The Relationship Between Job Crafting, Work Engagement, and Performance: A Meta-Analysis.

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Abstract

Although much research on the relationship between job crafting, work engagement, and performance has been conducted, mainly building on the job demands-resources (JD-R) model, it is still unclear whether work engagement mediates the relationship between the job crafting dimensions and performance as assumed by the JD-R model. To test this we statistically integrated 44 primary studies via random effects meta-analysis and examined the assumed mediation through work engagement via meta-analytic structural equation modelling. Moreover, we conducted exploratory moderator analyses to identify systematic variations in the relationships under study. Results showed that increasing structural and social job resources, as well as increasing challenging job demands were positively related to work engagement and performance, whereas decreasing hindering job demands was negatively related to work engagement and unrelated to performance. The relationships between job crafting practices and performance were mediated by work engagement to various extents. Exploratory moderator analyses demonstrated that the employees' culture (individualistic vs. collectivistic) consistently moderated the relationships under study.

Keywords: job crafting, work engagement, performance, job demands-resources model, meta-analysis

The Relationship Between Job Crafting, Work Engagement, and Performance: A Meta-Analysis.

Even though lots of research on job design focused on how managers and organizations should design jobs to increase employees' motivation and performance, research paid less attention to how employees themselves design their job (Oldham & Fried, 2016). However, employees redesign their job regularly on their own initiative by engaging in job crafting. Job crafting was first introduced by Wrzesniewski and Dutton (2001) and describes behaviors through which employees alter their job design and thereby, their work identity and work meaning. Because changes in work identity and work meaning are difficult to capture quantitatively, most research on job crafting as conceptualized by Wrzesniewski and Dutton (2001) used qualitative approaches. Tims and Bakker (2010) conceptualized job crafting within the job demands-resources (JD-R) model (Bakker & Demerouti, 2007; Demerouti, Bakker, Nachreiner, & Schaufeli, 2001). They understood job crafting as behavior whereby employees redesign their job by altering job demands and job resources and thus, improve their person-job fit and work motivation. Based on this job crafting concept, Tims, Bakker, and Derks (2012) developed the job crafting scale which stimulated an abundant amount of quantitative research on the relationship between job crafting and various individual as well as organizational outcomes, such as work engagement—a state of high motivation—and performance (Demerouti, 2014; Rudolph, Katz, Lavigne, & Zacher, 2017).

In their meta-analysis, Rudolph et al. (2017) provided a first summary of the extant literature on job crafting. Although they also investigated the relationship between job crafting, work engagement, and performance, they did not test whether work engagement mediates the relationship between the job crafting dimensions and performance as assumed by the JD-R model. Furthermore, Rudolph et al. (2017) did not conduct moderator analyses of this

relationship. Therefore, the goal of this meta-analysis is threefold: First, we aim at replicating the research of Rudolph et al. (2017) by conducting a meta-analysis on the relationship between job crafting and work engagement as well as performance using different statistical methods. Second, we test whether work engagement mediates the relationship between the job crafting dimensions and performance as assumed by the JD-R model by meta-analytically testing the specific proposed paths. Third, we conduct exploratory moderator analyses of this relationship. Thereby, we do not only extend the work by Rudolph et al. (2017) on the theory of job crafting, but also enable employees and managers to develop a more thorough understanding of the relationship between job crafting, work engagement, and performance. Thus, employees can engage in and managers can foster job crafting in a more conscious and purposeful way.

In the following, we will, first, briefly define the constructs job crafting, work engagement, and performance. Second, we will review relevant work on the JD-R model which serves as the theoretical framework for understanding the relationship between job crafting, work engagement, and performance. Third, we will explicate the relationship between job crafting, work engagement, and performance according to the JD-R model and thus, derive our hypotheses.

Job Crafting

Tims and Bakker (2010) defined *job crafting* as "a specific form of proactive behavior in which the employee initiates changes in the level of job demands and job resources" (p. 1). Tims et al. (2012) empirically distinguished four job crafting practices which describe how employees change their level of job demands and job resources: (a) increasing structural job resources, (b) increasing social job resources, (c) increasing challenging job demands, and (d) decreasing hindering job demands. *Increasing structural job resources* means that employees

actively strengthen their job resources such as autonomy, variety, and development opportunities. For example, employees increase their autonomy by deciding how they work on a task without discussing it with their supervisor. *Increasing social job resources* means that employees actively strengthen their job resources such as supervisory feedback and social support. For example, employees increase their social job resources by asking their colleagues and supervisors for advice, support, or feedback. *Increasing challenging job demands* means that employees actively raise challenging job demands such as workload. For example, employees increase their workload by adding tasks to their usual obligations. *Decreasing hindering job demands* means that employees actively reduce hindering job demands such as hassles. For example, employees decrease their hassles by minimizing contact with people causing them. Employees engage in these job crafting practices to improve their person-job fit and work motivation (Demerouti, 2014; Tims & Bakker, 2010; Tims et al., 2012). That is, job crafting is a form of bottom-up job design exercised by the employee contrary to top-down job design exercised by the manager (Demerouti, 2014; Tims & Bakker, 2010).

Work Engagement

Schaufeli, Salanova, Gonzáles-Romá, and Bakker (2002) defined *work engagement* as a "positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption" (p. 74). *Vigor* is characterized as "high levels of energy and mental resilience while working" (p. 74), *dedication* as "being strongly involved in one's work and experiencing a sense of significance, enthusiasm, inspiration, pride, and challenge" (p. 74), and *absorption* as "being fully concentrated and happily engrossed in one's work, whereby time passes quickly and one has difficulties with detaching oneself from work" (p. 75). That is, engaged employees dispose of high amounts of energy, are enthusiastic about their work, and do not recognize how time passes

by (Bakker & Demerouti, 2008).

Performance

Performance is the central outcome variable in work and organizational psychology, because *job performance* comprises "those actions and behaviors that are under the control of the individual and contribute to the goals of the organization" (Rotundo & Sackett, 2002, p. 66). Hence, fostering performance is in the interest of every organization. Borman and Motowidlo (1997) distinguished two types of performance: task performance and contextual performance.

Task performance is the "effectiveness with which job incumbents perform activities that contribute to the organisation's technical core either directly by implementing a part of its technological process, or indirectly by providing it with needed materials or services" (Borman & Motowidlo, 1997, p. 99). That is, the contents of task performance vary with the corresponding job descriptions. On the other hand, contextual performance comprises important activities that "contribute to organisational effectiveness in ways that shape the organisational, social, and psychological context that serves as the catalyst for task activities and processes" (Borman & Motowidlo, 1997, p. 100). For example, contextual performance comprises voluntary actions such as helping, cooperating, and organisational citizenship behaviour (Organ, 1988).

The JD-R Model

Since Tims and Bakker (2010) conceptualized job crafting within the JD-R model, it serves as the theoretical framework for understanding the relationship between job crafting, work engagement, and performance. The JD-R model, which has originally been applied to describe and explain job stress before it has been applied to job crafting, assumes that job demands and job resources play an important role in the emergence of employees' work engagement and burnout (Bakker & Demerouti, 2007; Demerouti et al., 2001). *Job resources* are "physical,

psychological, social, or organizational aspects of the job that may do any of the following: (a) be functional in achieving work goals; (b) reduce job demands at the associated physiological and psychological costs; (c) stimulate personal growth and development" (Demerouti et al., 2001, p. 501). According to the JD-R model, job resources can stimulate intrinsic motivation by fulfilling basic human needs, such as the need for autonomy (De Charms, 1968) and the need to belong (Baumeister & Leary, 1995). Furthermore, job resources can provoke extrinsic motivation by enabling employees to achieve their goals (Bakker & Demerouti, 2007; Meijman & Mulder, 1998). By stimulating these motivational processes, job resources can enhance employees' work engagement (Bakker & Demerouti, 2007; Demerouti et al., 2001).

Job demands refer to "physical, psychological, social, or organizational aspects of the job that require sustained physical or mental effort and are therefore associated with certain physiological and psychological costs (e.g., exhaustion)" (Demerouti et al., 2001, p. 501). In addition, LePine, Podsakoff, and LePine (2005) differentiated between two types of job demands: challenging and hindering job demands. *Challenging job demands* refer to work characteristics such as workload and time pressure that are appraised as "obstacles to be overcome in order to learn and achieve" (LePine et al., 2005, p.765). On the other hand, *hindering job demands* refer to work characteristics such as role conflict and red tape that are appraised as "unnecessarily thwarting personal growth and goal attainment" (LePine et al., 2005, p. 765). According to the JD-R model, job demands can cause energy depletion which leads to strain. By triggering this health-impairment process, job demands can increase employees' burnout (Bakker & Demerouti, 2007).

In their meta-analysis, Crawford, LePine, and Rich (2010) provided support for the JD-R model: Job resources were positively related to work engagement, whereas job demands were

positively related to burnout. Furthermore, job resources were negatively related to burnout. However, they found that the relationship between job demands and work engagement was moderated by the type of job demand: Challenging job demands were positively related to work engagement, whereas hindering job demands were negatively related to work engagement.

Crawford et al. (2010) explained the negative relationship between job resources and burnout with the conservation of resources theory (Hobfoll & Freedy, 1993): Employees disposing of a lot of job resources can deal with job demands without accumulating strain whereas employees with few job resources cannot. Furthermore, Crawford et al. (2010) explained the positive relationship between challenging job demands and work engagement as well as the negative relationship between hindering job demands and work engagement with the different emotions triggered by challenging and hindering job demands (Lazarus & Folkman, 1984; LePine et al., 2005): Challenging job demands predominantly trigger positive emotions due to their potential to stimulate personal growth and gains, whereas hindering job demands mostly trigger negative emotions due to their potential to impede personal growth and gains. Accordingly, employees facing challenging job demands are more willing to invest energy into coping with these challenging job demands and adopt a problem-focused coping style which leads to more work engagement. In contrast, employees facing hindering job demands are less willing to invest energy to cope with these hindering job demands and adopt an emotion-focused coping style which leads to less work engagement. By specifying the relationship between job resources and burnout as well as job demands and work engagement Crawford et al. (2010) refined the original JD-R model.

