1   A Meta-Analysis of Expressive Writing on Posttraumatic Stress, Posttraumatic Growth, and

2   Quality of Life

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Abstract

Expressive writing is beneficial for promoting both positive psychological and physical health outcomes. Unfortunately, inhibiting emotions is related to impairments in psychological and physical health. James Pennebaker and others have used expressive writing as an experimental manipulation to gauge its efficacy in treating a wide variety of physical and psychological outcomes. While many studies have been conducted that examine the efficacy of expressive writing across such outcomes, a considerable amount of these studies tend to neglect necessary considerations such as different levels of symptomatology, power, and meaningfulness of respective effect sizes. Six previous meta-analyses have been conducted that examine expressive writing's effect on psychological outcomes. However, these studies focus on the experimental versus control group effect size. Thus, our meta-analysis sought to examine the efficacy of an expressive writing task on only the experimental conditions in studies measuring posttraumatic stress, posttraumatic growth, and quality of life using random effects models. Results indicated a small overall effect size for posttraumatic stress and negligible to small effect sizes for posttraumatic growth and quality of life. However, those studies requiring a diagnosis of PTSD exhibited a medium to large effect size. Implications for future research design and interpretation of published research are discussed.

Keywords: meta-analysis, posttraumatic stress, posttraumatic grwoth, quality of life, expressive writing

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Expressive Writing

Expressive writing enhances both physical and psychological outcomes (Esterling, Antoni, Kumar, & Schneiderman, 1990; Fawzy et al., 1993; Lieberman & Goldstein, 2006; Rachman, 1980; Scheff, 1979). Pennebaker & Beall (1986) first pioneered expressive writing, which involved writing about the thoughts and feelings associated with either a "stressful or traumatic" or neutral event. Further, the original protocol included 3-5 writing sessions, each lasting 15-20 minutes in length. In their seminal study employing expressive writing methodology in comparison to a control group, Pennebaker & Beall (1986) discovered that participants assigned to write about thoughts and feelings related to the stressful/traumatic event reported a reduction in health visits at the university health center. Termed written emotional disclosure (WED), this protocol has since been employed across varying contexts. Indeed, as of 2014, the expressive writing literature recognizes over 400 studies across different populations and outcome variables (Niles, Haltom, Mulvenna, Lieberman, & Stanton, 2014). For example, WED is efficacious for physical outcomes, such as reduced doctor visits for those diagnosed with Type I diabetes (Bodor, 2002) or breast cancer (Stanton et al., 2002) and medication use in those suffering from chronic illness (i.e., asthma and rheumatoid arthritis; Smyth, Stone, Hurewitz, & Kaell, 1999). In regards to psychological outcomes, WED is efficacious for reducing depression symptoms (Gortner, Rude, & Pennebaker, 2006), posttraumatic stress (Di Blasio et al., 2015), and anxiety (Dean, Potts, & Barker, 2016). Although expressive writing is efficacious in producing favorable outcomes, avoiding thoughts or physiological sensations releveant to a given emotion is problematic across the aforementioned outcomes and contexts.

Individuals having experienced a traumatic or stressful life event are more likely to avoid thoughts and feelings about their experience compared to individuals who have not experienced such events, thereby subjecting them to potential negative outcomes (Bodor,

2002). For example, Posttraumatic Stress Disorder (PTSD) diagnostic criteria are characterized by repeated attempts to cognitively or behaviorally avoid thoughts, feelings, or places related to a given trauma (American Psychiatric Association, 2013). Trauma patients who avoid intrusive thoughts or physiological sensations experience various forms of psychopathology, such as depression and trauma-related symptoms (Marx & Sloan, 2005), anxiety (Levitt, Brown, Orsillo, & Barlow, 2004), substance use (García-Oliva & Piqueras, 2016), and social concerns (Pennebaker, 1989; Pennebaker & Beall, 1986). Although one proposed mechanism of change is the hypothesis that expressive writing interventions target the inhibition of thoughts and physiological sensations via imaginal exposure, there are other proposed mechanisms that may explain the efficacy of expressive writing (e.g., social integration model, distance perspective; Kross & Ayduk, 2011; Pennebaker & Graybeal, 2001). Although studies employing expressive writing have produced positive psychological and physical outcomes, some of these studies neglect necessary considerations, the most important of which is whether or not the effects are meaningful (Smyth, 1998). For a more in-depth review of the efficacy of WED across contexts, the authors turn to previously-conducted meta-analyses.

Meta-Analytic Techniques

Meta-analyses allow researchers the opportunity to collectively examine the efficacy of different psychological interventions/tasks on outcome variables by calculating an overall, weighted, population effect (Borenstein, Hedges, & Rothstein, 2007; Glass, 1976; Hedges, 1982). The following meta-analyses delineate the efficacy of expressive writing across outcomes and warrant individual explanation: Smyth (1998); Frisina, Borod, & Lepore (2004); Frattaroli (2006); Mogk, Otte, Reinhold-Hurley, & Kröner-Herwig (2006); Van Emmerik, Reijntjes, & Kamphuis (2013); and Reinhold, Bürkner, & Holling (2018).

Smyth (1998) conducted the seminal meta-analysis examining the efficacy of expressive writing on psychological well-being, general health, and physical functioning. They included

studies employing an expressive writing group and control group (i.e., neutral topic). In sum, 13 studies/effect sizes were included, and the authors found an overall medium effect size, $d = 0.47$, for the experimental group compared to the control group. A later meta-analysis conducted by Frisina et al. (2004) expanded these analyses and included studies with clinical samples. This meta-analysis included nine studies and found an effect size of $d = 0.19$ for physical outcomes and $d = 0.07$ for psychological outcomes. Mogk et al. (2006) conducted the next expressive writing meta-analysis to update the state of the literature regarding expressive writing. Studies employing Pennebaker's paradigm on experimental and control groups were included. Further, inclusion criteria were methodological techniques that included a four-week follow up and at least 10 participants. Thirty studies met inclusion criteria. Efficacy relating to somatic and psychological health outcomes were nonsigificant, corroborating findings from Frisina et al. (2004).

Frattaroli (2006) conducted perhaps the most notable meta-analysis to date examining the efficacy of emotional disclosure on the following constructs using only randomized and control conditions: psychological health, physiological functioning, reported health, health behaviors, and general functioning/life outcomes. Additionally, this meta-analysis was the first to employ random effects models, which estimate the mean of a proposed distribution of population effect sizes. Prior meta-analyses employed fixed effects models, which assume that all studies assess the same "true" population effect size. This assumption may be untenable across different populations (Borenstein et al., 2007). They included a wide range of studies, $N = 146$. Individual studies were again collapsed into one publication effect size, although these effects were also examined separately by health outcome. Overall, Frattaroli (2006) found $d = 0.16$ for all outcomes combined, which would be considered small. Additionally, they examined potential moderators and found larger effect sizes for the following samples: those with physical health problems, those with a history of having experienced traumatic or stressful events, samples not including college students, samples where expressive writing tasks were conducted at home and in private settings, paid

116 participants, more male participants, and fewer participants (see Frattaroli, 2006 for a

117 complete list of moderators). A recent analysis conducted by Van Emmerik et al. (2013)

118 employing Pennebaker's paradigm included six eligible studies that compared treatment to

119 control groups. In regards to inclusion criteria, they included studies where participants had

120 a diagnosis of Acute Stress Disorder or PTSD. They found that those who participated in

121 the expressive writing group experienced short-term reductions in PTS and comorbid

122 depressive symptoms, combined $d = 0.81$.

123 The most recently published meta-analysis was conducted by Reinhold et al. (2018)

124 and examined the efficacy of expressive writing on depression by randomizing participants to

125 conditions (expressive writing vs. control). They included 39 randomized controlled trials

126 and excluded individuals with diagnoses of PTSD. This study did not support utilizing

127 expressive writing for depression outcome measures for the specified sample, $d = -0.09$.

128 Further, they found that expressive writing did not yield any type of long-term effect on

129 depression outcomes. In sum, previous meta-analyses exhibit small to medium effect sizes for

130 a brief, innocuous intervention and therefore individuals having experienced trauma have

131 been shown to benefit from such interventions.

Posttraumatic Stress

132

133 Posttraumatic Stress Disorder is a condition involving re-experiencing thoughts or

134 events after a trauma. This generates a context where individuals are prone to affect-related

135 deficiencies and maladaptive behaviors (American Psychiatric Association, 2013). DSM-5

136 criteria are based on 20 symptoms structured into four different subsets in those having

137 experienced a traumatic event. These subsets are as follows: intrusion symptoms (i.e.,

138 re-experiencing), avoidance, negative alterations in cognition and mood, and increased

139 arousal (Crespo & Gomez, 2016). While the renewed DSM-5 criteria are now increasingly

140 utilized via structured clinical interviews, the current meta-analysis considers studies using

141 DSM-IV criteria. DSM-IV criteria are similar and include the following: exposure to a

traumatic event, intrusion, avoidance, and increased arousal (American Psychiatric Association, 2013). The studies employed in the current meta-analysis are divided according to these subsets (arousal, intrusion, and avoidance). Posttraumatic Stress Disorder affects a wide variety of populations, including sexual assault survivors (Klump, 2008), Iraq and Afghanistan war veterans (Gentes et al., 2014), and those exposed to natural disasters (Wang et al., 2000).

