	(0.117, 0.802)	12.9%	0.378	(-0.098, 0.853)	10.5%
15	15_Camera	0.378	(0.018, 0.738)	12.6%	0.375	(-0.088, 0.837)	10.9%
	Summary effect	**0.214**	**(-0.014, 0.442)**	**100%**	**0.355*** **	**(0.163, 0.546)**	**100%**

Forest plot (Meta-analysis 11: Option B)



Forest plot (Meta-analysis 12: Option A)



Heterogeneity and sensitivity analysis

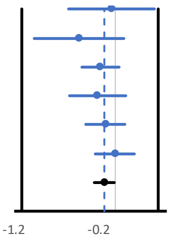
Model and ES	MA 11: Summary effect	CI95	Q	df	T²	I²	MA 12: Summary effect	CI95	Q	df	T²	I²
RM - UMD	0.214	(-0.014, 0.442)	22.281*	11	0.074	50.6%	0.355***	(0.163, 0.546)	15.468	11	0.032	28.9%
RM - Glass' d	0.229*	(0.034, 0.425)	18.952	11	0.046	42.0%	0.275***	(0.127, 0.424)	9.762	11	0.000	0.0%

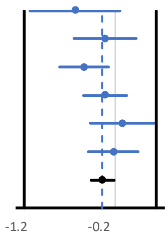
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$; alpha = 0.05

Note: CI_{95} = 95% confidence interval, ES = effect size, RM = random-effects model, UMD = unstandardized mean difference

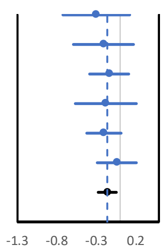
Forest plot (based on MetaXL): squares = ES per study (size of square is proportional to weight per study), diamond = summary effect across all studies, horizontal lines = CI_{95} per study

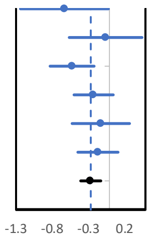
Figure 7: Meta-Analyses 13 to 18 on Evaluation of the Choice of Complementary Products



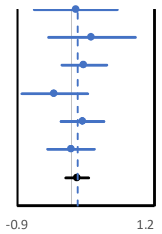


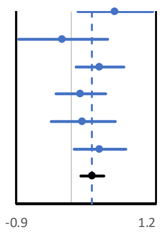
Model		Meta-analyses on satisfaction with choice of complementary products							
FM - UMD		**Meta-analysis 13: Option B**				**Meta-analysis 14: Option A**			
ID	Study name	Forest plot	UMD	CI_{95}	Weight	Forest plot	UMD	CI_{95}	Weight
10	10_BBQ grill		-0.046	(-0.555, 0.462)	5.2%		-0.480	(-1.025, 0.065)	6.1%
11	11_Camera		-0.431	(-0.957, 0.096)	4.8%		-0.116	(-0.492, 0.260)	12.9%
12	12_BBQ grill		-0.178	(-0.401, 0.044)	27.0%		-0.377	(-0.669, -0.084)	21.2%
13	13_Camera		-0.215	(-0.544, 0.115)	12.3%		-0.122	(-0.382, 0.138)	26.9%
14	14_Laptop		-0.122	(-0.348, 0.105)	26.1%		0.092	(-0.294, 0.477)	12.2%
15	15_Camera		-0.008	(-0.241, 0.225)	24.6%		-0.021	(-0.317, 0.276)	20.7%
Summary effect			**-0.131***	**(-0.247, -0.016)**	**100%**		**-0.150***	**(-0.285, -0.015)**	**100%**
Heterogeneity			*Q = 2.849, T² = 0.000, I² = 0.0%*				*Q = 6.025 , T² = 0.006, I² = 17.0%*		
FM - Hedges' g									
Summary effect			**-0.179***	**(-0.340, -0.019)**			**-0.184***	**(-0.360, -0.008)**	
Heterogeneity			*Q = 2.740, T² = 0.000, I² = 0.0%*				*Q = 6.025, T² = 0.011, I² = 17.4%*		