According to the JD-R model, work engagement and burnout can affect employees' performance: Work engagement is positively related to performance (Bakker & Demerouti,

2008; Christian, Garza, & Slaughter, 2011), whereas burnout is negatively related to performance (Bakker, Demerouti, & Verbeke, 2004; Bakker, Demerouti, & Sanz-Vergel, 2014). Engaged employees perform better, because they (a) often experience positive emotions (Fredrickson, 2001) which improves personal resources, (b) are healthier and therefore, can invest more energy into their job, and (c) trigger an upward positive gain spiral by creating their own job resources (Bakker, 2011; Bakker et al., 2014). On the other hand, burnout is negatively related to performance (Demerouti, Bakker, & Halbesleben, 2015), because employees who suffer from burnout (a) dispose of not enough resources to meet job demands which harms performance (Bakker et al., 2004; Taris, 2006) and (b) are simply unwilling to perform (Demerouti, Bakker, & Leiter, 2014). Thereby, work engagement and burnout can affect performance.

The Relationship Between Job Crafting, Work Engagement, and Performance

When employees engage in job crafting, they alter their job resources and job demands which triggers the processes assumed by the JD-R model as outlined above. Accordingly, both increasing structural and social job resources should stimulate motivational processes that increase work engagement and should enable employees to better deal with job demands which decreases burnout. Consequently, this should improve performance. Furthermore, increasing challenging job demands should trigger positive emotions that increase work engagement and should cause energy depletion and strain that increase burnout. Nevertheless, increasing challenging job demands should increase performance as challenging job demands are stronger related to work engagement than to burnout (Crawford et al., 2010). In addition, although decreasing hindering job demands should increase work engagement and decrease burnout, research suggests the opposite: Decreasing hindering job demands decreases work engagement and increases burnout, because it usually results in a lack of challenges which are necessary for

stimulating work engagement (Demerouti, Bakker, & Gevers, 2015) and it usually only defers hindering job demands which likely results in negative emotions in the long run (Petrou, Demerouti, & Schaufeli, 2015). Consequently, decreasing hindering job demands should decrease performance. Finally, the JD-R model suggests that both work engagement and burnout should mediate the relationship between job crafting and performance. As we focus on work engagement, it should, therefore, only partly mediate the relationship between job crafting and performance. It is important to note that each single job crafting practice should result in an incremental increase or decrease of work engagement and performance because each single job crafting practice affects different types of resources or triggers different processes. The theoretical framework and hypotheses outlined above are summarized in Figure 1.

Hypothesis 1. Increasing structural job resources is positively related to work engagement.

Hypothesis 2. Increasing social job resources is positively related to work engagement.

Hypothesis 3. Increasing challenging job demands is positively related to work engagement.

Hypothesis 4. Decreasing hindering job demands is negatively related to work engagement.

Hypothesis 5. Increasing structural job resources is positively related to performance.

Hypothesis 6. Increasing social job resources is positively related to performance.

Hypothesis 7. Increasing challenging job demands is positively related to performance.

Hypothesis 8. Decreasing hindering job demands is negatively related to performance.

Hypothesis 9. The relationship between job crafting and performance is partly mediated by work engagement.

Method

Literature Search

To provide a comprehensive integration of research on the relationship between job crafting, work engagement, and performance, we conducted an extensive literature search in May 2017. First, we searched the databases PsychINFO, PsychARTICLES, and Web of Science using the search term *job crafting*. Second, we scanned the EAWOP (2007 – 2017) and SIOP (2001 – 2017) conference programs and requested potentially relevant (unpublished) studies from the authors via a standardized e-mail if we could obtain the authors' e-mail address. Third, to avoid publication bias we wrote standardized e-mails to prominent job crafting researchers and asked them for any unpublished studies on job crafting. Fourth, we supplemented this search with a google scholar web-search using the search term *job crafting*. Fifth, we conducted a backward search of the positively screened papers, six reviews on job crafting / job design, and the meta-analysis of Rudolph et al. (2017). In total, this search yielded 660 records.

In the next step, we screened these 660 records by reading their title, abstract and any other available information. When it became evident that the study described in a record did not investigate a relationship between (a) the job crafting practices, (b) job crafting and work engagement, or (c) job crafting and performance, we excluded this study. Whenever possible we included doctoral dissertations. However, we excluded studies written in other languages than English or German due to practical reasons. This screening process resulted in 91 records of which we obtained the full papers.

To be included in the present meta-analysis these 91 papers had to fulfil predefined inclusion criteria. First, they needed to report at least one correlation either between (a) the job crafting practices, (b) job crafting and work engagement, (c) job crafting and performance, or (d)

work engagement and performance. As solely employees can engage in job crafting by definition, we only included studies which reported correlations based on employee samples. That is, we excluded all studies that reported results based on student samples or did not report employment information at all. This helps to ensure external validity of the results for the work context. Moreover, the included studies needed to investigate job crafting from the JD-R perspective as conceptualized by Tims and Bakker (2010). That is, we excluded all studies that investigated job crafting as conceptualized by Wrzesniewski and Dutton (2001) even when they investigated job crafting quantitatively (e.g. Leana, Appelbaum, & Shevchuck, 2009). We also excluded all studies that only reported one overall score for job crafting and did not distinguish between job crafting practices. The application of these inclusion criteria resulted in 42 papers reporting 44 studies. These 44 studies incorporated 48 independent samples with a combined sample size of 19116 employees. From these 48 samples, we extracted 364 independent correlations. The stages and results of the literature search are depicted in Figure 2.

Study Coding

We coded the 44 studies using a predefined coding manual (see Appendix A, Table A1). To guarantee precision of coding, a second coder coded the studies as well. Ambiguities were resolved by consensus. Along with the necessary data to calculate the effect sizes for our hypotheses on the relationship between job crafting, work engagement, and performance, we also coded numerous study, sample, and effect size variables for the exploratory moderator analyses. Because meta-analyses can be criticized for integrating studies of heterogeneous quality—a problem which is commonly referred to as the garbage-in-garbage-out problem (Sharpe, 1997)—we rated the quality of each study using an adapted version of Valentine's quality rating sheet which is described in Appendix A, Table A2 (Cooper, Hedges, & Valentine,

2009). In exploratory moderator analyses, we then tested whether the study quality moderated the calculated effect sizes.

Whenever studies reported multiple correlations per sample for a relationship, we transformed them into Fisher's *z*-values averaged them, and transformed them back into correlations (Borenstein, Hedges, Higgins, & Rothstein, 2009). Thereby, we avoided dependencies in the data which otherwise would have distorted the results because one sample would have influenced the overall effect size disproportionately (Borenstein et al., 2009). We used Fisher's *z*-transformed correlations because they have better characteristics than correlations when averaged (Silver & Dunlap, 1987).

Such dependencies frequently occurred when studies used a longitudinal design. As most of the studies deployed a cross-sectional design, we only coded the repeated cross-sectional correlations of the longitudinal studies to ensure comparability of the effect sizes across studies. That is, we only coded the correlations between job crafting, work engagement, and performance at one point of time and not the correlation between two different points of time. It is important to note that there were too few longitudinal correlations which would have been suitable for examining our research questions.

As we did not distinguish between different types of performance in our hypotheses, dependencies also occurred when a study reported the relationship between job crafting and both task performance and contextual performance. In these cases, we only coded task performance as the presumably more important performance type.

Some studies reported correlations between all three facets of work engagement (vigor, dedication, and absorption) and job crafting or performance. In such cases, we calculated an estimate for the overall correlation (via Fisher's *z*-values; see above) between work engagement

and these constructs to ensure comparability of the effect sizes across studies as most studies reported correlations with the overall score of work engagement only. The number of studies reporting facets of work engagement was too small (7 studies) to conduct any meaningful moderator analyses regarding the facets.

Meta-Analytic Procedures

We conducted the statistical analyses with the open-source software R (R Core Team, 2017) using the *metafor* package (Viechtbauer, 2010). Prior to our analyses, we transformed the extracted correlations into Fisher's *z*-values. This transformation corrects the skewness in the distribution of *r* (Borenstein et al., 2009; Silver & Dunlap, 1987) which induces a negative bias in averaged correlations (Silver & Dunlap, 1987). Although averaged Fisher's *z*-values are positively biased, they are always less biased than averaged correlations when the averaged Fisher's *z*-values are transformed back into *r* (Silver & Dunlap, 1987). That is, averaged Fisher's *z*-values yield a better estimate of the true average correlation than averaged correlations (Silver & Dunlap, 1987). As primary studies included in the present meta-analysis differ substantially in their study characteristics, we decided a random-effects model to be most appropriate (Veroniki et al., 2016, Viechtbauer, 2010). We weighted Fisher's *z*-values with the inverse of the total variance, which consists of the sum of the within-studies variance v_i and the between-studies variance τ^2 (see Appendix B for more details).

Mediation analyses. To test whether the relationship between the job crafting practices and performance is partly mediated via work engagement as suggested by the JD-R model, we conducted mediation analyses via meta-analytic structural equation modelling using the *lavaan* package (Rosseel, 2012). First, we created a meta-analytic correlation matrix using the results of the random effects models described above. Second, the associated sample size was computed

via the harmonic mean, which can be considered a conservative approach (see Appendix B for details). Third, we conducted mediation analysis by calculating the hypothesized mediation model using maximum-likelihood-estimation. Then we tested whether the effects of each job crafting practice on performance (direct effects) and the effects of each job crafting practice on performance via work engagement (indirect effects) were significant and in the direction as suggested by the hypothesized mediation model (see Figure 1). This procedure for calculating a meta-analytic structural equation model has been used before (Schepers & Wetzels, 2007; Tett & Meyer, 1993; Van Eerde & Thierry, 1996).