Research conducted on the efficacy of expressive writing on PTSD symptoms presents intriguing results. Sloan, Marx, Epstein, & Lexington (2007) examined individuals with at least moderate PTSD symptom severity and found that individuals assigned to an expressive writing condition reported fewer PTSD and depression symptoms during follow up. Sloan, Marx, & Greenberg (2011) found that PTSD symptoms decreased after a written emotional disclosure task, although this decrease was not significantly different than a control group change. Di Blasio et al. (2015) recruited women who had just given birth and assessed them a few days after experiencing childbirth along with a three-month follow-up. Results showed that women who had participated in the expressive writing task had lower depression and posttraumatic stress symptoms than the group assigned to a neutral writing condition. Additionally, regression models showed that expressive writing was significantly linked to a reduction of PTSD symptoms across different dimensional levels of symptom severity. Only 20 of the 113 women recruited for this study qualified for a diagnosis of PTSD, but those who reported mild symptomatology responded better to the task than those meeting criteria for PTSD. This limitation suggests that those with moderate distress could perhaps benefit more from an expressive writing task than those diagnosed with or meeting the qualifications for PTSD. It may also explain the differences in results in comparing to Sloan et al. (2011), as they found that those with a clinical diagnosis of PTSD did not respond to an emotional disclosure writing task. Perhaps it may be more advantageous to examine effect sizes separately for diagnoses of PTSD and subclinical symptoms.

Sloan, Marx, Bovin, Feinstein, & Gallagher (2012) adapted a writing protocol to focus

169 primarily on the emotions, meaning, and "hot spots" associated with the trauma. They

170 referred to this procedure as the written exposure therapy (WET) protocol, distinguishable

171 from the paradigm adapted by Pennebaker & Beall (1986). In their seminal study examining

172 the efficacy of WET for motor-vehicle accident related PTSD, they found that those in the

173 WET condition experienced significant reductions in PTSD symptoms throughout the course

174 of the study. Since then, a small number of other studies employing the WET procedure

175 have been employed in those with PTSD. Indeed, Sloan, Marx, Lee, & Resick (2018) found

176 that WET was noninferior (i.e., just as effective) as Cognitive Processing Therapy,

177 considered first-line treatment for PTSD. Further, treatment gains were maintained at 24

178 and 36-week follow up. While studies employing this protocol will be included in the current

179 review, the newness of this protocol does not allow exclusive examination using

180 meta-analytic techniques.

Posttraumatic Growth

182 While the literature mostly discusses potentially harmful outcomes to traumatic events

183 such as emotional distress, traumatic events also provide opportunities for personal growth

184 (Aslam & Kamal, 2013). Traumatic events, either natural or human-inflicted, may lead to

185 positive outcomes by allowing the individual to take a different perspective (Cobb, Tedeschi,

186 Calhoun, & Cann, 2006; Taku, Calhoun, Cann, & Tedeschi, 2008). The relationship between

187 positive growth after a traumatic event and symptom reduction is unclear, as it is a complex

188 process. Thus, it is necessary to examine how expressive writing might influence each

189 variable separately, which is one of the key goals of this meta-analysis (Slavin-Spenny, Cohen,

190 Oberleitner, & Lumley, 2011). Models receiving empirical support within the last decade

191 suggest that traumatic events offer opportunities for both negative and positive experiences

192 (Tedeschi & Calhoun, 1995; Weiss, 2002). Posttraumatic Growth (PTG) is a positive

193 experience after a traumatic event (Aslam & Kamal, 2013; Yilmaz & Zara, 2016).

194 Specifically, PTG is classified as broad cognitive benefits that are seen after a traumatic

experience. These benefits can be categorized into building closer relationships, examining new possibilities, appreciating life, recognizing personal strengths, and undergoing spiritual changes (Dursun, Steger, Bentele, & Schulenberg, 2016; Tedeschi & Calhoun, 2004). (???) further suggest that traumatic experiences disrupt one's core beliefs, thereby leading to emotional or cognitive difficulties (e.g., rumination). Given the wide range hypotheses on the underlying mechanisms (i.e., cognitive and emotional), perhaps expressive writing serves as a way for individuals to process the emotions related to the trauma via higher-order cognitive processes or imaginal exposure. For this reason, the current meta-analysis sought to test whether expressive writing has any effect on PTG.

PTG is associated with a variety of desired outcomes (Dursun et al., 2016). PTG has been studied in those experiencing natural disasters, war, and other harms such as sexual assault. Finally, PTG has been studied in those experiencing medical diagnoses such as different types of cancer and diseases. Although the relationship between PTG and symptom reduction is not yet fully understood, perhaps expressive writing allows the individual to fully comprehend the event. Pennebaker & Graybeal (2001) speculated that expressive writing allows an individual to feel more connected with his or her surroundings. Although this speculation does not directly explain positive outcomes after an expressive writing task, perhaps individuals gain a better appreciation for life after gaining a better sense of connectedness with that individual's surroundings. One might expect effect sizes to be larger for those studies requiring a diagnosis of PTSD, as such growth may not be possible in those with subclinical symptomatology.

Quality of Life

Quality of Life (QOL), according to Theofilou (2013) is an evaluation of the "goodness" that an individual experiences, separated into domains of reactions to life events, disposition, life fulfillment, and satisfaction with life experiences. More generally, QOL refers to an individual's attitude towards the target life situation (Costanza et al., 2007), delineated into

objective and subjective components. Objectively, QOL refers to components outside of an individual and measurable by others, while subjective QOL is an individual's assessment of his or her own experiences (Costanza et al., 2007). The current meta-analysis will focus solely on the subjective components of QOL, as it is obtainable through questionnaires. Similar to the conceptualization of PTG, Pennebaker & Graybeal (2001) proposed that engaging in expressive writing results in connectedness to the environment. Further, they explain that expressive writing allows people to see things in a different way and better understand themselves. By understanding a traumatic or stressful event, one is said to see things differently and perhaps look at the situation with a more positive mindset. The changes that occur after expressive writing may also allow one to find meaning in the traumatic event, thereby increasing the QOL of that individual (Frankl, 1959). Higher QOL may be considered a type of PTG, which is why the current meta-analysis sought to examine the efficacy of studies utilizing expressive writing to improve QOL and PTG in the same study.

Current Meta-Analysis

The purpose of the current meta-analysis is to examine studies employing expressive writing procedures using Pennebaker's paradigm (WED) and the more recent WET protocol on variables relevant to the field of positive psychology (PTG and QOL) and PTS, with effect sizes separated by the paper's indication of PTSD diagnosis when sample sizes are large enough. Based on recently published literature regarding efficacy of expressive writing for different levels of PTSD symptoms, this diagnostic marker is an important facet to consider (Di Blasio et al., 2015; Reinhold et al., 2018; Sloan et al., 2011). No review has examined the efficacy of expressive writing on PTS separated by diagnosis. Additionally, no meta-analysis has been conducted that examines the efficacy of expressive writing on positive outcome variables such as PTG and QOL, in line with the fields of positive psychology and psychology more generally. The meta-analyses described sequentially above also focused on experimental versus control group effect sizes or *p*-values, rather than

emphasizing change for the expressive writing group. This focus is likely because of the analyses provided in these publications, especially when using randomized controlled trial research designs. While this design is the gold standard for medicine, the current meta-analysis sought to examine the magnitude of change for participants who experienced an expressive writing task. For example, a comparison group may increase their quality of life scores by two points in a controlled study, while the experimental group increases their quality of life scores by four points; thus, creating a significant difference in change between the two groups. This information is valuable, but it does not tell the reader the magnitude of the change for the writing group, wherein four points might only be a small effect when examined within the group who received the writing task.

This analysis will also focus on changes across time for groups who received the expressive writing task to determine what size of effects one might expect given a specific measurement schedule (i.e., one to three months, three months to six months, etc.). Indeed, Sloan et al. (2018) discovered long-term gains for those in the WET condition. This analysis should present researchers with a renewed examination of the efficacy of expressive writing on the aforementioned variables using newer meta-analytic techniques. Newer methods of meta-analysis, including *p*-curve (Simonsohn, Nelson, & Simmons, 2014; Simonsohn, Simmons, & Nelson, 2015), *p*-uniform (Van Aert, Wicherts, & Van Assen, 2016), PET-PEESE (Stanley & Doucouliagos, 2014), selection models (Vevea & Hedges, 1995), and trim and fill methods (Carter & McCullough, 2014) allow for better estimation of meta-analytic effect sizes. These analyses would be best performed by examining each potential effect separately, rather than averaging effects of each publication into one study effect size (a common trend in the previously mentioned meta-analysis). In addition to an estimate of overall effect sizes using updated techniques, the current meta-analysis estimates power for effects on writing groups, as research has shown a consistent under powering of psychological studies, combined with a misunderstanding of the sample size needed for adequately powering one's work (Bakker, Hartgerink, Wicherts, & Van Der Maas, 2016).

²⁷⁴ **Method**

²⁷⁵ **Data Collection**

²⁷⁶   Studies were collected through online databases, such as PsycINFO and Google
²⁷⁷ Scholar, using the following search terms and their combinations: *Posttraumatic Growth,*
²⁷⁸ *PTG, Quality of Life, QOL, Posttraumatic Stress, PTS, Expressive Writing, Emotional*
²⁷⁹ *Disclosure, Written Emotional Disclosure (WED), Written Exposure Therapy (WET).*
²⁸⁰ Within these articles, the change in outcome variables (PTS, PTG, QOL) from pre- to
²⁸¹ post-test was the dependent variable of interest. Generally, groups were separated into an
²⁸² experimental and control group and then examined at different time points. For purposes of
²⁸³ this meta-analysis, only participants assigned to the experimental condition were examined
²⁸⁴ due to having received the expressive writing task. If a study included multiple assessment
²⁸⁵ time points, then these measurements were examined sequentially (i.e., time 1 to time 2,
²⁸⁶ time 2 to time 3) to determine change across time for the dependent variable. The time
²⁸⁷ variable was coded as the number of months between two comparison points. For example, if
²⁸⁸ a study included three time points (baseline, one month, three months), two pairwise effect
²⁸⁹ sizes would be calculated (baseline to one month, one month to three months) and the time
²⁹⁰ variable would be one month for comparison one and two months for comparison two. If a
²⁹¹ study included multiple experimental conditions (i.e., different instructions or forms for
²⁹² WED), all experimental conditions were included in the dataset.