Model		Meta-analyses on confidence in choice of complementary products							
FM - UMD		**Meta-analysis 15: Option B**				**Meta-analysis 16: Option A**			
ID	Study name	Forest plot	UMD	CI_{95}	Weight	Forest plot	UMD	CI_{95}	Weight
10	10_BBQ grill		-0.300	(-0.724, 0.125)	7.6%		-0.618	(-1.226, -0.010)	5.4%
11	11_Camera		-0.208	(-0.594, 0.178)	9.2%		-0.055	(-0.554, 0.445)	8.0%
12	12_BBQ grill		-0.136	(-0.385, 0.114)	21.9%		-0.513	(-0.817, -0.209)	21.5%
13	13_Camera		-0.181	(-0.571, 0.209)	9.0%		-0.222	(-0.492, 0.048)	27.3%
14	14_Laptop		-0.202	(-0.415, 0.010)	30.2%		-0.121	(-0.518, 0.275)	12.6%
15	15_Camera		-0.035	(-0.283, 0.213)	22.1%		-0.161	(-0.442, 0.120)	25.2%
Summary effect			**-0.157****	**(-0.273, -0.040)**	**100%**		**-0.265*****	**(-0.406, -0.123)**	**100%**
Heterogeneity			*Q = 1.645, T² = 0.000, I² = 0.0%*				*Q = 5.667 , T² = 0.004, I² = 11.8%*		
FM - Hedges' g									
Summary effect			**-0.209***	**(-0.370, -0.048)**			**-0.318*****	**(-0.495, -0.142)**	
Heterogeneity			*Q = 1.827, T² = 0.000, I² = 0.0%*				*Q = 5.575, T² = 0.006, I² = 10.3%*		





Model		Meta-analyses on difficulty of choice of complementary products							
FM - UMD		**Meta-analysis 17: Option B**				**Meta-analysis 18: Option A**			
ID	Study name	Forest plot	UMD	CI_{95}	Weight	Forest plot	UMD	CI_{95}	Weight
10	10_BBQ grill		0.069	(-0.578, 0.716)	7.2%		0.678	(0.104, 1.252)	10.1%
11	11_Camera		0.319	(-0.359, 0.998)	6.5%		-0.129	(-0.809, 0.551)	7.2%
12	12_BBQ grill		0.201	(-0.148, 0.551)	24.7%		0.441	(0.076, 0.807)	25.0%
13	13_Camera		-0.263	(-0.776, 0.251)	11.4%		0.152	(-0.230, 0.534)	22.9%
14	14_Laptop		0.174	(-0.156, 0.503)	27.8%		0.179	(-0.315, 0.674)	13.6%
15	15_Camera		-0.004	(-0.372, 0.364)	22.3%		0.435	(0.038, 0.832)	21.2%
Summary effect			**0.093**	**(-0.081, 0.267)**	**100%**		**0.321****	**(0.138, 0.504)**	**100%**
Heterogeneity			*Q = 3.145, T² = 0.000, I² = 0.0%*				*Q = 4.972 , T² = 0.000, I² = 0.0%*		
FM - Glass' d									
Summary effect			**0.088**	**(-0.073, 0.249)**			**0.307****	**(0.128, 0.487)**	
Heterogeneity			*Q = 3.262, T² = 0.000, I² = 0.0%*				*Q = 7.251, T² = 0.023, I² = 31.0%*		

*** p < 0.001, ** p < 0.01, * p < 0.05; alpha = 0.05

Note: CI_{95} = 95% confidence interval, ES = effect size, FM = fixed-effects model, UMD = unstandardized mean difference

Forest plots (based on Excel): dots = ES per study (size of dot independent of weight of per study), horizontal lines = CI_{95} per study

Appendix

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Aguinis et al. (2011) *[Journal of Management]*	Impact of the method of the meta-analysis and judgement calls on the magnitude of the effect size of the meta-analysis	Methodological foundation of meta-analysis	196 meta-analyses from the time-period 1982-2009 with 5581 effect sizes	• 21 different meta-analysis methods ANCOVA • IV: methodological choices, judgment calls • DV: absolute-value meta-analytical derived effect sizes	• Choice of meta-analysis method and judgement calls have a small influence on the conclusion of the analysis and the effect size • Methodological choices and judgement calls are linked to the number of citations of the respective analysis • Increased magnitude of the effect sizes does not result in a higher citation rate • If a meta-analysis tests existing theory, the number of citation increases • If a meta-analysis tries to create new theory, the number of citations decreases