Exploratory moderator analyses. As the exploratory investigation of heterogeneity can (a) provide important insights into the nature of a phenomenon, (b) be useful for suggesting future research (Song, Sheldon, Sutton, Abrams, & Jones, 2001), and (c) improve the quality of inference (Borenstein et al., 2009) we conducted exploratory moderator analyses. Therefore, we calculated a model for each potential moderator (see Appendix A, Table A1) separately and then, performed moderator analyses for each relationship including all previously significant moderators. For brevity, we will only report the results of the significant moderators in the paper.

Additional analyses. In addition, we investigated potential for publication bias by calculating Rosenthal's fail-safe *N* (Rosenthal, 1979) and creating funnel plots that we tested for asymmetry with Egger's test (Egger, Smith, Schneider, & Minder, 1997).

Results

Descriptive Statistics

Descriptive statistics of the included studies are depicted in Table 1. Most included studies stemmed from journals (80%), whereas the other studies stemmed from conference papers (5%), dissertations (5%), or unpublished studies (10%). Most of these studies were peer-

reviewed (86%). The samples came from a variety of industries and educational backgrounds, were on average middle aged (M = 40.70, SD = 5.35), and had a mean tenure of M = 12.51 years (SD = 5.65). However, some statistics are striking as (a) most studies used cross-sectional designs (73%), (b) most samples (79%) came from western countries, (c) most samples stemmed from individualistic cultures (81%), (d) most samples came from the Netherlands (44%), and (e) most correlations contained common-method variance (92%). The overall quality of the studies was good (M = 6.75, SD = 1.1 on a 8-point Likert scale).

The Relationship between Job Crafting, Work Engagement, and Performance

Table 2 displays the main meta-analytic results. As hypothesized, increasing structural job resources (r = .483, p < .001, 95%-CI = [.442, .521]), increasing social job resources (r = .309, p < .001, 95%-CI = [.282, .335]), and increasing challenging job demands (r = .368, p < .001, 95%-CI = [.317, .417]) were positively related to work engagement, whereas decreasing hindering job demands (r = -.065, p = .013, 95%-CI = [-.116, -.014]) was weakly but negatively related to work engagement. However, the heterogeneity statistics Q and I^2 indicated significant and high heterogeneity among the true effect sizes of each hypothesis. Hence, a search for moderators of these relationships was justified. Appendix C, Figures C1–C4 depict the corresponding forest plots, which provide an overview of the effect size and precision of each study as well as the corresponding summary effects.

Further, as hypothesized, increasing structural job resources (r = .321, p < .001, 95%-CI = [.266, .374]), increasing social job resources (r = .154, p < .001, 95%-CI = [.106, .202]), and increasing challenging job demands (r = .210, p < .001, 95%-CI = [.144, .273]) were positively related to performance. The relationship between decreasing hindering job demands and performance (r = -.072, p = .171, 95%-CI = [-.174, .031]) was not significant, but still pointed in

the expected direction. The heterogeneity statistics Q and I^2 indicated marginal significant and medium to high heterogeneity among the true effect size of each hypothesis. Therefore, a search for moderators of these relationships was justified as well. Appendix C, Figures C5–C8 depict the corresponding forest plots which provide an overview of the effect size and precision of each study as well as the corresponding summary effects.

Mediation of the Relationship between Job Crafting and Performance through Work Engagement

We hypothesized that the relationship between job crafting and performance is partly mediated by work engagement. The meta-analytic correlation matrix and its approximate sample size are depicted in Table 3. Results regarding the mediation analysis are depicted in Table 4 and Figure 3. Our results suggest that increasing structural job resources (β = .104, p < .001, 95%-CI = [.054, .154]), increasing social job resources (β = .027, p = .001, 95%-CI = [.012, .043]), and decreasing hindering job demands (β = -.031, p < .001, 95%-CI = [-.048, -.015]) were indirectly related to performance via work engagement, but increasing challenging job demands (β = -.013, p = .066, 95%-CI = [-.027, .001]) was not.

Furthermore, our results indicate that increasing structural job resources (β = .418, p < .001, 95%-CI = [.318, .518]) was positively related to performance, whereas increasing challenging job demands (β = -.122, p = .009, 95%-CI = [-.214, -.030]) and decreasing hindering job demands (β = -.131, p < .001, 95%-CI = [-.190, -.072]) were negatively related to performance. Increasing social job resources (β = .021, p = .559, 95%-CI = [-.049, .091]) was unrelated to performance. That is, the relationship between increasing structural job resources as well as decreasing hindering job demands and performance was partly mediated via work engagement, whereas the relationship between increasing social job resources and performance

was fully mediated via work engagement. The relationship between increasing challenging job demands and performance was not mediated by work engagement.

The mediation model explained 22.3% of the variation in performance and 45% of the variation in work engagement. Above all, it was striking that (a) the relationship between increasing challenging job demands and work engagement was reversed (β = -.081, p = .041), (b) increasing social job resources and performance were not related (β = .021, p = .559), (c) the relationship between increasing challenging job demands and performance was reversed (β = -.122, p = .009), and (d) decreasing hindering job demands and performance were negatively related (β = -.131, p < .001) in the mediation model compared to the corresponding estimated meta-analytic correlations (see Table 2). Therefore, we tested in exploratory analyses whether the relationships between each single job crafting dimension (when not including the other dimensions) and performance was partly mediated via work engagement as hypothesized. The results of these exploratory analyses partly support this suggestion (see Table 5). In particular, the indirect effect of increasing challenging job demands on performance via work engagement was positive (β = .161, p < .001) when not controlling for other job crafting practices.

Exploratory Moderator Analyses

We conducted exploratory moderator analyses for each relationship between job crafting, work engagement, and performance with various variables (see Appendix A, Table A1). We coded the culture (individualism vs. collectivism) of each country according to the meta-analytic results of Oyserman, Coon, and Kemmelmeier (2002). The significant moderators of the separate moderator analyses are shown in Appendix D, Table D1. The results of the moderator analyses containing all previously significant moderators are depicted in Table 6. In the following, we focus on the most consistent moderator of the relationship between job crafting, work

engagement, and performance: the employee sample's culture.

The positive relationship between increasing social job resources and work engagement was smaller, when the employee sample stemmed from an individualistic culture (b = -.077, p = .029, 95%-CI = [-.146, -.008]). The relationship between increasing challenging job demands and work engagement was smaller when the employees stemmed from an individualistic vs. collectivistic culture (b = -.090, p = .048, 95%-CI = [-.180, -.001]). The negative relationship between decreasing hindering job demands and work engagement was larger when the employees stemmed from an individualistic vs. collectivistic culture (b = -.163, p = .006, 95%-CI = [-.279, -.046]). Whereas the relationship between decreasing hindering job demands and performance turns significantly positive when the employees stem from a collectivistic culture (b = .332, p = .005, 95%-CI = [.102, .562]), it turns negative when the employees stem from an individualistic culture (b = -.339, p = .008, 95%-CI = [-.589, -.089]).

Sensitivity Analyses

The results regarding Rosenthal's fail-safe N and Egger's test are depicted in Table 7. Rosenthal's fail-safe N was larger than y for all relationships except for decreasing hindering job demands and performance. However, Egger's test was non-significant for each calculated random-effects model. Taken together these results suggest that publication bias is unlikely. The corresponding funnel plots are depicted in Appendix D, Figures D1–D8.

Discussion

This meta-analysis aimed at (a) investigating the relationship between job crafting, work engagement, and performance, (b) testing whether work engagement partly mediates the relationship between job crafting and performance as suggested by the JD-R model, and (c) conducting exploratory moderator analyses on the relationships. Below, we discuss our findings

in detail.

The Relationship Between Job Crafting, Work Engagement, and Performance

We found support for our hypotheses that increasing structural and social job resources, as well as increasing challenging job demands are positively related to work engagement. Furthermore, results supported our hypothesis that decreasing hindering job demands is negatively related to work engagement. In addition, we found increasing structural and social job resources, as well as increasing challenging job demands to be positively related to performance as hypothesized and as proposed in the JD-R model.

However, contrary to our expectations, we found decreasing hindering job demands to be unrelated to performance. We consider three possible explanations for this finding: First, decreasing hindering job demands may decrease burnout which improves performance and balances the small negative effect of decreasing hindering job demands on performance via work engagement. Second, it is conceivable that burnout indeed mediates the relationship between decreasing hindering job demands and performance as suggested by the JD-R model, but that a third variable, such as reduced effort spent at work or higher activation is positively related to or even mediates the relationship between decreasing hindering job demands and performance. This variable would outweigh the negative effect of burnout on performance. Third, perhaps burnout does not mediate the relationship between decreasing hindering job demands and performance at all. This would imply that there is another third variable which is positively related to or even mediates the relationship between decreasing hindering job demands and performance. As Tims, Bakker, and Derks (2013) found decreasing hindering job demands unrelated to burnout, the third explanation seems most plausible. In the following, we will tentatively suggest a theory-based third variable which may be positively related to or even mediate the relationship between

decreasing hindering job demands and performance. The variable is based on the idea that simply engaging in job crafting may already have positive effects (Oldham & Hackman, 2010; Tims et al., 2013): occupational self-efficacy.

Occupational self-efficacy is defined as "the competence that a person feels concerning the ability to successfully fulfill the tasks involved in his or her job" (Rigotti, Schyns, & Mohr, 2008, p. 239). It builds on Bandura's (1977a) concept of self-efficacy, but embraces the requirement to describe self-efficacy specifically for a domain (Bandura, 1977b). As employees with high occupational self-efficacy perceive their capabilities as sufficient to successfully perform tasks, they might be more likely to persist longer on and take on more challenging tasks. Consequently, they might perform better than employees not engaging in job crafting (Bandura, 1977a; Harrison, Rainer, Hochwarter, & Thompson, 1997; Judge & Bono, 2001; Rigotti et al., 2008; Wood & Bandura, 1989). It is also plausible that employees with high occupational self-efficacy per se engage more in job crafting (Tims, Bakker, & Derks, 2014). Therefore, the relationship between job crafting and occupational self-efficacy may be reciprocal. Accordingly, occupational self-efficacy might be a mediator of the relationship between job crafting and performance. Hence, occupational self-efficacy could be a third variable which outweighs the negative effects of decreasing hindering job demands on performance via work engagement. It is important to note that this constitutes one possible theoretical explanation and future research should further explore this and other possible explanations for our findings.