²⁹³   264 citations focusing on PTS, PTG, and QOL were identified through the literature
²⁹⁴ search and previous meta-analyses. Citations for PTS were separated by diagnostic criteria
²⁹⁵ (intrusions, avoidance, and hyperarousal), where possible. After screening these studies, 53
²⁹⁶ articles were retained for containing the appropriate information for this meta-analysis. This
²⁹⁷ manuscript was written with *papaja* in *R* (Aust & Barth, 2017) with the analyses inline with
²⁹⁸ the text. The complete set of data, excluded article list with reasoning, and other relevant
²⁹⁹ information can be found at: https://osf.io/4mjqt. Generally, studies were included if they
³⁰⁰ utilized WED or WET, included relevant numbers to compute an effect size, and included

the relevant outcome variables. The questionnaire for each relevant outcome variable is coded in the online data provided on the Open Science Framework (link above). These varied across study, however, the nature of Cohen's d allows for different Likert-type scales, as it takes into consideration the study standard deviation in the denominator to create standardized scores for comparison across studies.

After having two reviewers independently code articles, 223 effect sizes were calculated. On average, each study represented $M = 4.21$, $SD = 3.31$ effects, ranging from 1 to 16 effects. 163 effects were calculated for PTS, 21 for PTG, and 37 for QOL. Studies were coded for PTSD diagnosis as no (not mentioned or not included), mixed (mentioned number of participants but all included), and yes (included as criteria). After examining the number of effects in each of these categories for each variable, only the PTS results will be split by PTSD diagnosis with 16 no mention, 16 in the mixed category, and 86 yeses.

Calculations for Effect Size, Variance, and Confidence Intervals

For our purposes, we used Cohen's (1988) standards for nomenclature for small (0.20), medium (0.50), and large (0.80) d values, although it is important to note that Cohen himself suggested that these values should be based on the area of study. Generally, however, these effect size criteria are used within the social sciences. Each study implemented a pre-test to post-test style repeated measures design, usually with paired t-tests, ANOVA, or regression analyses. The means, standard deviations, and N values were collected from each study. In general, Cohen's d values were calculated using the following formula for paired t using means and standard deviations for each time point:

$$d_{av} = \frac{M_1 - M_2}{\frac{SD_1 + SD_2}{2}}$$

This equation is described in detail in Cumming (2012) as an alternative to the traditional calculation of d for paired samples t, wherein the denominator is the standard deviation of the difference scores:

$$d_z = \frac{M_1 - M_2}{SD_{diff}}$$

This equation for d_{av} not only allows for calculations from published articles that do not include SD_{diff} (i.e., most articles included), but also has been shown to be less upwardly biased than d_z. Alternative formulas include controlling for r between paired levels, as described in Lakens (2013); however, these values were not available in the selected articles, and Lakens also recommends d_{av} as an effect size for paired designs. When only mean differences and standard deviation of the difference scores were available, the second equation for d_z was used.

We planned to use traditional and newer methods of meta-analysis, following guidelines from Cooper, Hedges, & Valentine (2009) and Borenstein et al. (2007), as well as Van Aert et al. (2016). Sampling variance of the effect sizes were estimated using the *escalc()* function from the *metafor* package in R (Viechtbauer, 2010). The variance formula was originally published in Morris & DeShon (2002) and is shown below:

$$v = \frac{1}{n}\left(\frac{n-1}{n-3}\right)(1 + n * d^2) - \frac{d^2}{[c(n-1)]^2}$$

In this formula, n is the number of paired observations, d is the calculated effect size, and c is a correction factor, wherein *df* are $n - 1$ (Hedges, 1982):

$$c = 1 - \frac{3}{4 * df - 1}$$

We used the *metagen()* function in the *metafor* package to calculate both fixed and random effects models, which uses standard error of the effect to calculate overall estimates of an effect and their confidence intervals. Thus, we took the square root of the variance estimate for standard error. Given these calculations, the goal of this analysis was to calculate a combined effect size, along with a confidence interval for study planning and an assessment of the literature. A fixed effects model requires the assumption that there is a true population effect size across all studies. By including multiple measures of psychological

outcomes, this assumption may be tenuous, and therefore, a random effects model was also

calculated. In random effects models, the true effect is assumed to vary across studies

(Borenstein et al., 2007). For a fixed effects model, the effect sizes are weighted by their

inverse variance (v; Sánchez-Meca & Marín-Martínez, 2008), which is calculated

automatically in *metafor* by:

$$w_i^{FE} = \frac{1}{v}$$

The advantage to this procedure is that analyses are weighted by their precision, that

is, that studies with more information (often, larger samples), are given larger weights in the

overall estimated effect size (Borenstein et al., 2007). Random effects models are also

weighted by inverse variance, with an additional correction for variance between studies, τ_{DL}^2,

as described by DerSimonian & Laird (1986):

$$w_i^{RE} = \frac{1}{v + \tau_{DL}^2}$$

Confidence intervals were calculated in two ways for this study. Cumming (2012),

Kelley (2007), and Smithson (2001) have shown that the distribution of d values are

non-normal, and thus, CIs should be estimated using the non-centrality parameter and a

non-normal distribution. These values were calculated using the functions in the *MOTE*

library which iteratively estimates the appropriate non-centrality parameter and converts

back to d values (i.e., non-centrality parameter divided by the square root of n; Buchanan,

Valentine, & Scofield, 2017; Smithson, 2001, 2003). However, the *metafor* package in R uses

central distributions to estimate CIs for each study and overall effect sizes. Therefore, we

present both sets of values for the interested reader, as meta-analytic procedures have not

implemented non-central distributions of effect sizes.

Additional Meta-Analytic Techniques

367   **p-Curve and p-Uniform.**   We used *p*-curve.com to conduct a *p*-curve analysis

368 (Simonsohn et al., 2014). The purpose of this type of analysis is to detect true effects.

369 Specifically, *p*-curve is used to reveal possible *p*-hacking in published literature in order to

370 decipher whether or not a true effect exists. Broadly, *p*-hacking occurs when researchers use

371 questionable research practices to create significant results by manipulating dependent

372 variables or covariates. Additionally, authors may add participants if the initial findings are

373 not significant (Bruns & Ioannidis, 2016). Researchers may also decide to exclude

374 participants for final analyses if that exclusion leads to a significant difference (John,

375 Loewenstein, & Prelec, 2012). Thus, it is necessary to distinguish between true and false

376 effects in order to effectively interpret effect sizes corresponding to those *p*-values. *p*-curve

377 accomplishes this task by examining the distributions of the published *p*-values. If an effect

378 exists, or rather the results should be interpreted as presented, the distribution of *p*-values

379 will be positively skewed (Simonsohn et al., 2014). If, however, no effect exists, then the

380 distribution of *p*-values will be flat. *p*-curve analyses ultimately provide evidence of

381 *p*-hacking in groups of studies and has become an important tool for interpreting

382 meta-analyses. In order to accurately estimate effect sizes because of scrutiny associated

383 with effect size estimation of *p*-curve, we also conducted *p*-uniform. *p*-uniform analyses, too,

384 are interpreted by examining the distribution of *p*-values in a set of studies (Van Aert et al.,

385 2016). However, it is assumed that the population effect size equals the effect size from the

386 dataset. Because of this assumption, the population effect size is referred to as uniform. This

387 analysis also examines for publication bias and presents the researcher with a corrected effect

388 size. Publication bias occurs when only select studies are published, usually only significant

389 studies, although many factors can bias a study's publication (McShane, Böckenholt, &

390 Hansen, 2016). *p*-uniform was calculated from code provided by Van Aert (2017) on GitHub.

391   **PET-PEESE.**   Originally, meta-analyses relied on the calculation of Egger's

392 regression test which examined the relationship of the standard error (predictor) to the effect

393 size estimates (criterion). In this regression, the intercept values were used to determine if

effect size measures were different than zero, by providing a meta-analytic estimate (Egger, Davey Smith, Schneider, & Minder, 1997; Stanley, 2005). PET-PEESE analyses examine for publication bias by adapting parts from Egger's traditional regression tests: PET (Precision Effect Test) and PEESE (Precision Effect Estimate with Standard Error, Carter & McCullough, 2014). PET is a more reliable test of publication bias with effect size estimates of zero, $b_0 = 0$, while PEESE is more accurate with non-zero effect size estimates, $b_0 \neq 0$ (Stanley & Doucouliagos, 2014). PET-PEESE was calculated using Hilgard's (2016) code provided on GitHub.

Selection Models.   Selection model analyses provide the researcher with a test of publication bias and effect size estimates using maximum likelihood estimation (Vevea & Hedges, 1995; Vevea & Woods, 2005). Using selection models, researchers are able to discover effect size estimates as well as evidence of publication bias (McShane et al., 2016) by using a mixed general linear model to estimate these values. Selection models were calculated with the *weightr* package in *R* (Coburn & Vevea, 2017).

Trim and Fill.   Trim and Fill analyses, in contrast to PET-PEESE, regress standard error (criterion) and effect size estimates (predictor). Specifically, the purpose of Trim and Fill techniques is to examine whether or not publication bias may influence the regression equation (Carter & McCullough, 2014). Effect sizes and standard error terms are graphically displayed on x and y-axes, respectively, in a funnel plot. If this graphical representation indicates asymmetry, considered a gap of missing data points in the lower center area of the plot, the study set can be assumed to have studies that are both non-significant and small in sample size (Van Assen, Van Aert, & Wicherts, 2015). This funnel is then trimmed until symmetry is achieved. Missing studies from the symmetrical graph are imputed (filled) while maintaining the given symmetry (Duval & Tweedie, 2000). The meta-analytic effect size is then estimated from the trimmed and filled funnel plot. Trim and fill analyses, as well as funnel plots included below, were calculated with the *metafor* package.