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Churchill Jr. and Peter (1984) *[Journal of Marketing Research]*	Impact of research design effects on the reliability of rating scales	• Measurement theory • Psychometric theory	101 studies including information on reliability leading to a total of 154 measures	Meta-analysis IV: • Sampling characteristics • Measure characteristics • Measure development processes DV: • Reliability coefficient Regression analysis	• The influence of following research design characteristics are investigated: sampling and measure characteristics and measure development processes • The measure characteristics have a strong impact on the reliability estimates • The characteristics of measures account for 22% of variance in the estimate of reliability Sampling characteristics and measure development processes have a very small influence

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Cochran (1954) *[Biometrics]*	Mathematical theory and discussion of methods regarding the combination of estimates from different experiments	-	-	Mathematical models	• Derivation and presentation of methods regarding the estimates from different experiments • The simplest estimator is the arithmetic mean of the estimates • Unweighted mean is the best estimator in case of experiments which are of the same type • The best estimator across experiments is the weighted mean if the variance per observation is the same and the experiments differ • The presence of interactions impacts the choice of the estimator • The estimator of the unweighted mean fits most settings in practice

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
DerSimonian and Laird (1986) *[Clinical Trials]*	Consistent assessment of homogeneity of treatment effect	Methodological foundation of meta-analysis: random-effects model	n = 8 published reviews	Random-effects model	• Discussion of a random-effects method that examines the heterogeneity regarding the overall effect • Heterogeneity is an important indicator to be assessed during the analysis • Derivation of an estimator of the amount of heterogeneity • A weighted noniterative approach is a suggested approach to estimate the total effect of the treatment and its variation in the effect over all studies Analysis of further influencing factors that have an impact on heterogeneity is included in this method

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Dhar and Simonson (2003) *[Journal of Marketing Research]*	Impact of a no-choice option on the attraction and compromise effect	• Forced choices • Independence of irrelevant alternatives • Compromise effect	Study 1 : n = 140 visitors to a science museum Study 2: n = 322 visitors to a science museum Study 3: n = 120 passengers to a major airport Study 4: n = 110 visitors of a science museum Study 5: n = 216 undergraduate students	• Logit model • Between-subject design with random assignment	• The introduction of a no-choice option increases the attraction effect • The introduction of a no-choice option decreases the compromise effect • The introduction of a no-choice option results in a decrease of the share of the alternative, which performances on average regarding the dimensions in comparison to the no-choice option • The proportion of the no-choice option increases if attributes are displayed in form of ranges • The share of a no-choice option is higher if a forced-choice takes place beforehand

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Eisend (2015) *[Journal of Marketing]*	Measurement of the created progress and value of knowledge in the field of marketing research	• Marketing research • Marketing knowledge • Method meta-analysis	• n = 176 meta-analyses from the time period 1918 to 2012 including more than 7500 primary studies • 1841 effect sizes	Meta-meta-analysis • Main IV: time, maturity, intensity • DV: effect size	• A substantial amount of knowledge is created in marketing which is represented by a medium-sized mean correlation in meta-analysis of 0.24 • The highest effects are provided by the areas pricing and consumer behavior • The amount of created knowledge varies across research areas • Knowledge has been created during a long period of time with a declining rate • Maturity in marketing knowledge is obvious

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Fern and Monroe (1996) *[Journal of Consumer Research]*	Challenges of the estimation of the effect size	Methodological foundation of the meta-analysis	-	-	• The interpretability of an effect size depends on the nature of research, i.e. relational vs. experimental, the research objective, i.e. testing of theory or applicational focus, and the history in this research field • The factors, that influence the size of the effect, need to be considered before analyzing and interpreting the value • The analysis of heterogeneity is essential in a meta-analysis

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Glass (1976) *[Educational Researcher]*	Introduction to the method meta-analysis illustrated by example	• Educational research • Methodological foundation of the meta-analysis	800 measured effect sizes from 375 studies	Meta-analysis from the field of therapy to illustrate the method meta-analysis	• Meta-analysis is defined as analysis that examines analyses • Condensing the information from various studies is an essential and difficult issue for educational researchers