Mediation of the Relationship between Job Crafting and Performance through Work Engagement

Overall, the results of the mediation analyses provided support for our hypothesis that the relationship between job crafting and performance is partly mediated by work engagement.

However, there were some findings which deserve further discussion.

First, the relationship between increasing social job resources and performance was fully mediated via work engagement even though only a partial mediation is predicted by the JD-R model. This result was only confirmed when including social job resources alone in the mediation model, but no other job crafting practice. Second, the relationship between increasing challenging job demands and performance was not mediated by work engagement. Moreover, the direct relationship between increasing challenging job demands and performance had the opposite sign (negative) when including other job crafting practices as well. In contrast, when including challenging job demands as the only job crafting practice, the relationship with performance was positive and partly mediated by work-engagement. Accordingly, it appears that increasing challenging job demands is only of little incremental value to the prediction of performance and is even detrimental to performance once other job crafting practices are taken into account as the positive effect seems to be due to a general positive effect of job crafting.

This is certainly surprising since the effect of increasing challenging job demands on performance is usually assumed to be based on entirely different mechanisms (e.g., personal growth and gains in positive emotions) than the effect of other job crafting practices. One interpretation may be that trying to increase challenging job demands (in terms of a job crafting practice) is unrelated to increasing challenging job demands. The same result was found by Tims et al. (2013). Possibly other variables being affected by all job crafting practices may cause the relationship between increasing challenging job demands and performance—for instance occupational self-efficacy, which might provide an explanation why no incremental value of increasing challenging job demands could be found. In addition, increasing challenging job demands may involve negative costs such as increased strain—especially in the long run—which

then results in a negative effect on performance (Lepine et al., 2005).

Lastly, the finding that decreasing hindering job demands is negatively related to performance both directly and indirectly via work engagement in the mediation analyses may be explained as follows: As decreasing hindering job demands is unrelated to burnout (Tims et al., 2013), it is likely that employees engaging in decreasing hindering job demands directly impair their ability to perform well, for instance by minimizing contact with people who are important for performing well. A potential third variable such as occupational self-efficacy did not seem to balance out this direct negative effect, since the mediation analyses indicated the incremental value of decreasing hindering job demands for the prediction of performance. Overall, the results of our mediation analyses suggest that the relationship between job crafting, work engagement, and performance may be more complex than suggested by the JD-R model—especially for increasing challenging and decreasing hindering job demands.

Exploratory Moderator Analyses

To gain new insights into the nature of the phenomenon of job crafting, we conducted exploratory moderator analyses. In the following, we will focus our discussion to the most consistent moderator of the relationship between job crafting, work engagement, and performance: employees' culture.

First, the relationship between increasing social job resources and work engagement was smaller in samples from individualistic cultures. Group membership is central to the identity of collectivists and hence, their need to belong is stronger (Baumeister & Leary, 1995; Oyserman et al., 2002). Consequently, collectivists may experience more work engagement than individualists when they ask their supervisor or colleagues for feedback as this fulfils their need to belong. Second, in samples from collectivistic cultures, the relationship between increasing challenging

job demands and work engagement was larger. Perhaps, collectivists experience more positive emotions when they engage in increasing challenging job demands as they perceive their behavior as a service to the community due to the higher saliency of group membership compared to individualists (Oyserman et al., 2002). Consequently, these additional positive emotions increase work engagement. Third, the relationship between decreasing hindering job demands and work engagement was negative only in samples from individualistic cultures. One explanation may be that collectivists may simply not engage in decreasing hindering job demands as they feel responsible for the group and strive for harmonic relationships. Hence, they may not reduce the mental intensity of their work, avoid difficult decisions at work, or even minimize contact with people whose problems affect them emotionally and people whose expectations are unrealistic. Consequently, their work engagement is not reduced in comparison to individualists who engage in decreasing hindering job demands. In any case, the effects of job crafting vary substantially between individualistic and collectivistic cultures, which is new and interesting, but requires further investigation.

Future Research Questions

The results of the present meta-analysis inaugurate interesting future research questions. First, the results raise the question whether the relationship between job crafting, work engagement, and performance is more complex than suggested by the JD-R model. This seems to be particularly true for the relationships of increasing challenging and decreasing hindering job demands on the one side and performance on the other side. Hence, future research should examine more closely possible variables that could explain these findings, for example burnout and occupational self-efficacy.

Second, our mediation analyses suggest that it might be interesting to design job crafting

interventions which aim at increasing structural and social job resources as well as preventing decreasing hindering job demands as this might be sufficient to enhance work engagement and performance. Engaging in increasing challenging job demands beyond increasing structural and social job resources seems to have no or even negative effects on work engagement and performance, although solely increasing challenging job demands boosts work engagement and performance. Hence, future research should examine which component of increasing challenging job demands is detrimental to work engagement and performance compared to increasing structural job resources and increasing social job resources.

Third, it might be promising for future research to replicate the results of our exploratory moderator analyses. Research should especially pay attention to culture. As culture is related to self-construal (Gardner, Gabriel, & Lee, 1999; Markus & Kitayama, 1991), it would be interesting to investigate whether the self-construal of the employee moderates the relationship between job crafting, work engagement, and performance in order to refine the theory on job crafting. For this purpose, our theoretical explanations of the moderator effects constitute a first starting point. In sum, although it seems secured that job crafting, work engagement, and performance are related to each other, future research should further elaborate the underlying mechanisms and contextual factors.

Limitations

There are some limitations to our meta-analysis. First, we did not investigate whether burnout mediates the relationship between job crafting and performance as suggested by the JD-R model, as the number of studies providing the necessary data was too small (cf. Jackson & Turner, 2017). Nevertheless, we could draw some conclusions by logical means as the results of our mediation analyses suggest that the relationship between job crafting and performance may

be more complex than suggested by the JD-R model which should be investigated in the future.

Second, regarding our exploratory moderator analyses, it is important to note that the number of studies was rather small in some models leading to presumably low statistical power of the respective analysis. Therefore, non-significant moderators do not necessarily imply that there is in fact no moderation. Similarly, significant moderators should also be interpreted cautiously when they are based on a small number of studies (Jackson & Turner, 2017) and should thus be replicated in the future to ensure their value.

Third, this meta-analysis does not allow conclusions on causality as our analyses were only based on cross-sectional correlations. Besides, it is rather difficult to show causal effects conclusively in a meta-analysis—even with longitudinal correlations. Hence, we aimed at maximizing the accuracy of the estimate of the cross-sectional correlations in the population by including as many cross-sectional correlations as possible and by combining longitudinal correlations to cross-sectional correlations. It is important to note that the hypothesized effects are based on sound theoretical considerations and should also emerge in cross-sectional correlations as they should be the result of the same processes. Furthermore, it would not even be reasonable to assume a pure causal effect of job crafting on work engagement at least for increasing structural job resources and increasing social job resources as it is plausible that work engagement also leads to more increasing structural and social job resources. Thereby, job crafting and work engagement may form a positive gain spiral (Bakker, 2011; Demerouti, 2014; Sonnentag, 2003). The causality in the relationship between job crafting, work engagement, and performance should be examined via longitudinal studies to provide more conclusive answers.

Fourth, regarding our meta-analytic structural equation models, it has to be noted that not all studies provided information on all relationships between the variables under study. Hence,

the meta-analytic correlations combined in the overall correlation matrix are not all based on the same set of studies. Whether this influenced our results in a relevant manner is hard to predict. We can only point to the necessity of investigating all variables in the JD-R model at once in future primary studies.

Fifth, a further caveat of the present meta-analysis is that many correlations included common-method variance, since correlations overestimate the relationship between two constructs whenever they were obtained with identical or similar methodologies (Podsakoff, MacKenzie, Lee, Podsakoff, 2003). This is a common problem in many primary studies and consequently corresponding meta-analyses and not easily avoidable, since non-self-report measurement of variables is often practically infeasible.

Practical Implications

Our research findings on the relationship between job crafting, work engagement, and performance have various practical implications. First, our findings suggest that employees should consciously engage in job crafting as job crafting seems to be associated with higher work engagement and performance. In this context, employees are well advised to focus on increasing structural job resources and increasing social job resources as our findings imply that this may be sufficient for stimulating higher work engagement and better performance. Employees can craft their jobs by simply engaging in the activities that are measured by Tims et al.'s (2012) or Petrou et al.'s (2012) job crafting instruments. For instance, employees may try to (a) develop themselves professionally by taking additional courses relevant to their work, (b) deciding on their own how to do tasks based on their knowledge and experience when they see potential for improvement, and (c) asking their supervisor to coach them.

It is important to note that not only the employee benefits from job crafting, but also the

company the employee works for. Therefore, managers should likewise enable their employees to engage in increasing structural job resources and increasing social job resources by (a) promoting the employees' autonomy which enables them to engage in job crafting (Demerouti, 2014), (b) paying attention to and value employees' job crafting efforts (Demerouti, 2014), and (c) implementing job crafting interventions to stimulate job crafting (e.g. Van Wingerden, Derks, & Bakker, 2017). However, job crafting is not always beneficial for work engagement and performance as decreasing hindering job demands seems to be detrimental to work engagement. Consequently, employees should not necessarily engage in decreasing hindering job demands, but seek other ways to deal with emotionally intense work, persons whose problems affect them emotionally, or persons whose expectations are unrealistic (Tims et al., 2012). For example, they could seek social support or engaging in conversations. Managers should foster such efforts and support their employees whenever possible.

The results of our moderator analyses suggest that employees and managers trying to engage in or foster job crafting should take culture into account. Employees from collectivistic cultures in East Asia, Africa, and the Middle East should especially increase their social job resources as this seems to have a larger impact on their work engagement and performance than when individualists increase their social job resources. Likewise, managers should harmonize their measures according to the cultural background of their employees. For example, they should especially value job crafting when employees from collectivistic countries engage in increasing social job resources. This may be of importance in international teams with different cultural backgrounds.