<div align="center">

Results

</div>

Posttraumatic Stress

Overall Effect Size. As described above, both fixed effects and random effects models with centralized confidence intervals are presented in Table 1. Studies were examined for potential outliers using the *metafor* package in *R*. This package calculates traditional regression influence values, such as Cook's and hat values (Cohen, 1988). These values indicate change in overall meta-analytic model with and without the effect; thus, determining their impact on the pooled effect size (Viechtbauer, 2010). Because published studies likely represent the range of the sampling distribution of effect sizes, we included the analyses with and without outliers to present evidence for both paths a researcher might take when examining an overall effect.

2 outliers were detected with this procedure, all showing very large effect sizes, average $d = 2.81$. The fixed and random effects estimates without these points are also included in Table 1. Figures 1, 2, 3, and 4 portray the effect sizes for PTS studies, separated by intrusions, avoidance, hyperarousal, and total scores for easier viewing (i.e., over 100+ effect sizes did not fit easily on one combined graph). Although these categories are not reflective of updated DSM-5 criteria, researchers have not yet conducted enough studies using expressive writing on PTS with updated PTSD criteria to warrant a meta-analysis. Name acronym coding can be found in the data online. This forest plot includes the non-centralized confidence interval calculated from the *MOTE* library (Buchanan et al., 2017). Shape size indicates study weight, and these values were taken from the overall random effects meta-analysis and normalized by dividing by the mean weight. The dashed lines indicate the average non-weighted lower and upper confidence interval limit for the non-centralized estimates. Overall, PTS studies include a small effect size that appears to be significantly greater than zero across all estimate types (fixed, random, with or without outliers).

We further calculated the overall effect sizes by PTSD diagnosis category using a random effects model. Studies only including individuals with a diagnosis of PTSD exhibited

447 a medium effect size (before and after outlier exclusion): with outliers $d = 0.64$ [0.48, 0.79];

448 without outliers $d = 0.55$ [0.41, 0.69], while studies not requiring (or listing) a PTSD

449 diagnosis showed a small to medium effect size: $d = 0.32$ [0.24, 0.40]. Similarly, the mixed

450 category showed a small to medium effect size : $d = 0.35$ [0.16, 0.54]. Complete estimates of

451 all the following analyses split by diagnosis are included online at https://osf.io/4mjqt/, and

452 their pattern of results is similar to the overall pattern here.

453   **Homogeneity.**   A prerequisite for newer meta-analytic techniques includes the

454 assessment of homogeneity of the effects (Van Aert et al., 2016). Using the *metafor* package

455 in R, we calculated the Q-statistic and the I^2 index (Cochran, 1954; Huedo-Medina,

456 Sánchez-Meca, Marín-Martínez, & Botella, 2006). Significant values imply inconsistencies

457 across the variable or variables of interest and are represented by Q. In contrast, I^2 indicates

458 the percentage of heterogeneity along with a 95% CI. Both can, however, be biased with a

459 small number of experiments included for analyses (Higgins, Thompson, Deeks, & Altman,

460 2003; Huedo-Medina et al., 2006). Thus, we sought to calculate an overall level of

461 heterogeneity after examining each variable separately before and after excluding outliers.

462 For PTS studies including outliers, we found significant heterogeneity, $Q(162) = 776.74$, $p <$

463 .001 and $I^2 = 79.1$, 95% CI[75.9 - 81.9]. These values were reduced slightly with the

464 exclusion of outliers, $Q(160) = 677.98$, $p < .001$ and $I^2 = 76.4$, 95% CI[72.6 - 79.7]. While

465 heterogeneity is present for PTS, some researchers indicate that heterogeneity is inevitable

466 (**???**), especially in analyses including a wide range of studies.

467   **Power.**   Power was calculated in two different ways using the *pwr* package in R

468 (Champely, 2016). *Post hoc* power was first calculated using sample size and effect size

469 statistics from each individual study. Additionally, we calculated power using the study

470 sample size and estimated overall effect size from the random effects model with and without

471 outliers, as explained by Francis (2012) and Francis (2014). The first estimate indicates the

472 likelihood of finding an effect from our sample statistics, while the second indicates the

473 likelihood of finding the true population effect size. If each study had been conducted on

only the change in the experimental group, 46.6% of studies would have been considered

significant at $\alpha < .05$. The average power of these studies based on their original study

characteristics was .48 ($SD = .36$). Power for the random-effects meta-analytic effect size

with outliers was .52 ($SD = .25$) and without outliers was .49 ($SD = .25$). Therefore, power

consistently was around 40-50% for studies examining PTS, regardless of outlier effects. In

these studies, only 28.8% achieved recommended 80% power for their found effect size, a

smaller 24.5% for the random-effect outlier effect size, and even smaller 20.2% for power

calculations on the random-effect size without the outliers. Overall, most of the studies in

the current meta-analysis do not achieve recommended .80 power for detecting true effects,

which may warrant caution in interpreting the overall effects presented.

Other Meta-Analytic Estimates. As noted in Van Aert et al. (2016), *p*-curve

and *p*-uniform analyses are upwardly biased when heterogeneity is high. Therefore, we use

caution when interpreting these analyses on PTS outcomes. As seen in Table 1, the

estimates for *p*-uniform were higher than other techniques, likely because of the focus on

significant *p*-values and the great degree of heterogeneity described earlier. *P*-curve pictures

can be found at https://osf.io/4mjqt/ online, and this analysis indicated evidentiary value at

$p < .001$. Additionally, the *p*-uniform analysis indicated that there was likely no publication

bias present, $Z = -5.71$, $p = 1.000$. When examining the PET analysis, we found that the

intercept was significant, which indicated that PEESE was likely a better estimator of the

meta-analytic effect size. PEESE estimates were lower than the original meta-analytic

estimate, but confidence intervals indicated that the effect is small to medium, and still

larger than zero. Selection models indicated a larger effect size, especially with the

random-effects models, and these effects were influenced by the outliers found in the

published studies. Trim and fill models are shown in Table 1, and figures are included online.

Nineteen missing studies were imputed for both models with and without outliers. Across all

these effect size estimates, we found that expressive writing was likely to decrease PTS

symptoms in a small to moderate way. The correlation of effect size with time between

measurement times was $r = -.01$, 95% CI $[-.17, .14]$, $t(161) = -0.15$, $p = .879$, and $r = -.08$, 95% CI $[-.23, .08]$, $t(159) = -1.00$, $p = .320$ without outliers. This result indicated that the effect of expressive writing slightly decreased across time. Together, these results suggest no evidence of publication bias, as well as support our conclusion of a small to medium effect size for the efficacy of expressive writing on PTS.

Postraumatic Growth

Overall Effect Size.   Both fixed and random effects models with centralized confidence intervals for PTG are presented in Table 2. When examining expressive writing on PTG, no outliers were detected. Fixed and random effects estimates are included in Table 2, while Figure 5 shows effect sizes for PTG studies where shape size indicates the normalized weight of the study. Dashed lines indicate non-weighted lower and upper confidence intervals for non-centralized estimates. Overall, PTG studies indicated a negligible to small effect size across both random and fixed effects models, and the non-centralized confidence intervals indicated an effect that crossed zero.

Homogeneity.   Using the *metafor* package in R, we calculated both a Q statistic and I^2 index. Since PTG studied did not contain any outliers, we did not calculate two separate analyses to examine heterogeneity both with and without outliers. We did not find significant heterogeneity across PTG studies, $Q(20) = 14.18$, $p = .821$ and $I^2 = 0.0$, 95% CI$[0.0 - 25.3]$. While heterogeneity is typically expected, these results suggest that individuals can be confident in the effect size interpretation for PTG. ### Power

First, we calculated *post hoc* power using both sample and effect size statistics from individual studies. Individual studies examining change in experimental groups showed that 9.5% of studies would have been considered significant at $\alpha < .05$. Average power of PTG studies was .15 ($SD = .16$). 0.0% achieved recommended 80% power for their found effect size. Additionally, we calculated power using study sample size and estimated effect size from our random effects model. Power for the true effect size was .08 ($SD = .02$). Again,

0.0% achieved recommended 80% power. These power results suggest that studies examining the efficacy of expressive writing on PTG were not adequately powered to detect effects. Therefore, the effect size derived from these studies may not adequately represent the relationship between expressive writing and PTG.

Other Meta-Analytic Estimates.   Due to no heterogeneity across PTG studies, we can use both p-curve and p-uniform analyses with more confidence. A pictorial representation of p-curve can be found at https://osf.io/4mjqt/. This analysis did not indicate evidentiary value, $p = .75$, as only two of the results would be considered significant at $\alpha < .05$. p-uniform estimates are presented in Table 2. Specifically, these analyses indicated that there was no publication bias present, $Z = 0.70$, $p = .243$. The p-uniform estimates of the effect size for PTG were negative, in contrast to the fixed and random effects overall model. The confidence interval for this analysis indicates a wide range of possible effects. In examining PET-PEESE analyses, we did not find a significant intercept, indicating that PET is most likely a better effect size estimator. PET analyses indicated that the effect size is negligible to small, with our confidence interval crossing zero. These results corroborated our original effect size calculations. Selection models indicated negligible to small effect sizes, again wherein the confidence interval includes zero effect. Trim and fill models are shown in Table 2, and figures are included online. Zero studies were imputed for our model, and thus, the effect size estimate is the same as the overall model. Across techniques, we found that expressive writing has little to no effect on PTG. The correlation of effect size across measurement times in PTG studies at subsequent time points was $r = .09$, 95% CI $[-.36, .50]$, $t(19) = 0.38$, $p = .707$, and no change over time was found. In sum, no publication bias was present, which is desired. However, the analyses suggest a wide range of possible effects for the efficacy of expressive writing on PTG.