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Glass (1977) *[Review of Research in Education]*	Description of statistical approaches to integrate the results	Methodological foundation of the meta-analysis	-	-	• Description of various concepts and approaches regarding meta-analysis • Presentation of the vote-counting method • Interpretation of study results • Variance heterogeneity is an issue for the standardized measures • Glass' d is recommended if variance heterogeneity is the case as the standardization is based on the standard deviation of the control group

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Grewal, Puccinelli, and Monroe (2018) *[Review of Research in Education]*	Review of the application of the method meta-analysis in the field of marketing	Methodological foundation of the meta-analysis	n = 74 meta-analysis from leading marketing journals from 1981 to 2017	Descriptive statistic (frequencies) of the meta-analyses conducted in the field of marketing regarding their application of the method meta-analysis	• Meta-analyses help to make sense of the increasing amount of studies in the marketing filed • Most meta-analyses in the field of marketing cover the topics consumer behavior, product management, communication and sales • Three different types of meta-analyses are applied in marketing: standard approach, analysis with replication focus and second-order meta-analysis • 52 meta-analyses use the standard meta-analyses approach, 20 apply the replication method and the second-order analysis is conducted by 2 meta-analyses in the field of marketing • Over the last three decades, meta-analysis in marketing increasingly apply correlations, use a weighting method, adjust for reliability, and make a test for homogeneity • The main steps of meta-analysis cover the definition of the research objective and the research questions, the identification of relevant studies

					to be included, the calculation of the effect sizes per individual study, choice of the model to integrate the effect sizes, a test for homogeneity and analysis of essential moderators

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Hall and Brannick (2002) *[Journal of Applied Psychology]*	Comparison of the two random-effects methods Schmidt-Hunter method and Hedges-Vevea method	Methodological foundation of the meta-analysis: random-effects model	4 meta-analyses	Monte Carlo simulation • Manipulation of the population effect, standard deviation of the population, sum of studies and the attenuation • Random variable: sample size per study Meta-analysis of four published meta-analysis applying both methods	• The choice of the method has a smaller effect on the result of the study than the procedure of the consideration and correction of the artefacts • The Monte Carlo simulation shows that the credibility interval of the Schmidt-Hunter method is better as the Hedges-Vevea method tends to calculate credibility intervals which include zero erroneously • The re-analysis of the four meta-analyses using both methods only gives indications on which method is preferred • If the correction regarding reliability is not part of the analysis, both methods calculate very similar results • Schmidt-Hunter-method computes credibility intervals which reflect reality to a better extend • Schmidt-Hunter-method creates more precise estimates and credibility intervals

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Hedges (1981) *[Journal of Educational Statistics]*	Distribution theory for Glass's estimator of effect size and related estimators	Methodological foundation of the meta-analysis: effect size by Glass	-	Statistical model	• Derivation of the distribution of the effect size of Glass • The estimator of Glass' effect size is slightly biased • Creation of a correction for the influence of the measurement error on the estimated effect size • Derivation of accurate weights

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Hedges (1982) *[Psychological Bulletin]*	Estimation effect sizes in case of series of independent experiments	Methodological foundation of the meta-analysis: effect size by Glass	Simulation study	Statistical model	• Presentation of an unbiased form of estimator for the effect size by Glass • Based on the data of various experiments, a weighted estimator of the effect size is provided • Description of a test for homogeneity, which is applicable for big samples • Precision of the weighted estimator and the test for homogeneity is demonstrated if the sample size of the control group is larger than 10 and the values of the effect sizes are lower than 1.5

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Hedges (1983) *[Psychological Bulletin]*	Random-effects model	Methodological foundation of the meta-analysis: random-effects model	-	Statistical model	• A random-effects model considers the effect sizes as “sample realizations from a distribution of possible population effect sizes” (Hedges 1983, p. 388) • The fixed-effect model assumes fixed effect sizes • Description of a test that addresses whether the variance of the distribution of the effect size is zero • This test is applicable in case of large samples • Derivation of an estimator referring to the variance of the distribution of the effect size, which is considered to be unbiased

Author/s (Year) ***[Journal]***	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Hedges and Olkin (1980) *[Psychological Bulletin]*	Method of vote-counting	-	-	Statistical model	• The vote-counting method is intuitive but low in power • Vote-counting is about counting the studies in which the mean of the treatment group is larger than the mean of the control group. In case of the relative share of studies, in which the mean of the treatment group is greater than the mean in the control group, is large, the treatment is considered to have an effect • The power of this method further declines if the amount of studies included rises • Description of further methods like the calculation of confidence intervals of the effect size