Although the true relationship between job crafting, work engagement, and performance may be smaller than reported in this meta-analysis due to common-method variance, both

employees and managers should not underestimate the effect of employees engaging in job crafting as even small increases in work engagement and performance can make a significant difference in the earnings of companies (Post & Byron, 2015; Xanthopoulou, Bakker, Demerouti, & Schaufeli, 2009).

Conclusion

Although much remains to be learned about job crafting, the results of this meta-analysis provide valuable insights into its relationship with work engagement and performance. Specifically, the results suggest that increasing structural and social job resources as well as to some extent increasing challenging job demands are positively related to both work engagement and performance, whereas decreasing hindering job demands is negatively related to work engagement and unrelated to performance. Testing the mediation of the relationship between job crafting and performance through work engagement via meta-analytic structural equation modelling showed that the relationship between job crafting, work engagement, and performance may be more complex than suggested by the JD-R model. Consequently, future research should further examine this relationship. Furthermore, our exploratory moderator analyses yielded first evidence that the relationship between job crafting, work engagement, and performance is moderated in particular by the employees' culture. Although the results suggest that job crafting may be powerful for increasing employees' work engagement and performance, they also demonstrate that further research on the interplay of these variables is required.

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Tables

Table 1
Descriptive Statistics for Important Study, Sample, Effect Size, and Computed Variables of the Included Studies

Variable	Categories	Frequency	%	M	SD	Min	Max
		Study Variables					
Publication Year	2012	5	11	-	-	-	-
	2013	2	5				
	2014	4	9				
	2015	12	27				
	2016	10	23				
	2017	10	23				
	Unpublished	1	2				
Medium	Journal	35	80	-	-	-	-
	Conference Paper	2	5				
	Dissertation	2	5				
	Unpublished Paper	5	10				
Peer-reviewed?	Yes	38	86	-	-	-	-
	No	6	14				
Discipline	Psychology	44	100	-	-	-	-
Theory	JD-R	44	100	-	-	-	-
Quality (8-point Likert scale)	-	-	-	6.75	1.10	4	8
		Sample Variables					
Region	Western	38	79	-	-	-	-
	Non-Western	10	21				

Variable	Categories	Frequency	%	M	SD	Min	Max
Country	Brazil	1	2	-	-	-	-
	Canada	2	4				
	Denmark	1	2				
	Egypt	1	2				
	Europe	1	2				
	Finland	4	8				
	Germany	2	4				
	Greece	2	4				
	India	1	2				
	Iran	2	4				
	Japan	2	4				
	Netherlands	21	44				
	Norway	1	2				
	South Africa	3	6				
	USA	2	4				
	Mixed	2	10				
Design	Cross-Sectional	35	73	-	-	-	-
	Longitudinal	10	21				
	Intervention	3	6				
Sample Size	-	-	-	398.20	375.08	58	1877
Women %	-	-	-	55.73	20.77	16.00	98.60
Predominant Gender	female	28	58	-	-	-	-
	male	19	40				
	NA	1	2				
Age	-	-	-	40.70	5.35	25.59	50.30
Tenure	-	-	-	12.51	5.65	2.11	24.50

Variable	Categories	Frequency	%	M	SD	Min	Max
Education	University	4	8	-	-	-	-
	Vocational Training	1	2				
	Mixed	29	60				
	NA	14	30				
Industry	Mixed	21	44	-	-	-	-
	Art	1	2				
	Aviation	1	2				
	Chemistry	1	2				
	Council	1	2				
	Education	4	9				
	Finance	1	2				
	Healthcare	7	15				
	Manufacturing	3	6				
	Mining	1	2				
	Police	4	9				
	Post	1	2				
	Technology	1	2				
	Telecommunications	1	2				
Leader %	-	-	-	18.70	11.76	0	33.10
Attrition	-	-	-	34.05	27.26	0	85.70
Task Interdependence	Low	4	8	-	-	-	-
	Medium	43	90				
	High	1	2				
Participants	Employees	48	100	-	-	-	-
			Effect Size Variables				
Likert-Scale	-	-	-	5.34	0.98	5	7

Variable	Categories	Frequency	%	M	SD	Min	Max
Number of Items	-	-	-	5.71	2.53	2	9
Correlations	ISTJR & WE	21	6	-	-	-	-
	ISOJR &WE	33	9				
	ICHJD & WE	30	8				
	DHIJD & WE	25	7				
	ISTJR & P	9	2				
	ISOJR & P	17	5				
	ICHJD & P	16	4				
	DHIJD & P	14	4				
	ISTJR & ISOJR	29	8				
	ISTJR & ICHJD	26	7				
	ISTJR & DHIJD	23	6				
	ISOJR & ICHJD	42	11				
	ISOJR & DHIJD	36	10				
	ICHJD & DHIJD	33	9				
	WE & P	10	3				
Report 1	Self-Report	363	100	-	-	-	-
	Objective	1	0				
Report 2	Self-Report	334	92	-	-	-	-
	Other-Rating	21	6				
	Objective	9	2				
		Computed Variables					
Netherlands / Other	Netherlands	21	44	-	-	-	-
	Other	27	56				
Variable	Categories	Frequency	%	M	SD	Min	Max
Culture	Individualistic	39	81	-	-	-	-
	Collectivistic	9	19				

Variable	Categories	Frequency	%	M	SD	Min	Max
Common-Method Variance	Yes	335	92	-	-	-	-
	No	29	8				

Note. We treated seeking resources as increasing social job resources, seeking challenges as increasing challenging job demands, and reducing demands as decreasing hindering job demands, when studies operationalized job crafting with Petrou et al.'s (2012) general-level and day-level job crafting questionnaire. When studies named the dimensions of the job crafting measures differently, we coded the correlations according to the original dimensions. Frequencies in absolute numbers and % were only calculated for categorical variables. *M, SD, Min, Max* were only calculated for numeric variables. *M* = mean; *SD* = standard deviation; *Min* = minimum; *Max* = maximum; ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands; WE = work engagement; P = performance.

Table 2
Results of the Random-Effects Models for the Relationship Between Job Crafting, Work Engagement, and Performance

				95% CI				
Variable	*k*	*N*	r	*LL*	*UL*	τ^2	$Q(df)$	I^2
Work Engagement								
ISTJR	21	11406	.483*** (.526***)	.442 (.475)	.521 (.578)	0.0112	126.84(20)***	85.24%
ISOJR	33	14543	.309*** (.319***)	.282 (.290)	.335 (.349)	0.0040	82.77(32)***	62.70%
ICHJD	30	13632	.368*** (.386***)	.317 (.329)	.417 (.444)	0.0214	258.29(29)***	90.31%
DHIJD	25	9634	-.065* (-.065*)	-.116 (-.117)	-.014 (-.014)	0.0130	139.82(24)***	82.64%
Performance								
ISTJR	9	2134	.321*** (.333***)	.266 (.273)	.374 (.393)	0.0034	14.71(8)†	42.80%
ISOJR	17	4144	.154*** (.156***)	.106 (.107)	.202 (.204)	0.0052	33.53(16)**	54.78%
ICHJD	16	3748	.210*** (.213***)	.144 (.145)	.273 (.280)	0.0128	49.40(15)***	74.00%
DHIJD	14	3136	-.072 (-.072)	-.174 (-.176)	.031 (.031)	0.0319	90.19(13)***	87.13%

Note. Values in parentheses are Fisher's *z*-values. τ^2, $Q(df)$, and I^2 are based on Fisher's *z*-values. ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands; *k* = cumulative number of studies; *N* = cumulative sample size; r = summary effect estimate; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; τ^2 = estimated amount of total heterogeneity; $Q(df)$ = Cochran's Q-test with $k-1$ degrees of freedom, variability in the observed effect sizes; I^2 = Higgin's I^2, percentage of true heterogeneity between studies.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 3
Meta-Analytic Correlation Matrix Used for Conducting the Mediation Analyses

Variable	1	2	3	4	5	6
1. ISTJR	–	0.0176	0.0470	0.0569	0.0264	0.0307
2. ISOJR	.3910	–	0.0142	0.0262	0.0150	0.0249
3. ICHJD	.6586	.4583	–	0.0287	0.0294	0.0344
4. DHIJD	.1028	.1177	.0589	–	0.0263	0.0527
5. WE	.5266	.3192	.3863	-.0652	–	0.0223
6. P	.3327	.1555	.2129	-.0722	.3052	–

Note. N = 945. Values are Fisher's *z*-values. The meta-analytic correlations r_z between the constructs are presented below the diagonal and the standard errors of the meta-analytic correlations SE_z are presented above the diagonal. ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands; WE = work engagement; P = performance.

Table 4
Parameter Estimates of the Direct and Indirect Effects in the Mediation Model

Variable Effects	β	95% CI *LL*	*UL*
	Performance		
ISTJR[a]	.418***	.318	.518
ISTJR • WE[b]	.104***	.054	.154
ISOJR[a]	.021	-.049	.091
ISOJR • WE[b]	.027**	.012	.043
ICHJD[a]	-.122**	-.214	-.030
ICHJD • WE[b]	-.013[†]	-.027	.001
DHIJD[a]	-.131***	-.190	-.072
DHIJD • WE[b]	-.031***	-.048	-.015
Total	.273***	.192	.355

Note. N = 945. ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands; WE = work engagement; Total = sum of direct and indirect effects; β = standardized beta-weight of the variable effects; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

[a] Direct Effect.

[b] Indirect Effect: X • Y = indirect effect of variable X on Performance via Y.

[†] $p < .10$. ** $p < .01$. *** $p < .001$.