Quality of Life

₅₅₂ **Overall Effect Size.** Finally, for QOL, both fixed and random effects models with

₅₅₃ centralized confidence intervals are presented in Table 3. Two outliers were detected with

₅₅₄ this procedure, average $d = $ -0.07. While the average effect of these outliers indicates a small

₅₅₅ number, it is important to note that these two outliers were the largest positive and negative

₅₅₆ effects found from the Possemato, Ouimette, & Geller (2010) study. Fixed and random

₅₅₇ effects estimates without these points are also included in Table 3, while Figure 6 shows

₅₅₈ effect sizes for QOL studies. Overall, QOL studies indicated a negligible to small effect that

₅₅₉ showed a non-significant decrease in quality of life as a result of expressive writing.

₅₆₀ **Homogeneity.** For QOL studies including outliers, we found significant

₅₆₁ heterogeneity from our random effects model, $Q(36) = 200.09$, $p < .001$ and $I^2 = 82.0$, 95%

₅₆₂ CI[75.9 - 86.5]. After excluding outliers, our random effects model still indicated

₅₆₃ heterogeneity, $Q(34) = 93.18$, $p < .001$ and $I^2 = 63.5$, 95% CI[47.6 - 74.6]. As mentioned,

₅₆₄ heterogeneity in meta-analyses is expected (**???**) especially when utilizing studies across

₅₆₅ diverse samples and methodologies.

₅₆₆ **Power.** In conducting *post hoc* power using sample and effect size statistics from

₅₆₇ individual studies, we found that 21.6% of studies would have been considered significant at

₅₆₈ $\alpha < .05$. Average power based on actual study characteristics was .33 ($SD = .32$). Power for

₅₆₉ the random effects meta-analytic effect size with outliers was .05 ($SD = .00$) and without

₅₇₀ outliers was .05 ($SD = .00$). Unfortunately, power was around 5% for both random effects

₅₇₁ models with and without outliers. In these studies, 18.9% achieved adequate power of 80%

₅₇₂ on their found effect size, while 0.0% achieved 80% power for our random effects model with

₅₇₃ outliers. Finally, without outliers, 0.0% achieved 80% power. Similar to PTG, very few

₅₇₄ studies were adequately powered at .80 to detect effects, warranting caution in the

₅₇₅ interpretation of the aforementioned effect sizes.

₅₇₆ **Other Meta-Analytic Estimates.** We exert caution in interpreting *p*-curve and

₅₇₇ *p*-uniform analyses on QOL outcomes with and without outliers due to heterogeneity. As

₅₇₈ seen in Table 1, *p*-uniform estimates were stronger and positive than other techniques

because of the high degree of heterogeneity recently described. p-curve pictures can be found

at the following OSF Link: https://osf.io/4mjqt. Eight studies were significant at $\alpha < .05$,

and the studies indicated evidentiary value, $p = .004$. p-uniform analyses did not indicate

publication bias, $Z = $ -2.75, $p = .997$. In PET-PEESE analyses, we found that the intercept

was not significant, and therefore, PET was a better estimator of the meta-analytic effect.

Table 1 indicates that both of these analyses estimate the effect size around zero, with a

confidence interval that includes zero. Selection models correspondingly show small effects

crossing zero, except for random effects models with outliers, that appear to be heavily

influenced by the outliers. Trim and fill models are shown in Table 3, and figures are

included online. No studies were imputed for these analyses, and therefore, the effect size

estimates match the original meta-analysis. Overall, these results appear to point to no

effects, ranging across zero with several negative estimates. Interestingly, the correlation of

effect sizes across measurement times with outliers was $r = -.37$, 95% CI $[-.62, -.05]$,

$t(35) = -2.33$, $p = .026$ and $r = -.64$, 95% CI $[-.80, -.39]$, $t(33) = -4.75$, $p < .001$ without

outliers. The effect of expressive writing appears to be positive at short time intervals and

decreases into negative effects at longer time intervals. Together, these analyses indicated no

publication bias and support a null effect. Although, these results should be taken into

consideration within the context of low power.

Discussion

In examining pre- to post-test comparisons across each variable separately, we found

that PTS studies indicated a small effect size across all meta-analytic estimates. This

suggests that a brief, easy-to-administer intervention can produce positive outcomes. As

mentioned, PTS is operationally defined as re-experiencing thoughts and feelings associated

with a traumatic event and subsequently seeking to avoid these thoughts and feelings.

DSM-IV criteria for a PTSD diagnosis include exposure to a traumatic event, intrusions,

avoidance, and hyperarousal. Interestingly, those studies requiring a diagnosis of PTSD for

inclusion resulted in a medium effect size, while those studies not requiring a PTSD diagnosis resulted in a small to medium effect size. These results suggest that those with clinical symptoms of PTSD may benefit more from expressive writing interventions. Further, these results are in contrast to recently-conducted studies, which suggest that those with subclinical symptoms benefit more from expressive writing tasks (Di Blasio et al., 2015; Sloan et al., 2011). While both conditions exhibited effects, the difference in magnitude is difficult to pinpoint. One possible explanation for these alternative findings is the lack of adequately powered studies in the PTS condition, which may lead to a misrepresentation of the true population effect. Although, Sloan et al. (2018) recently conducted a noninferiority trial comparing WET, an evidence-based protocol (5 sessions), to Cognitive Processing Therapy (12 sessions) and found WET to be noninferior. Their protocol included a treatment rationale as well as psychoeducation for PTSD prior to commencing treatment. In order to participate in this study, individuals were required to have a diagnosis of PTSD. Studies from this protocol were also included in the analysis condition requiring a diagnosis of PTSD. It is therefore possible that psycheducation and a treatment rationale provide additional benefits above and beyond simply writing. Additionally, perhaps individuals not meeting criteria for PTSD do not engage in the maladaptive avoidance behaviors at a higher frequency than individuals meeting diagnostic criteria. In this case, an intervention with roots in imaginal exposure (one of the proposed mechanisms) may be less efficacious for individuals not avoiding thoughts and physiological sensations. Another explanation may be heterogeneity, where effects are unequal across included studies. While heterogeneity is expected, significant heterogeneity may misrepresent the true effect across those studies requiring and not requiring a PTSD diagnosis.Given that expressive writing is an innocuous, easy-to-administer intervention, even small effect sizes should be considered important when interpreting these results. While small, these effect sizes exhibit a profound impact of expressive writing on PTS.

Both PTG and QOL studies indicated a negligible to small effect size using random

effects models. Although the PTG effect in our overall meta-analysis estimate was significant, other methods indicate this small effect is likely not different from zero. These findings may be due to the lack of power in each of these conditions, given that a very low percentage of studies achieved adequate power. These results should also be considered within the context of the intervention. Perhaps simply writing about a stressful or traumatic event was unable promote positive change above and beyond symptom reduction (i.e., low dose). Indeed, conceptualizations of PTG suggest that various forms of social support and other contextual contingencies are imperative for growth after a trauma. As mentioned, PTG is characterized into building social connections, behaviorally activating towards new life values and appreciating those values/experiences, uncovering personal strengths, and spiritual changes. An intervention that only targets the thoughts and physiological sensations may not promote PTG, given its limited (but important) focus on internal events. For QOL, aside from low power, null results may also be due to the conceptualization of QOL, which suggests that QOL is achieved through reactions to life events and experiences. Expressive writing interventions do not address these contextual factors (i.e., life experiences), which may be a possible explanations for the null findings.

Additionally, our analyses focus on the change for the experimental group across time, rather than an experimental group to a control group. This focus allowed us to estimate the changes for individuals who received a WED/WET intervention, therefore estimating the impact on participants who used written expression. Potentially, these effects could be contributed to other factors (such as the simple passage of time), but we demonstrate here that for both PTS and PTG, there was no relationship between effect size and time. For QOL studies, a medium to large negative correlation was found. A negative relationship between time and effect size implies that writing tasks were more effective in the initial time points, and effects decreased over longer time spans.

The authors note several limitations. Generally, ineffective emotional expression may be a contributing factor. If participants/clients are not deeply engaged with the material, an

659 expressive writing task may not be effective, as Pennebaker & Graybeal (2001) imply that
660 connectedness is an important factor for the task. However, it may be difficult to implement
661 a check for engagement in these types of research designs. Doing so may also set a context
662 that will inhibit emotional processing and general responses. Research on expressive writing
663 has found a wide range of outcomes for different variables (Frattaroli, 2006), and these
664 various results may explain the large heterogeneity found in this study. Encouragingly, we
665 did not find much evidence of publication bias, and therefore, these estimates may represent
666 a true population effect size. Regardless, methodology of expressive writing studies is
667 variable, as it is applied in different forms across different contexts. Ideally, it would be
668 possible to control for these varied instructions and protocols. However, this is simply not
669 feasible, as most studies do not use measures that examine how engaged an individual is
670 with the material. As such, this current meta-analysis sought to provide readers with a
671 global effect of expressive writing on the aforementioned outcome variables. More studies are
672 needed to examine potential moderating effects of participant engagement.

673   The authors also note limitations in regards to the specific outcome variables. The
674 nature of the construct of PTG makes it difficult to analyze rigorously. For example, on the
675 Posttraumatic Growth Inventory (commonly used to study PTG), one could respond 0 to
676 the item "I have a greater appreciation for the value in my own life" because they already
677 had a high level of appreciation in their life (i.e., ceiling effect). This conceptual issue may
678 account for the non-effect of expressive writing on PTG. Logically, it would be difficult to
679 determine whether or not an individual experiences growth from trauma without having
680 experienced trauma. In conducting the literature search for the present meta-analysis, an
681 insufficient number of studies requiring a diagnosis of PTSD employed PTG as an outcome
682 variable. Thus, it was difficult to determine whether participants in the studies employed
683 had experienced trauma in line with DSM-IV criteria. For PTS, studies not specifying
684 whether or not participants had a diagnosis of PTSD were included. It is possible that
685 studies included in the subclinical symptom category did in fact include participants without

PTSD diagnosis (perhaps it was simply not assessed by means of a structured clinical interview). It is also crucial to consider mainstream issues not specific to expressive writing and the outcome variables utilized in the present study.