Author/s (Year) ***[Journal]***	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Hedges and Vevea (1998) *[Psychological Methods]*	Fixed- and random-effects models in meta-analysis	Methodological foundation of the meta-analysis: fixed and random-effects model	-	Statistical model	• The choice of the fixed-effect model is appropriate if the objective of the analysis is to derive findings only with regard to the studies, which are included in the analysis • Measures of heterogeneity can indicate that the fixed-effects model is not suitable • A random-effects model should be applied if the objective is "making inferences about the distribution of effect parameters in a population of studies from a random sample of studies" (Hedges and Vevea 1998, p. 486) • The disadvantage of the random-effects model is the lower power of the test of significance and the wider confidence intervals in comparison to the fixed-effects model

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Higgins and Thompson (2002) *[Statistics in Medicine]*	Measurement of heterogeneity in meta-analysis	Methodological foundation of the meta-analysis: measurement of heterogeneity	Exemplary studies used for illustration	Application of all three heterogeneity measures on an exemplary data set	• Proposition of the heterogeneity parameter H, R and I^2 which are independent of the amount of trials included • All three measures are considered to be more important than the test for homogeneity • All three measures target the magnitude of heterogeneity • Description and interpretation of these heterogeneity measures and their intervals based on five exemplary data sets • H and I^2 are preferred over R • H is the "ratio of confidence interval widths for single summary estimates" (Higgins and Thompson 2002, p. 1553) • I^2 is the share of variation due to real differences than based on sampling error

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Higgins et al. (2003) *[British Medical Journal]*	Measurement of inconsistency in meta-analysis	Methodological foundation of the meta-analysis: measurement of heterogeneity	Exemplary studies used for illustration	Meta-analysis with focus on heterogeneity measures	• Description of the heterogeneity parameter I^2 • The disadvantage of the test for homogeneity is its dependence on the number of studies incorporated • The parameter I^2 is independent of the amount of trials included in the analysis and is comparable across various data • I^2 measures the share of the “total variation across studies due to heterogeneity” (Higgins et al. 2003, p. 559) • I^2 ranges from 0% to 100% • It is also applicable in subgroup analysis • 25% is considered as low, 50% as moderate and 75% as high heterogeneity

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Johnson, Mullen, and Salas (1995) *[Journal of Applied Psychology]*	Comparison of three meta-analytic methods	Methodological foundation of the meta-analysis: models of meta-analysis	Exemplary studies used for illustration	Meta-analyses based on three distinct meta-analysis methods	• All three models produce similar estimates of the summary effect and the variability of the individual effect sizes • In general, the model by Hedges and Olkin leads to similar results regarding the significance of the summary effect or the analysis of moderators as the approach by Rosenthal and Rubin • The results of the technique by Hunter, Schmidt and Jackson deviate from the previous models: the significance level is more conservative • The model by Hunter, Schmidt and Jackson is more complex as it corrects for further factors like the reliability of the dependent variable • The model by Hunter, Schmidt and Jackson should be applied carefully

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Kivetz, Netzer, and Srinivasan (2004) *[Journal of Marketing Research]*	Integration of the compromise effect in formal choice models	• Standard value maximization model • Formal choice model • Contextual concavity model • Relative advantage model • Normalized contextual concavity model • Loss-aversion model	Empirical application 1: n = 1.088 travelers waiting for their flights at domestic terminals in a major airport Empirical application 2: n = 205 students at a private West Coast University	Empirical application 1: • Parthworth function preference model Empirical application 2: • Conjoint analysis parthworths	• Four distinct context-dependent choice models are tested whether they can display the compromise effect • The results and the fit of the models are better if they include the local choice context in contrast to the value maximization model • The compromise effect systematically influences the decision “in larger sets of products and attributes than has been previously shown” (Kivetz, Netzer, and Srinivasan 2004, p. 237) • Local concavity and loss aversion are similar constructs • Approaches that apply one reference point are preferred over models which use every alternative as reference point