Table 5
Parameter Estimates of the Direct, Indirect, and Total Effects for Each Separate Mediation Model of the Job Crafting Practices

Variable Effects	β	95% CI LL	UL
	Performance		
ISTJR[a]	.293***	.219	.366
ISTJR • WE[b]	.129***	.081	.177
Total	.421***	.364	.479
ISOJR[a]	.054	-.010	.118
ISOJR • WE[b]	.149***	.115	.182
Total	.203***	.140	.265
ICHJD[a]	.114**	.047	.181
ICHJD • WE[b]	.161***	.124	.198
Total	.275***	.214	.337
DHIJD[a]	-.062*	-.121	-.003
DHIJD • WE[b]	-.033*	-.058	-.008
Total	-.095**	-.158	-.031

Note. N = 945. ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands; WE = work engagement; Total = sum of direct and indirect effects; β = standardized beta-weight of the variable effects; CI = confidence interval; *LL* = lower limit; *UL* = upper limit.
[a] Direct Effect.
[b] Indirect Effect: X • Y = indirect effect of variable X on performance via Y.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Table 6

Results of the Integrative Mixed-Effects Models Including All Significant Moderators of the Exploratory Moderator Analyses on the Relationship Between Job Crafting, Work Engagement, and Performance Separated by Job Crafting Practice

				95% CI					
Moderator	*k*	$Q_B(df)$	*b*	*LL*	*UL*	τ^2	$Q_E(df)$	I^2	R^2
Increasing Social Job Resources & Work Engagement									
Culture	33	4.75(1)*				0.0035	77.44(31)***	59.49%	10.65%
Collectivistic[a]	7		(.379***)	(.318)	(.441)				
Individualistic vs. Collectivistic	26		(-.077*)	(-.146)	(-.008)				
Increasing Challenging Job Demands & Work Engagement									
	30	59.03(4)***				0.0042	63.15(25)***	64.10%	80.25%
Culture									
Collectivistic[a]	5		(.261***)	(.141)	(.380)				
Individualistic vs. Collectivistic	25		(-.090*)	(-.180)	(-.001)				
Country									
Other vs. Netherlands	17		(.103**)	(.030)	(.176)				
Constructs									
ICHJD vs. Seeking Challenges	21		(.188***)	(.110)	(.267)				
Increasing Job Demands vs. Seeking Challenges	1		(.161)	(-.140)	(.463)				
Decreasing Hindering Job Demands & Work Engagement									
	25	12.82(2)**				0.0076	77.98(22)***	71.64%	41.28%
Culture									
Collectivistic[a]	6		(.043)	(-.088)	(.175)				
Individualistic vs. Collectivistic	19		(-.163**)	(-.279)	(-.046)				

Moderator	k	$Q_B(df)$	b	95% CI *LL*	95% CI *UL*	τ^2	$Q_E(df)$	I^2	R^2
Country									
Other vs. Netherlands	12		(.019)	(-.084)	(.121)				
Increasing Structural Job Resources & Performance									
	9	5.69(2)†				0.0014	7.47(6)	23.70%	57.21%
Medium									
conference[a]	1		(-.091)	(-.517)	(.336)				
journal vs. conference	8		(.100)	(-.149)	(.349)				
Quality	9		(.048)	(-.029)	(.125)				
Increasing Social Job Resources & Performance									
	16	17.29(5)**				0.0000	8.96(10)	0.00%	100%
Culture									
Collectivistic[a]	2		(-.041)	(-.259)	(.176)				
Individualistic vs. Collectivistic	14		(.077)	(-.109)	(.264)				
Percentage Women	16		(.002†)	(-.000)	(.003)				
Constructs									
Increasing Job Resources vs. Seeking Resources	1		(.040)	(-.238)	(.318)				
ISOJR vs. Seeking Resources	8		(.020)	(-.049)	(.089)				
Relational Crafting vs. Seeking Resources	1		(.246*)	(.027)	(.466)				
Increasing Challenging Job Demands & Performance									
	10	10.19(5)†				0.0104	13.60(4)**	71.67%	40.00%
Region									
Non-Western[a]	1		(.081)	(-.411)	(.573)				

Moderator	k	$Q_B(df)$	b	95% CI *LL*	95% CI *UL*	τ^2	$Q_E(df)$	I^2	R^2
Western vs. Non-Western	9		(.098)	(-.271)	(.467)				
Country									
Other vs. Netherlands	2		(.109)	(-.176)	(.395)				
Tenure	10		(-.007)	(-.027)	(.014)				
Constructs									
ICHJD vs. Seeking Challenges	5		(.189*)	(.000)	(.377)				
Increasing Job Demands vs. Seeking Challenges	1		(-.149)	(-.513)	(.214)				
Decreasing Hindering Job Demands & Performance									
	14	21.93(3)***				0.0088	23.86(10)**	61.85%	72.56%
Culture									
Collectivistic[a]	1		(.332**)	(.102)	(.562)				
Individualistic vs. Collectivistic	13		(-.339**)	(-.589)	(-.089)				
Constructs									
Decreasing Job Demands vs. DHIJD	2		(-.053)	(-.254)	(.148)				
Reducing Demands vs. DHIJD	5		(-.224**)	(-.369)	(-.079)				

Note. We did not include country in the moderator analyses when we included culture in the model as both share much common variance and we wanted to draw inferences on the influence of culture. Furthermore, we did not include predominant gender in the moderator analyses when percentage women moderated a relationship as percentage women is a continuous moderator enabling more precise inferences. Values in parentheses are Fisher's *z*-values. *k* = number of studies in subgroups; $Q_B(df)$ = Omnibus test of moderators with df degrees of freedom; b = regression coefficient of the moderator; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; τ^2 = estimated amount of residual heterogeneity; $Q_E(df)$ = Omnibus test for residual heterogeneity with df degrees of freedom; I^2 = percentage of true residual heterogeneity between studies; R^2 = amount of explained heterogeneity between studies; ISOJR = increasing social job

resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands. $Q_B(df)$, τ^2, $Q_E(df)$, I^2, and R^2 are based on Fisher's *z*-values.
[a] Reference Group.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Table 7
Results of Rosenthal's Fail Safe N & Egger's Test

REM	*k*	*y*	*N*	*z*
		Work Engagement		
ISTJR	21	115	19988	0.272
ISOJR	33	175	14621	1.605
ICHJD	30	160	19189	-1.254
DHIJD	25	135	375	0.830
		Performance		
ISTJR	9	55	692	-0.364
ISOJR	17	95	529	-0.327
ICHJD	16	90	908	-1.675
DHIJD	14	80	52	-0.519

Note. N and *z* are based on Fisher's *z*-values. All Egger tests were nonsignificant (*p* > .05). REM = Random-Effects Model; *k* = number of studies used to calculate the REM; $y = 5k + 10$, value which indicates when publication bias is unlikely; *N* = fail-safe *N*, number of studies that would be necessary to reduce the significance level of an effect to *p* = .05 (nonsignificant); *z* = *z*-Value of Egger's test; ISTJR = increasing structural job resources; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands.

Figures

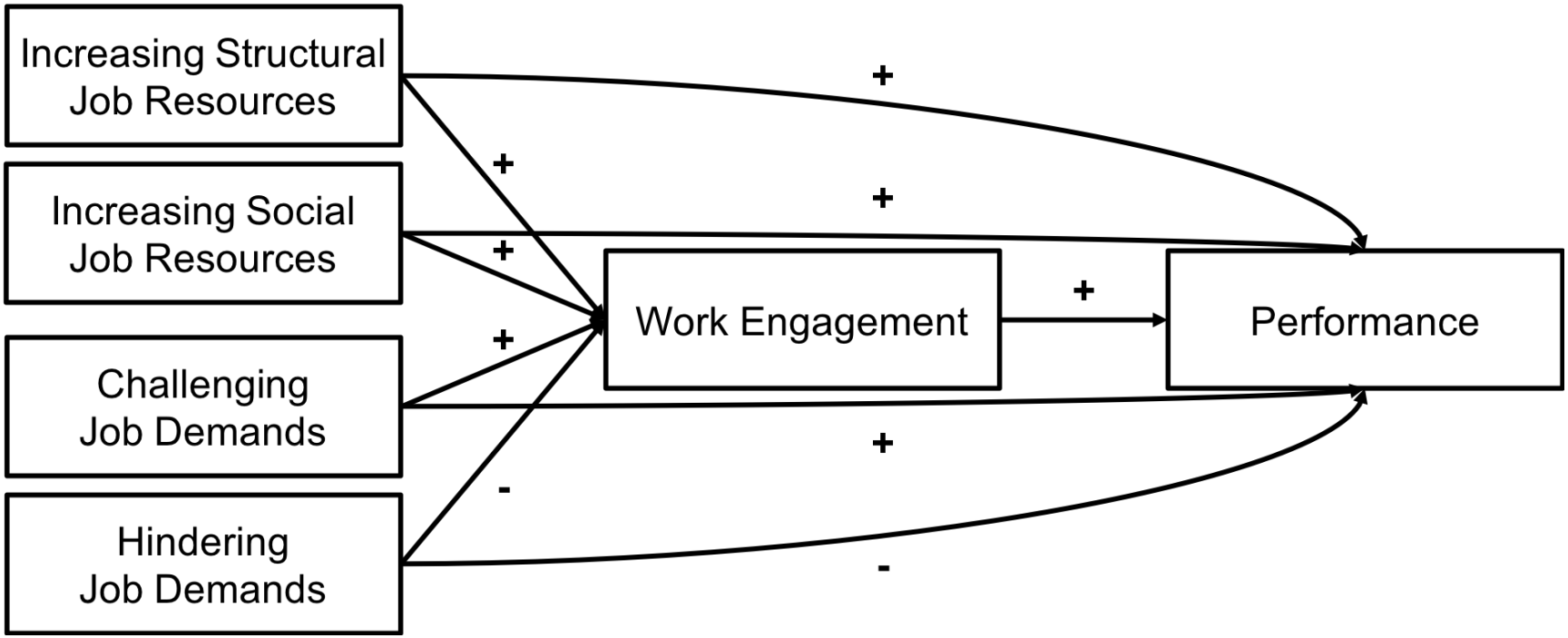

Figure 1. Conceptual model of the present meta-analysis for describing the effects of the job crafting practices on work engagement and performance. + indicate positive effects - indicate negative effects.

Figure 2. Flowchart depicting the stages and results of the literature search.