The psychological scientific community has shifted focus to reproducibility and research design in the last several years (Nelson, Simmons, & Simonsohn, 2018), and much of this discussion has focused on adequately powering studies for publication (Bakker et al., 2016; Maxwell, Lau, & Howard, 2015). Maxwell et al. (2015) and Open Science Collaboration (2015) have shown that the "replication crisis" may be attributed to low power in published studies. The power found in the current meta-analysis was very poor, with very few studies reaching the suggested 80% criterion to adequately power their study. This result was the same when considering individual study characteristics or the estimate true population effect size. Research by Bakker et al. (2016) indicates that researchers' intuitions about power are particularly poor, and many studies could benefit from more informed power analyses. Although, personnel and time required to conduct an expressive writing study is high. While the expressive writing task itself is relatively easy to administer, screening multiple participants and collecting data at multiple time points is time consuming. Anderson, Kelley, & Maxwell (2017) recently published a primer on power, with an online application to help with sample size planning for many types of research designs. Additionally, we encourage researchers to report power analyses of studies in order to better understand methodology for replication and reproducibility.

Meta-analyses, while useful tools to pool for population effect sizes, contain various limitations to their usefulness (Van Elk et al., 2015). As mentioned previously, these analyses can be affected by high heterogeneity, which was found in this study (Van Aert et al., 2016). Selection models have been criticized when using a smaller number of studies (Van Assen et al., 2015), and trim and fill analyses may not always estimate accurate confidence intervals and funnel plots may be biased with heterogeneity (Terrin, Schmid, Lau, & Olkin, 2003). When focusing on improving the psychological sciences, Van Elk et al.

(2015) suggest that the reliability and size of effects may be best elucidated by conducting

large preregistered studies. This suggestion will also improve the outlook for power in

published studies, and projects such as Many Labs and the Psychological Science Accelerator

can aide in subsidizing large samples (Klein et al., 2014; Moshontz et al., 2018). For example,

studies can be proposed to the Psychological Science Accelerator and labs across the globe

can be recruited to improve sample size for a study, which is a similar procedure to the Many

Labs projects. Distributed networks of research teams can solve the problems with power

that are present across all types of psychological research (Bakker et al., 2016). Even with

limitations, meta-analyses allow researchers to examine the state of a research area, and we

find potential with expressive writing on reducing PTS symptoms, and an overall need for

better sample size and power planning for studies.

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Table 1

Effect Size Estimates for PTS Results

Model	Fixed Effects	Random Effects	Fixed No Outliers	Random No Outliers
Overall Effects	0.36 [0.34, 0.39]	0.42 [0.35, 0.49]	0.36 [0.33, 0.38]	0.40 [0.33, 0.46]
Z Values	24.64, $p < .001$	12.35, $p < .001$	23.97, $p < .001$	12.38, $p < .001$
p-Uniform	0.63 [0.54, 0.72]	-	0.61 [0.52, 0.70]	-
PET	0.09 [0.01, 0.18]	-	0.14 [0.06, 0.22]	-
PEESE	0.24 [0.20, 0.29]	-	0.26 [0.22, 0.31]	-
Selection Models	0.33 [0.28, 0.37]	0.45 [0.33, 0.57]	0.29 [0.24, 0.33]	0.39 [0.27, 0.50]
Trim and Fill	0.28 [0.25, 0.31]	0.28 [0.21, 0.36]	0.28 [0.25, 0.31]	0.28 [0.21, 0.35]

Note. [] indicates the 95 percent confidence interval for each effect size estimate.

Table 2

Effect Size Estimates for PTG Results

Model	Fixed Effects	Random Effects
Overall Effects	0.10 [0.02, 0.17]	0.10 [0.02, 0.17]
Z Values	2.45, $p = .014$	2.45, $p = .014$
p-Uniform	-0.11 [-1.43, 0.42]	-
PET	0.06 [-0.20, 0.32]	-
PEESE	0.08 [-0.04, 0.20]	-
Selection Models	0.09 [-0.01, 0.18]	0.09 [-0.03, 0.20]
Trim and Fill	0.10 [0.02, 0.17]	0.10 [0.02, 0.17]

Note. [] indicates the 95 percent confidence interval for each effect size estimate.

Table 3

Effect Size Estimates for QOL Results

Model	Fixed Effects	Random Effects	Fixed No Outliers	Random No Outliers
Overall Effects	-0.01 [-0.07, 0.05]	-0.01 [-0.16, 0.13]	-0.01 [-0.07, 0.05]	-0.01 [-0.11, 0.09]
Z Values	-0.33, $p = .745$	-0.18, $p = .860$	-0.25, $p = .805$	-0.20, $p = .838$
p-Uniform	0.79 [0.33, 1.61]	-	0.62 [0.10, 0.96]	-
PET	0.05 [-0.26, 0.36]	-	0.05 [-0.29, 0.38]	-
PEESE	0.00 [-0.17, 0.17]	-	0.00 [-0.19, 0.19]	-
Selection Models	-0.06 [-0.12, 0.01]	0.51 [-0.09, 1.12]	-0.04 [-0.11, 0.03]	0.05 [-0.15, 0.24]
Trim and Fill	-0.01 [-0.07, 0.05]	-0.01 [-0.16, 0.13]	-0.01 [-0.07, 0.05]	-0.01 [-0.11, 0.09]