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Lichters et al. (2016) *[Journal of Marketing Research]*	Influence of serotonin on the compromise effect	• Consumer decision making • Compromise effect	Study 1: n = 47 male students Study 2: n = 98 male students Study 3: n = 51 male students Study 4: n = 49 male students	Study 1 and 2: Fisher's exact test Study 3 Mixed-effects logit model Study 4 McNemar test	• A decreased level of brain serotonin results in choice deferral and reduces the compromise effect • The findings hold for both within- and between subjects designs • The compromise effect is not based on intuitively making decisions but on complex and intentional thinking process

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Mao (2016) *[Journal of Consumer Psychology]*	Influence of maximizing tendencies on the compromise effect	• Context effects • Compromise effect • Maximizing tendencies • Cognitive capacity • Regulatory focus	Study 1: n = 226 participants Study 2: n = 228 participants Study 3: n = 206 participants Study 4: n = 137 undergraduate students	Study 1: • Logistic model Study 2 • Correlation matrix • Regression analysis • Mediation analysis Study 3: • MANOVA • Multilevel logistic regression • Mediation analysis Study 4: • ANOVA	• Maximizers aim at maximizing their benefit regarding all attributes of a product • Satisfiers focus on a single attribute which is considered to be the most important one • Maximizers “make more compensatory tradeoffs” (Mao 2016, p. 66) and thus select more frequently compromise options than satisfiers • This result is independent of whether the measurement of the maximization is based on individual difference variable or “activated as a decision mindset” (Mao 2016, p. 66) • In case of deciding for a maximizer fictionally, participants tend to select less compromise choices

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
McShane and Böckenholt (2017) *[Journal of Consumer Research]*	Single-paper meta-analysis	Methodological foundation of the meta-analysis	Illustration of the single-paper meta-analysis in case studies	Single-paper meta-analyses in form of case-studies for illustration of the method	• A single-paper meta-analysis is an easy understandable technique for wide usage in the field of behavior research • Illustration of the single-paper analysis by application of the method to three publications in marketing journals • It bears the advantage of summarizing trials on the same phenomenon • The method is only based on fundamental data which are very frequently available in the publications

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Neumann, Böckenholt, and Sinha (2016) *[Journal of Consumer Psychology]*	Meta-analysis of extremeness aversion	• Extremeness aversion • Compromise effect	72 studies resulting in 426 effect size measures based on 142 experimental comparisons based on 22 distinct studies	Multivariate meta-analysis	• The robustness of extremeness aversion is demonstrated: the middle alternative is significantly more frequently chosen than the other alternatives • Methodological factors have a high impact on the results • Extremeness aversion is reduced if the two attributes of the alternatives shown are price and quality, if the product is a nondurable items and if "binary-trinary choice-set comparisons" (Neumann, Böckenholt, and Sinha 2016, p. 193) are applied • Extremeness aversion increases if a higher amount of dimensions of the alternatives are applied, if these attributes are non-numeric and if utilitarian products are presented • The choice of the measurement technique of the extremeness aversion influences the magnitude of the summary effect and even leads to opposite results

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Peterson, Albaum, and Beltramini (1985) *[Journal of Consumer Psychology]*	Effect sizes in experiments on consumer behavior experiments	Methodological foundation of the meta-analysis: effect sizes	118 experiments and 1036 effects (1970-1982)	Meta-analysis	• Across all included experiments, “11% of the variance in a response variable was explained or accounted for” (Peterson, Albaum, and Beltramini 1985, p. 97) • Future experiments on behavior can use this number to compare the results with • Small effect sizes are often calculated in research on behavior • Experiments on behavior rarely include all variables which have an influence • The characteristic regarding the method has an influence on this percentage • The usage of a non-student sample leads to an increase of the effect size by 42%

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Rosenthal (1978) *[Psychological Bulletin]*	Combination of probabilities across various studies	Methodological foundation of the meta-analysis	Five fictional studies	Application of the methods to the five fictional studies: • Adding logs • Adding probabilities • Adding Zs • Adding ts • Adding weighted Zs • Testing the mean p • Testing the mean Z • Counting • Blocking	Nine methods are presented which “combine the probabilities obtained from two or more independent studies” (Rosenthal 1978, p. 185)