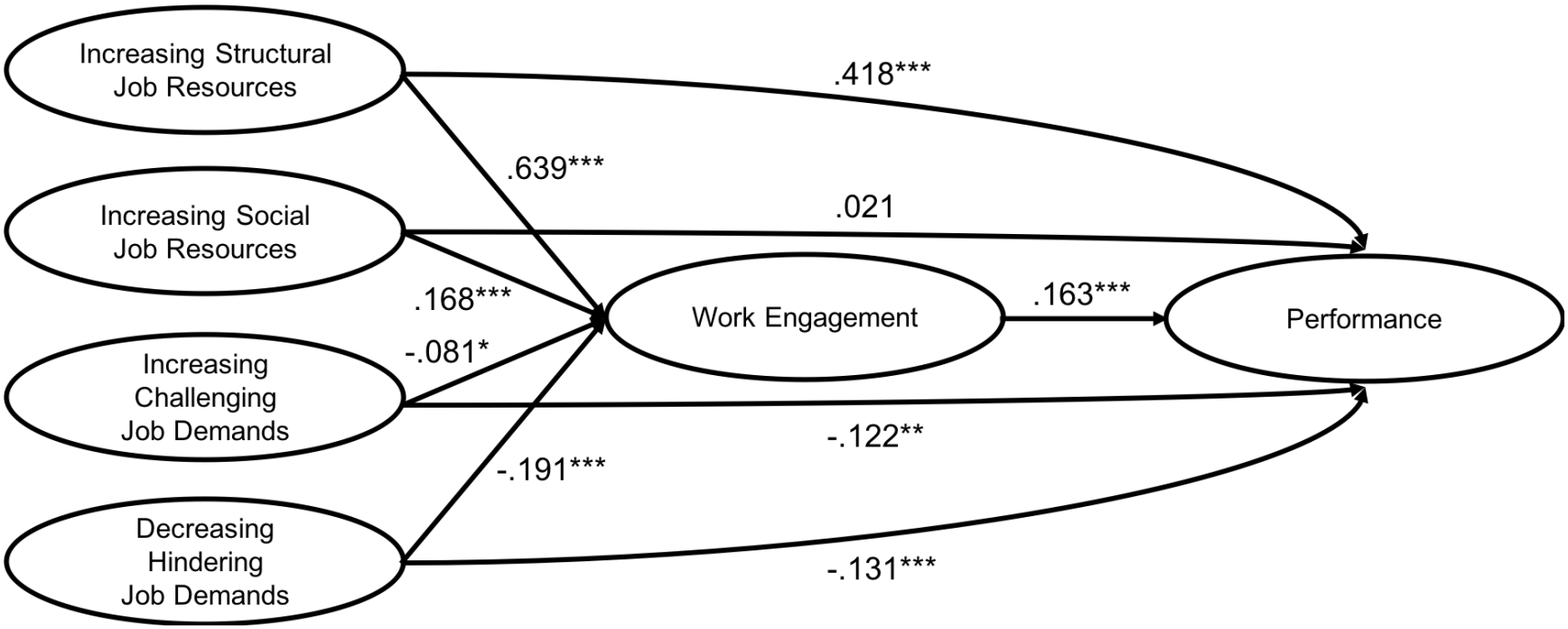

Figure 3. Structural equation modelling results of the mediation analysis. * $p < .05$. ** $p < .01$. *** $p < .001$.

Appendix A

Table A1
Coding Manual

Variable	Type / Values
sampleID[a]	FirstAuthor_etal_year_X[_a | t1]
studyID[a]	FirstAuthor_etal_year[_X]
name of study study_name[a]	string Author et al. (year)
coder[a]	BS / AK
date coded date[a]	dd.mm.yy
first author author1[a]	string last name
year of publication year_publication[ab]	numerical
region country[ab]	categorical (1) western (0) non-western
country country_string[ab]	string
culture ind_col[ab]	categorical (1) individualistic (English-speaking, Europe, Latin/South America, rest Asia) (2) collectivistic (East Asia, Africa, Middle East)
medium[ab]	categorical (1) journal (2) conference-paper (3) unpublished_paper (4) dissertation
peer-reviewed? peer[ab]	categorical (1) yes (0) no
discipline[a]	categorical (1) psychology

Variable	Type / Values
discipline (continued)	(2) other
theoretical conceptualization job crafting theory[a]	categorical (1) JD-R (2) WD (Wrzesniewski & Dutton)
quality[ab]	numerical (8-Likert scale)
design[ab]	categorical (1) cross-sectional (2) longitudinal (3) intervention (4) other
mean age employees age[ab]	numerical
sample size size[ab]	numerical
percentage women in sample percwom[ab]	numerical
predominant gender of sample predomgen[ab]	categorical (1) male (2) female
attrition[ab]	numerical (%); -999 = NA
industry[ab]	string
tenure[ab] (average)	numerical
educational level edu[ab]	string
task-interdependence taskint[ab]	categorical (1) high (2) medium (3) low
percentage leaders in sample percleader[ab]	numerical

Variable	Type / Values
participants[ab]	categorical (1) employees (0) students
variable1[a]	categorical 1) increasing structural job resources (2) increasing social job resources (3) increasing challenging job demands (4) decreasing hindering job demands (5) work engagement (6) task performance (7) contextual performance
variable2[a]	cf. variable1*
correlation identifier corID[ab]	categorical "istjr_isojr"; "istjr_we"; "istjr_taskp"; "istjr_contp"; "istjr_cwb"; "isojr_we"; "isojr_taskp"; "isojr_contp"; "isojr_cwb"; "we_taskp"; "we_contp"; "we_cwb"; "ichjd_we"; "dhijd_we"; "ichjd_taskp"; "ichjd_contp"; "ichjd_cwb"; "dhijd_taskp"; "dhijd_contp"; "dhijd_cwb"; "istjr_ichjd"; "istjr_dhijd"; "isojr_ichjd"; "isojr_dhijd"; “ichjd_dhijd" 1st construct_2nd construct (abbreviation) istjr = increasing structural job resources isojr = increasing social job resources ichjd = increasing challenging job demands dhijd = decreasing hindering job demands we = work engagement taskp = task performance contp = contextual performance
effect size es[a]	numerical
type of reliability variable 1 typerel1[a]	categorical (1) internal consistency (2) split-half (3) test-retest (4) can’t tell (5) none given
type of reliability variable 2 typerel2[a]	cf. type of reliability variable 1

Variable	Type / Values
reliability variable 1 rel1[a]	numerical
reliability variable 2 rel2[a]	numerical
likert-scale type variable 1 likert1[a]	numerical (5-point etc.)
likert-scale type variable 2 likert2[a]	numerical (5-point etc.)
number of items variable 1 numitems1[a]	numerical
number of items variable 2 numitems2[a]	numerical
type of report variable 1 report1[a]	categorical (1) self-report (2) other-rating (3) objective
type of report variable 2 report2[a]	cf. type of report variable 2
construct variable 1 varname1[ab]	string (operationalization, original name of measure)
construct variable 2 varname2[a]	string (operationalization, original name of measure)

Note. Missing data were coded as -999.
[a] Names of the coded variables in the dataset.
[b] Variables included in the exploratory moderator analyses.

Table A2
Adapted Version of Valentine's Quality Rating Sheet

Variable	Type / Values
studyID	FirstAuthor_etal_year[a]_[1]
Internal Validity	
sampling strategy	(1) organisation (2) convenience sample (e.g. peer nomination)
type of report	(1) self-report (2) other-rating (3) objective data
Construct Validity	
construct	(1) job crafting (2) work engagement (3) performance
measure	string
is the measure appropriate for the construct?	(1) yes (0) no
metric for score reliability	(1) internal consistency (2) split-half (3) test-retest (4) can't tell (5) none given
reliability	numerical
Quality Rating	
quality	8-point Likert scale

Note. Quality rating was based on the internal validity and construct validity coding. Missing data were coded as -999.

Appendix B

Detailed Description of Meta-Analytic Procedures

As this meta-analysis focused on the relationship between job crafting, work engagement, and performance, we calculated correlations as summary effect sizes. Prior to our analyses, we transformed the extracted correlations into Fisher's *z*-values via

$$z = \frac{1}{2} ln\left(\frac{1+r}{1-r}\right)$$

which are approximately normal distributed with a variance of

$$Var_z = \frac{1}{n-3}$$

and a standard error of

$$SE_z = \sqrt{Var_z}\,.$$

This transformation corrects the skewness in the distribution of *r* (Borenstein et al., 2009; Silver & Dunlap, 1987). Due to this skewness in the distribution of *r*, averaged correlations are negatively biased (Silver & Dunlap, 1987). Although averaged Fisher's *z*-values are positively biased, they are always less biased than averaged correlations when the averaged Fisher's *z*-values are transformed back into *r* via

$$r = \frac{e^{2z-1}}{e^{2z+1}}$$

(Silver & Dunlap, 1987). That is, averaged Fisher's *z*-values yield a better estimate of the true average correlation than averaged correlations (Silver & Dunlap, 1987). As we use meta-analytic models that calculate a weighted mean to estimate the true population correlation, we always used Fisher's *z*-values in our meta-analytic procedures. we then transformed the results of the meta-analytic procedures back into *r* to ensure the best estimate for the true population correlation.

The relationship between job crafting, work engagement, and performance.

There are two ways to model the relationship between job crafting, work engagement, and

performance in meta-analyses: via fixed-effects and random-effects models. Differences in the observed effect sizes are attributed to within-study variation v_i (index *i* refers to the i^{th} study, with $i = 1, \ldots, k$) in a fixed-effects model, whereas they are attributed to within-study v_i and between-study variation τ^2 in a random-effects model (Veroniki et al., 2016, Viechtbauer, 2010). The within-study variation v_i hereby refers to differences in the effect sizes due to sampling error, whereas the between-study variation τ^2 refers to differences in the true effect sizes due to slight random differences in specific study characteristics such as the method and sample characteristics of a study (Veroniki et al., 2016, Viechtbauer, 2010). As the present meta-analysis includes studies that are not entirely identical regarding study characteristics, we decided a random-effects model to be appropriate for testing hypotheses 1–8.