Note. [] indicates the 95 percent confidence interval for each effect size estimate.
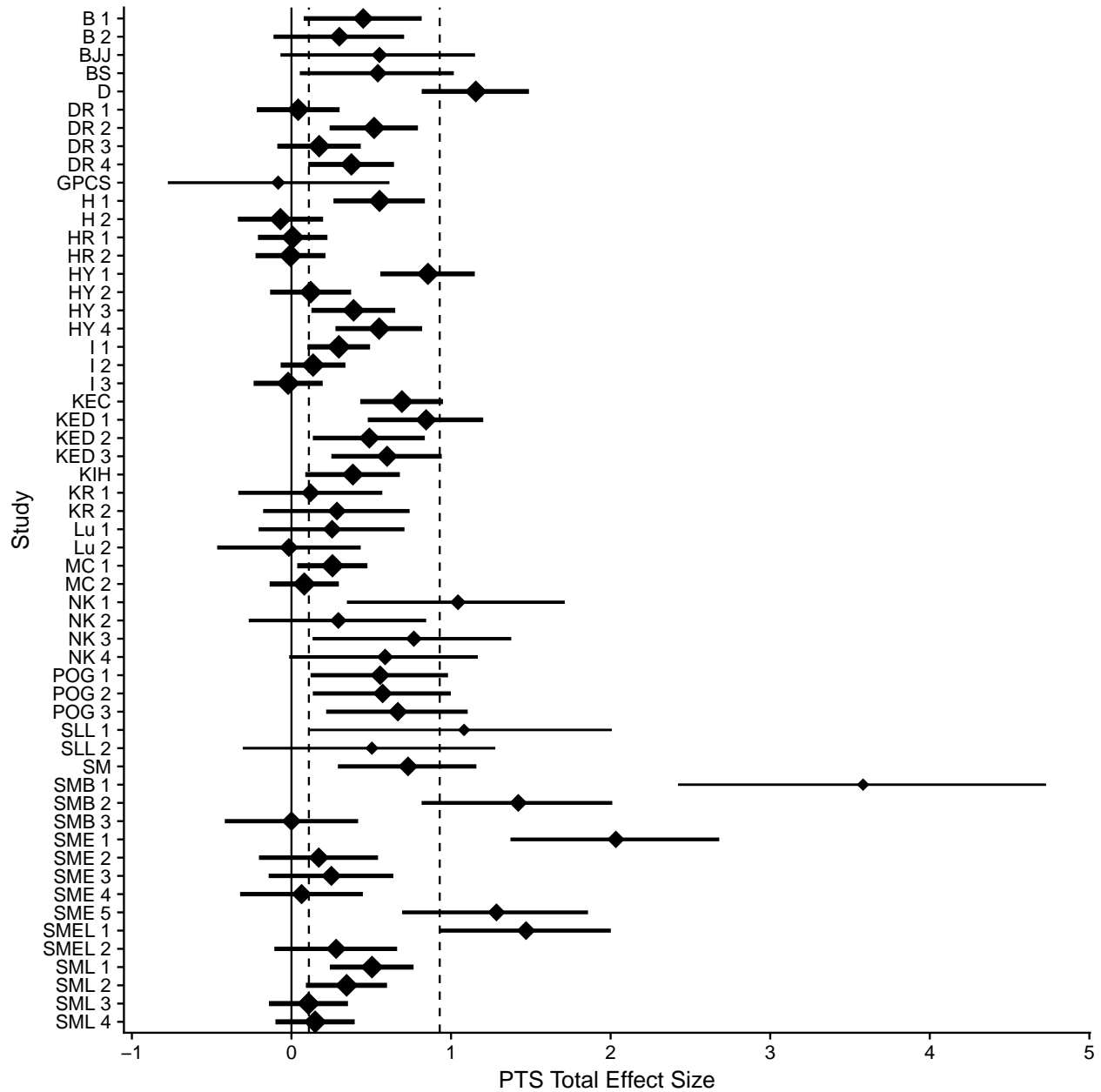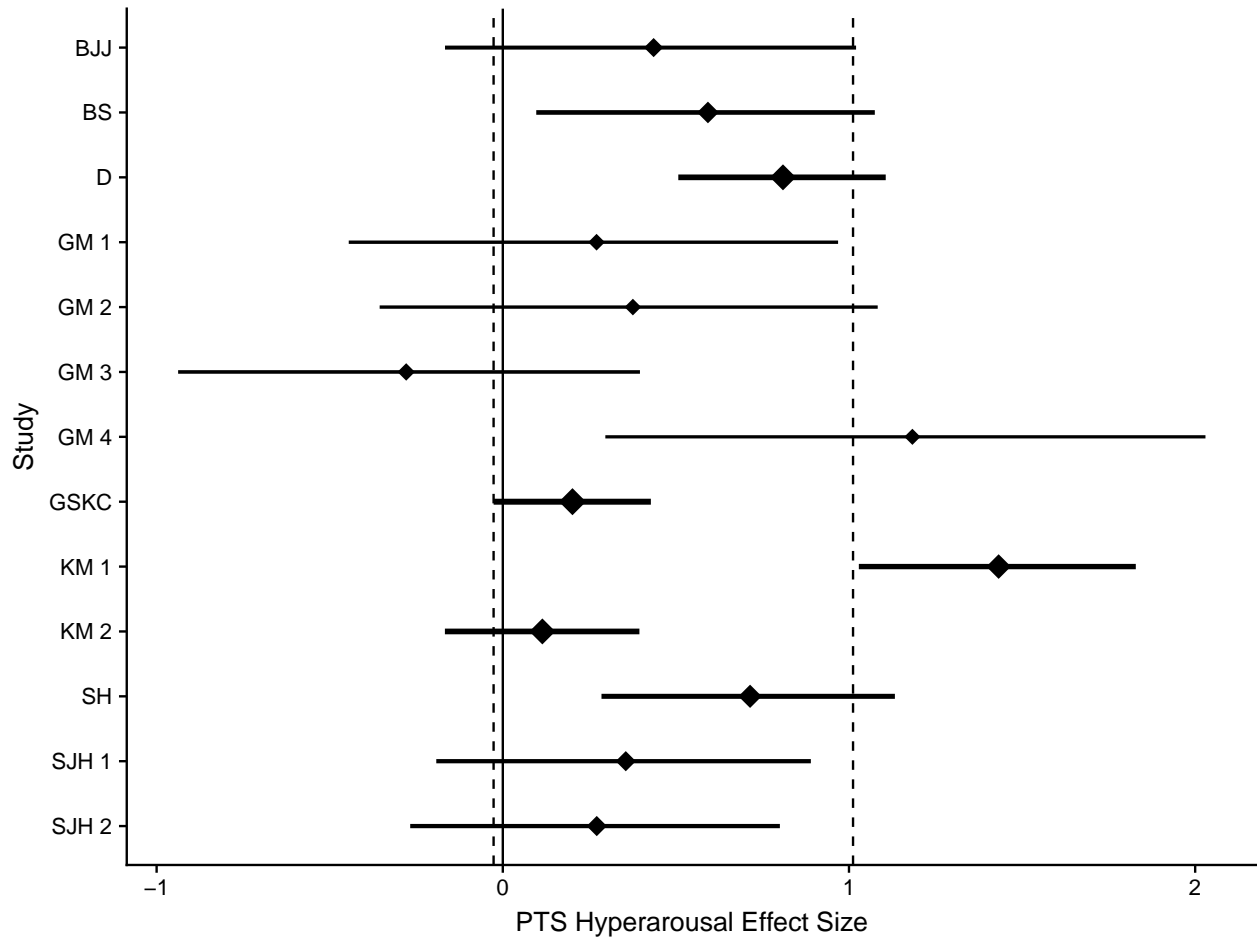
Figure 1. Effect sizes and their non-centralized confidence interval for PTS total scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 1 includes meta-analytic effect size for PTS overall.
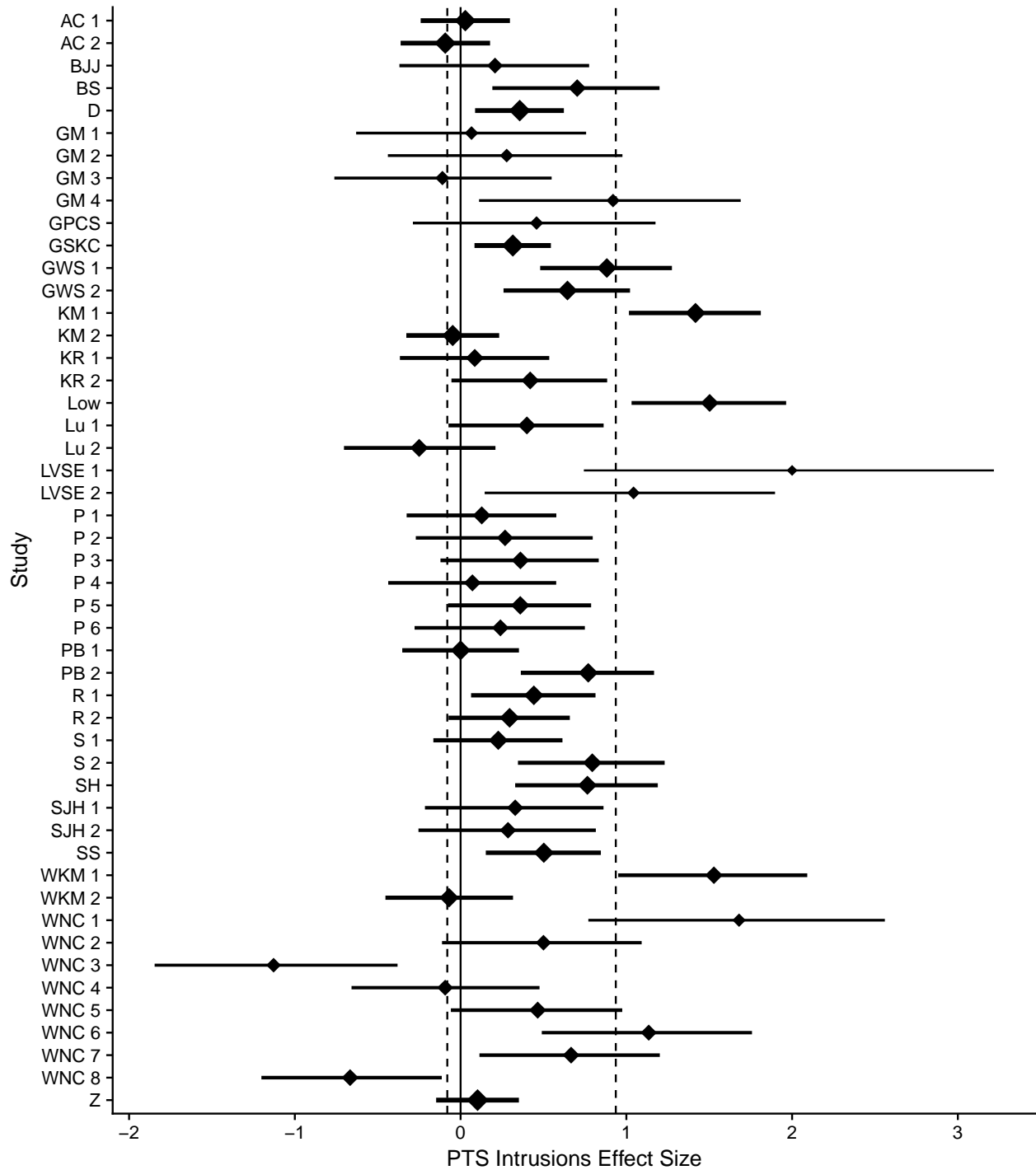
Figure 2. Effect sizes and their non-centralized confidence interval for PTS Hyperarousal. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 1 includes meta-analytic effect size for PTS overall.
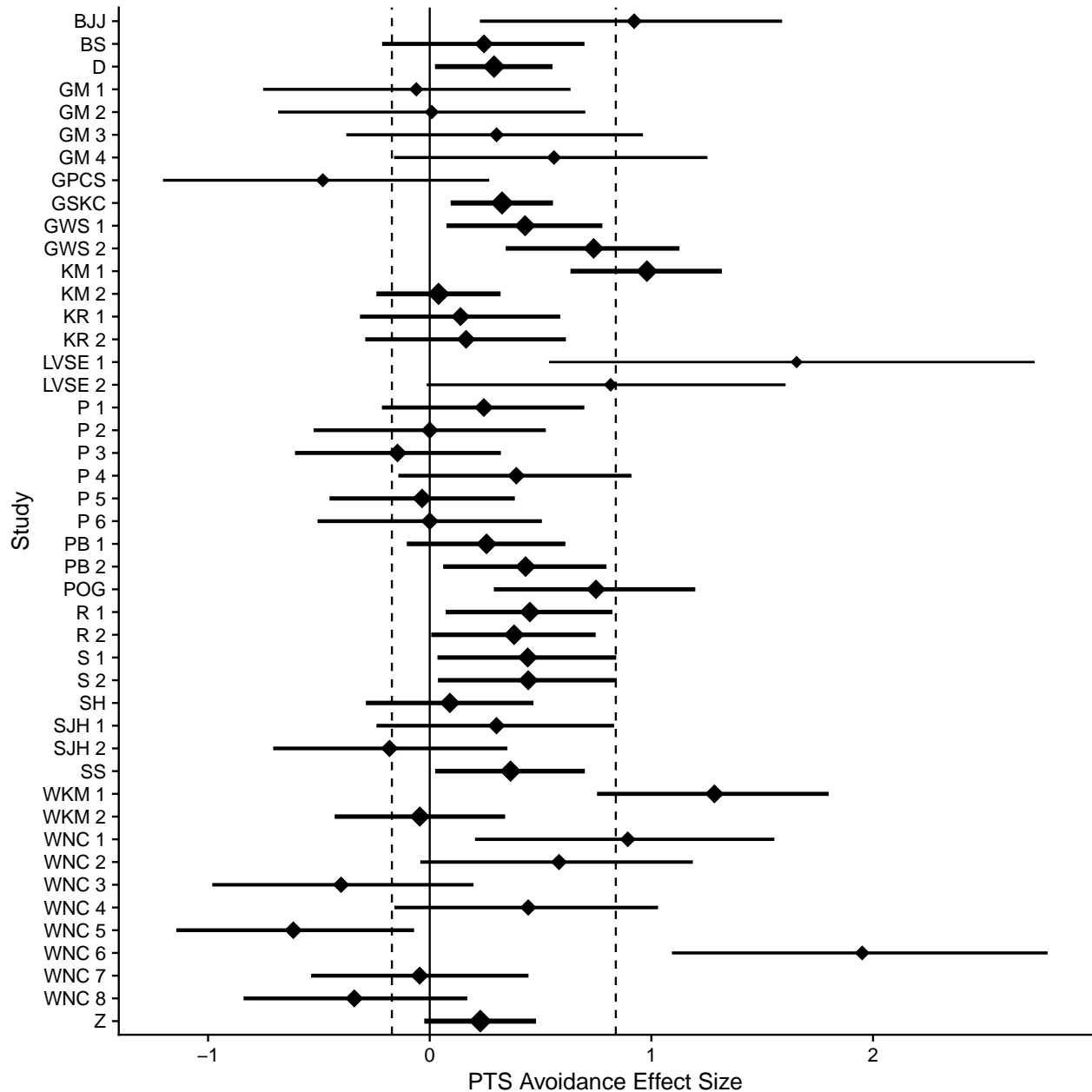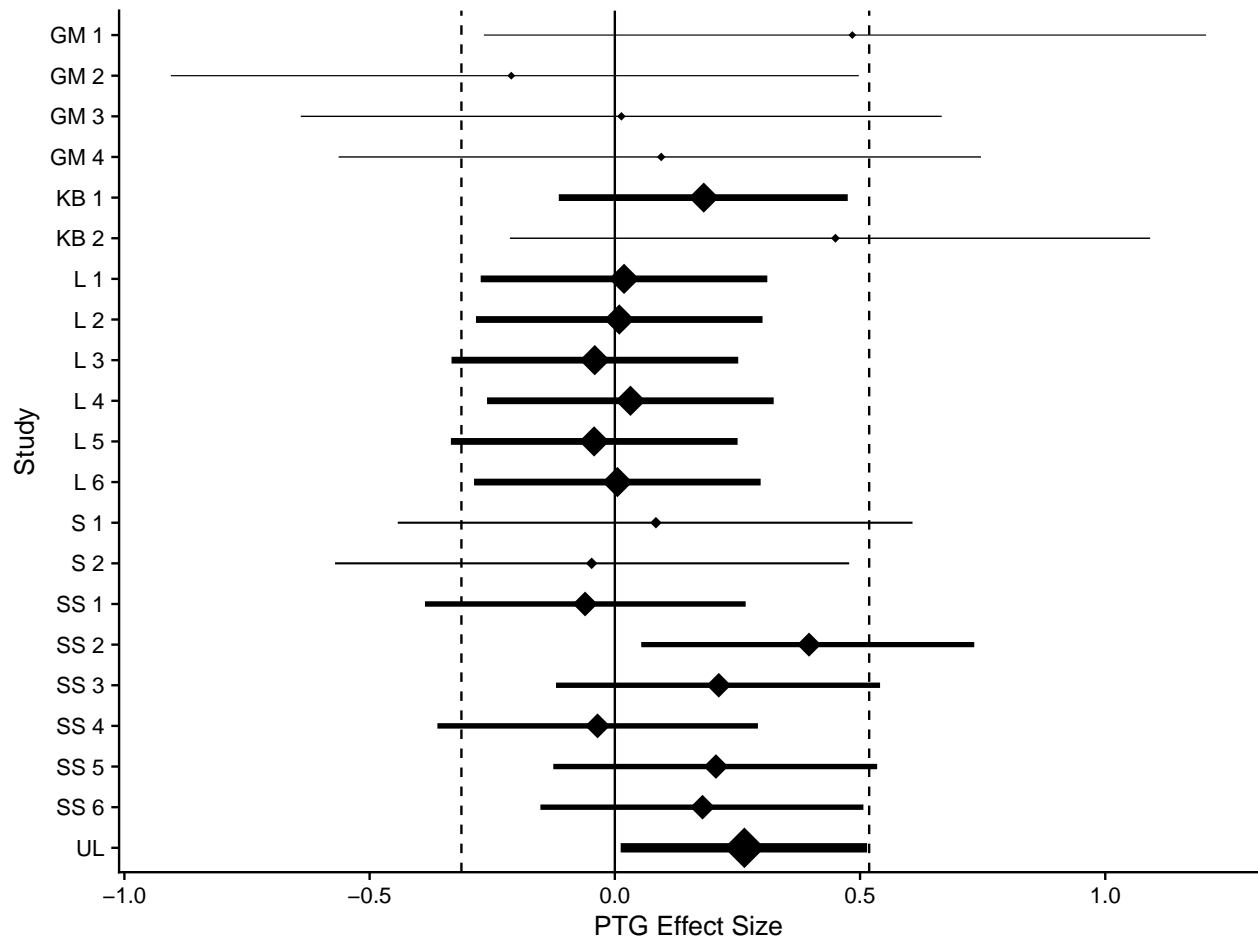
Figure 3. Effect sizes and their non-centralized confidence interval for PTS Intrusion scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 1 includes meta-analytic effect size for PTS overall.