Author/s (Year) *[Journal]*	**Research Focus**	**Theoretical Background**	**Sample**	**Method/Analysis**	**Main Findings**
Rust, Lehmann, and Farley (1990) *[Journal of Marketing Research]*	Estimation of the publication bias in meta-analysis	Methodological foundation of the meta-analysis	Application of the method to three meta-analyses	Derivation of a maximum likelihood method	• Publication bias results if studies with poor outcomes are less probable to be released in a journal • Description of a maximum likelihood method to estimate whether a publication bias exists • The approach further estimates the share of trials, which are censored, "the threshold past which censorship is avoided, and the probability of censorship if a potential observation is under the censorship threshold" (Rust, Lehmann, and Farley 1990, p. 220)

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Schmidt and Hunter (1977) *[Journal of Applied Psychology]*	• Bayesian statistical model • Validity generalization	Validity generalization	-	Bayesian approach	• Bayesian approach is preferred over maximum likelihood methods in order to assess validation • The Bayesian model also uses the outcome of previous studies to evaluate validity in contrast to the traditional techniques which only analyze validity based on the information of the current study • Presentation of a more precise term for the variance due to the size of the sample

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Shocker, Bayus, and Kim (2004) *[Journal of Marketing]*	Product complementarity and substitutes	• Economic theory • Intercategory effects	-	Literature review	• The demand regarding a product can be influenced directly or indirectly by the marketing activities regarding other products and by previous purchase decisions • Product complementarity means that the decrease in the price of the first products results in a sales growth of a second product • Substitutes are products if a price increase of the first product leads to a sales growth of the second product • Intercategory relationships can be static or dynamic • Complements can be enhanced if the introduction of a new product increases the sales of a current product in the market by "improving its functionality" (Shocker, Bayus, and Kim 2004, p. 32) • Complements can augment existing products by providing a new advantage which was not included by the former product

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Simonson (1989) *[Journal of Consumer Research]*	• Attraction effect • Compromise effect • Consumer behavior in case of uncertain preferences	• Prospect theory Attraction effect • Compromise effect	Pilot study: n = 147 college students Study 1: n = 372 students Study 2: n = 100 college students Study 3: n = 23 first-year graduate students	Pilot study: t-test Study 1-3: • Multinomial logit analyses • Multiple regression analysis • Think-aloud protocols	• If a brand becomes a compromise option, it is likely to gain market share • Both the compromise effect and the attraction effect are stronger in a situation in which it is expected that the choice is to be justified in front of others • The choice of the compromise and the dominating brands are linked to choices which are more complex

Author/s (Year) *[Journal]*	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Simonson and Tversky (1992) *[Journal of Marketing Research]*	• Context effects • Tradeoff contrast • Attraction effect • Compromise effect • Extremeness aversion	• Value maximization • Context effects • Tradeoff contrast • Extremeness aversion	• Sum of participants ranges from 100 to 220 • About two thirds: undergraduate and graduate students of business administration • One third: undergraduate and graduate students of psychology	22 experiments	• Context effects are a robust and frequent phenomenon • Asymmetric dominance effect implies that adding an inferior alternative to the choice set rises the share of the superior alternative • The compromise effect is explained by extremeness aversion • Adding an extreme alternative leads to a growth of the share of the compromise or middle option in relation to the other extreme • Polarization means that adding a middle alternative leads to a benefit of the alternative of high quality and price in relation to the alternative with low price and quality

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Tversky and Simonson (1993) *[Management Science]*	Context-dependent preferences	• Classical theory of choice • Value maximization • Trade-off contrast • Extremeness aversion	-	Development of a context-dependent model	• The context-dependent model describes the tradeoff contrast and extremeness aversion by two following elements • A weighting model includes the impact of the background context and a binary comparison model measures the influence of the local context

Author/s (Year) ***[Journal]***	Research Focus	Theoretical Background	Sample	Method/Analysis	Main Findings
Walters (1991) *[Journal of Marketing]*	Influence of retail price promotions on product substitution, complementary purchase and interstore sales displacement	Product complementarity and substitutes	Store level scanner data and company records over 26 weeks	Regression model	• Retail price promotions significantly result in effects for substitutes and complements within a store • The promotion activities in one store significantly result in a sales decline regarding complements and substitutes in the store of a competitor

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