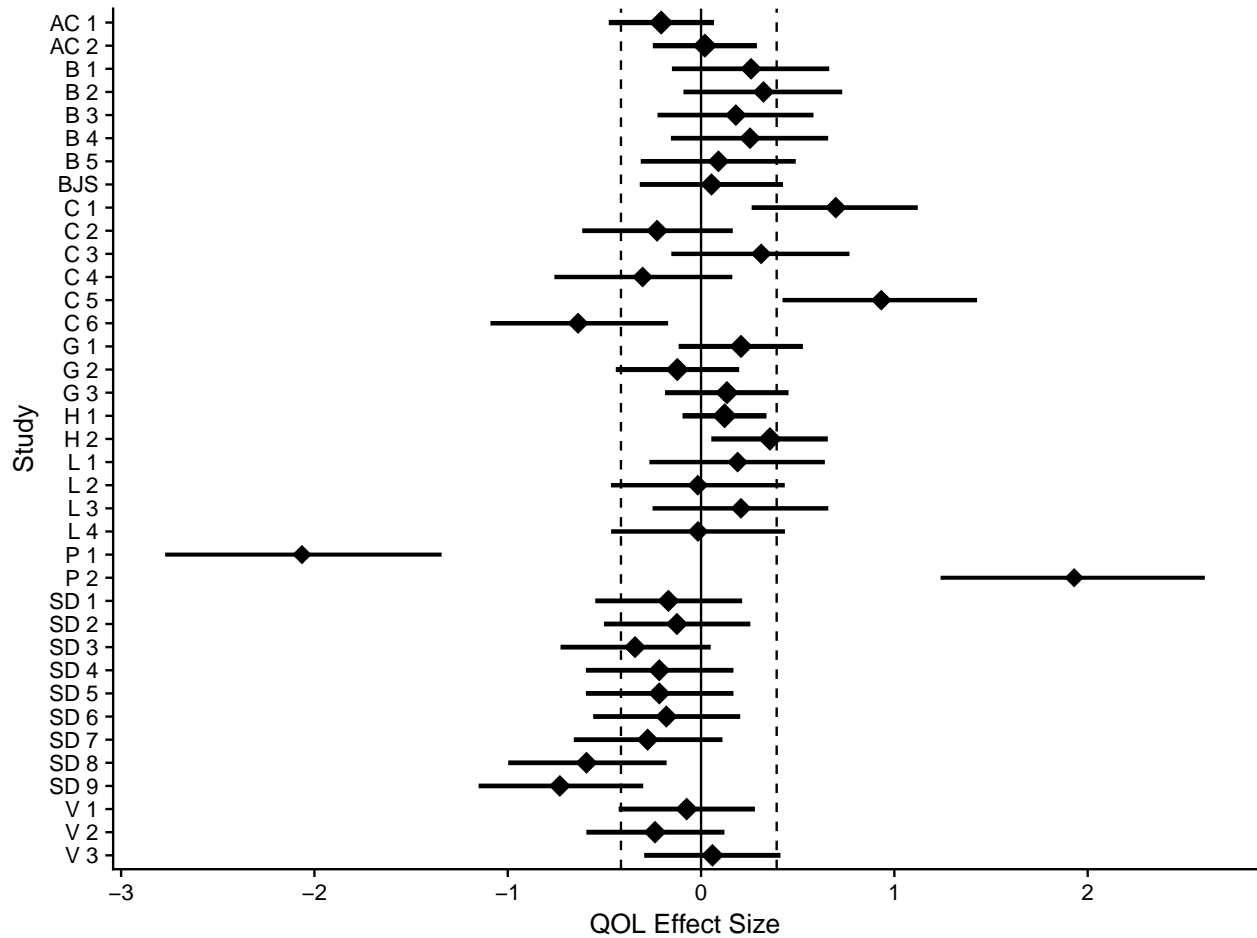
Figure 4. Effect sizes and their non-centralized confidence interval for PTS Avoidance Scores. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 1 includes meta-analytic effect size for PTS overall.

Figure 5. Effect sizes and their non-centralized confidence interval for PTG outcome variables. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 2 includes meta-analytic effect size for PTG.

Figure 6. Effect sizes and their non-centralized confidence interval for QOL outcome variables. Dashed lines indicated average non-weighted lower and upper confidence interval limits. Diamond size indicates normalized study weight from a random effects model. Y-axis labels indicate citation and pairwise time combination, these labels can be matched to the exact data by viewing the provided data online. Table 3 includes meta-analytic effect size for QOL.