Random-effects models estimate the summary effect of the studies $i = 1, \ldots, k$ by calculating the mean of the distribution of the true effects (in this case correlations) via

$$\hat{\rho} = \frac{\sum w_i r_i}{\sum w_i}$$

(Veroniki et al., 2016). w_i hereby refers to the inverse of the variance that is computed by

$$w_i = \frac{1}{v_i + \tau^2} .$$

The inverse of the variance decreases when $v_i + \tau^2$ becomes larger, whereas it increases when $v_i + \tau^2$ becomes smaller. As a smaller $v_i + \tau^2$ means a smaller standard error, the inverse of the variance provides information on the precision of each observed effect size r_i: The larger the inverse of the variance of r_i, the more precise is the true correlation in the population ρ estimated by r_i. That is, $\hat{\rho}$ as the estimate of the true correlation in the population ρ is calculated as a weighted mean whereat each observed effect size r_i is weighted corresponding to its precision with the inverse of the variance w_i. However, both v_i and τ^2 must be estimated to calculate the inverse of the variance. Whereas the within-study

variance v_i is estimated via

$$Var_z = \frac{1}{n-3}$$

when using Fisher's *z*-values, there are various estimators for the between-studies variance τ^2. As the restricted maximum-likelihood estimator (REML) is to be preferred when the effect size is a continuous outcome (e.g. a correlation) and studies with large samples are included as in the present meta-analysis, we decided the REML estimator to be appropriate for estimating the between-studies variance τ^2 (Veroniki et al., 2016; Viechtbauer, 2005). In sum, we calculated random-effects models using the restricted maximum-likelihood estimator (REML) for testing hypotheses 1–8.

Mediation analyses. To test whether the relationship between the job crafting practices and performance is partly mediated via work engagement as suggested by the JD-R model (hypothesis 9), we conducted a mediation analysis via structural equation modelling using the *lavaan* package (Rosseel, 2012). First, we created a meta-analytic correlation matrix by calculating a random-effects model using the REML estimator for each correlation to be estimated in the matrix. Second, as this correlation matrix contained Fisher's *z*-values, we converted the values within the matrix into *r*. Third, as each of these correlations stem from a different sample size due to the different number of studies included in the random-effects model used to estimate the correlations, we computed the harmonic mean of the different sample sizes n_i to obtain the number of observations n that formed the basis of the meta-analytic correlation matrix. For this purpose, we converted the Fisher's *z* standard error SE_{z_i} of each random-effects model $i = 1, \ldots, m$ that contributed an effect size to the meta-analytic correlation matrix into n_i via

$$n_i = \frac{1}{Var_{z_i}} + 3$$

which results from

$$SE_{z_i} = \sqrt{Var_{z_i}} \text{ with } Var_{z_i} = \frac{1}{n-3} .$$

Fourth, we conducted a mediation analysis by calculating the hypothesized mediation model using maximum-likelihood-estimation. Then we tested whether the effects of each job crafting practice on performance (direct effects) and the effects of each job crafting practice on performance via work engagement (indirect effects) were significant and in the direction as suggested by the hypothesized mediation model (see Figure 1). This procedure for calculating a meta-analytic structural equation model has been used before (Schepers & Wetzels, 2007; Tett & Meyer, 1993; Van Eerde & Thierry, 1996).

Exploratory moderator analyses. When calculating random-effects models one assumes that each study included in the model measures a different true effect size, because each study differs from the other studies in the model regarding its characteristics. If the studies in a random-effects model systematically differ in their true effect size due to their characteristics, heterogeneity is present (Higgins, Thompson, Deeks, & Altman, 2003).

Heterogeneity can be measured by two statistics: Cochran's Q and Higgin's I^2. Q is defined as

$$Q = \sum_{i=1}^{k} w_i(r_i - \bar{r}_w)^2 \text{ with } \bar{r}_w = \frac{\sum w_i r_i}{\sum w_i}$$

(Cochran, 1954) and approximately follows the χ^2 distribution with (k – 1) degrees of freedom, whereat k is the number of studies included in the model. A significant Q indicates heterogeneity. That is, the studies in the model systematically differ in their true effect sizes due to their characteristics. A nonsignificant Q indicates homogeneity. That is, any differences between the true effect sizes are due to chance.

However, Higgins et al. (2003) showed that Q is problematic for detecting true heterogeneity among studies due to its power characteristics. Therefore, they suggested I^2 as a statistic for detecting true heterogeneity which is based on Cochran's Q and is defined as

$$I^2 = \frac{(Q - df)}{Q} \times 100\%$$

with df degrees of freedom (Higgins et al., 2003). I^2 describes the percentage of total variation across the true effect sizes of the studies included in the random-effects model that results from heterogeneity rather than chance and takes values between 0% and 100% (Higgins et al., 2003). For ease of interpretation, Higgins et al. (2003) suggested the rule of thumb that I^2 = 25 % describes low, I^2 = 50 % describes moderate, and I^2 = 75 % describes high heterogeneity. If Cochran's Q and Higgin's I^2 indicate heterogeneity, moderator analyses for investigating the heterogeneity among the true effect sizes are justified.

When conducting moderator analyses one assumes that the included study characteristics can account for at least some heterogeneity among the true effects (Viechtbauer, 2010). To test this, one conducts the omnibus test of parameters which indicates significant heterogeneity among the true effects when the corresponding Q_B statistic is significant (Viechtbauer, 2010). Significant moderators in a mixed-effects model can be interpreted as study characteristics that influence the average true effect size (Viechtbauer, 2010). However, if moderators are not significant, one can only conclude that a study characteristic does not influence the average true effect size when the mixed-effects model had enough power to detect an influence (Borenstein et al., 2009).

In moderator analyses, τ^2 refers to the amount of residual heterogeneity among the true effects, Q_E to the test for residual heterogeneity (Cochran, 1954) and I^2 to the percentage of residual true heterogeneity among the true effect sizes (Viechtbauer, 2010). A significant Q_E and a large I^2 indicate that there is unaccounted heterogeneity among the true effect sizes. That is, the true effect sizes still differ from each other due to study characteristics despite the inclusion of the moderators in the model. In this case, a further search for moderators is justified.

Appendix C

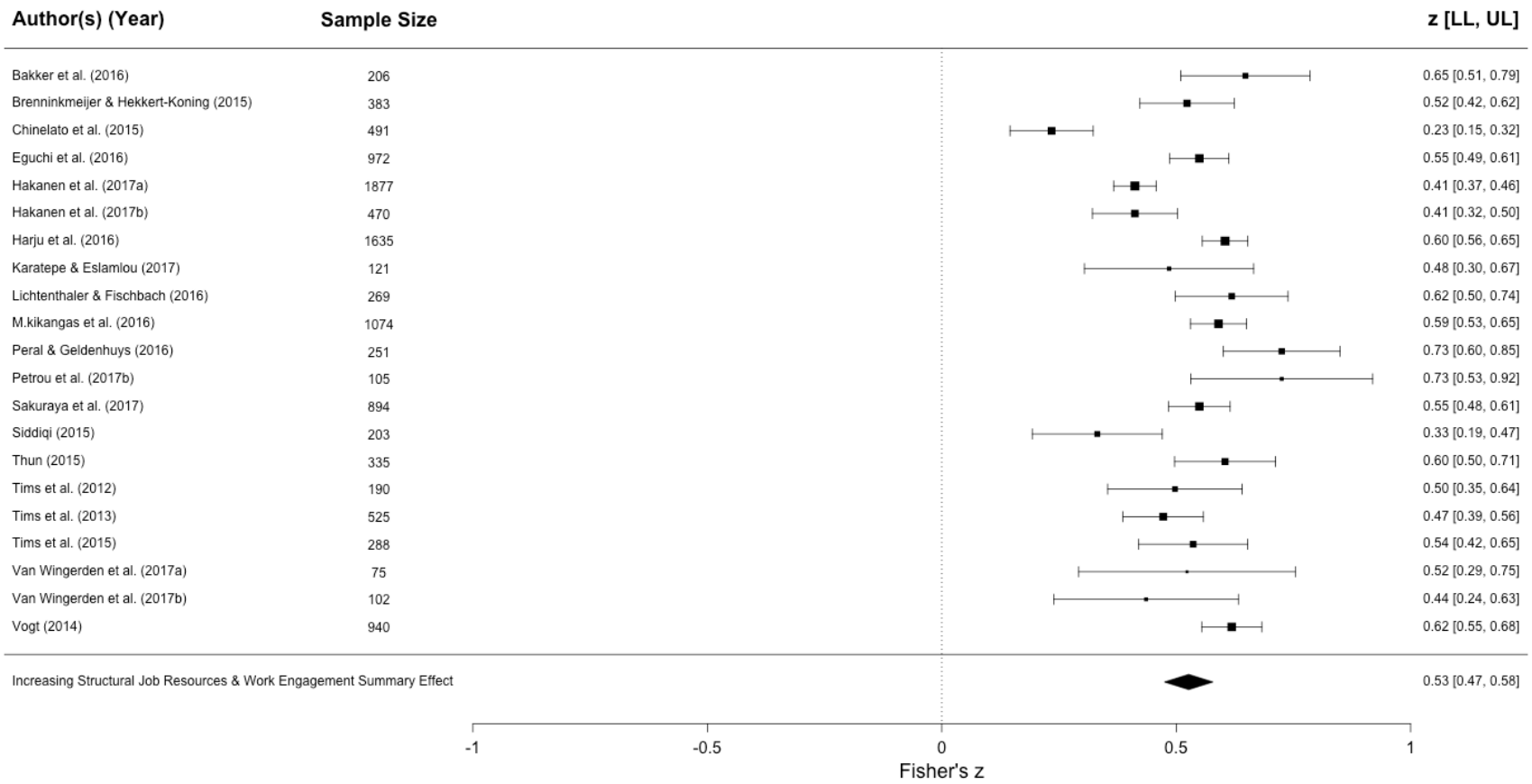

Figure C1. Forest plot depicting each effect size per study which contributed to the summary effect of increasing structural job resources and work engagement. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

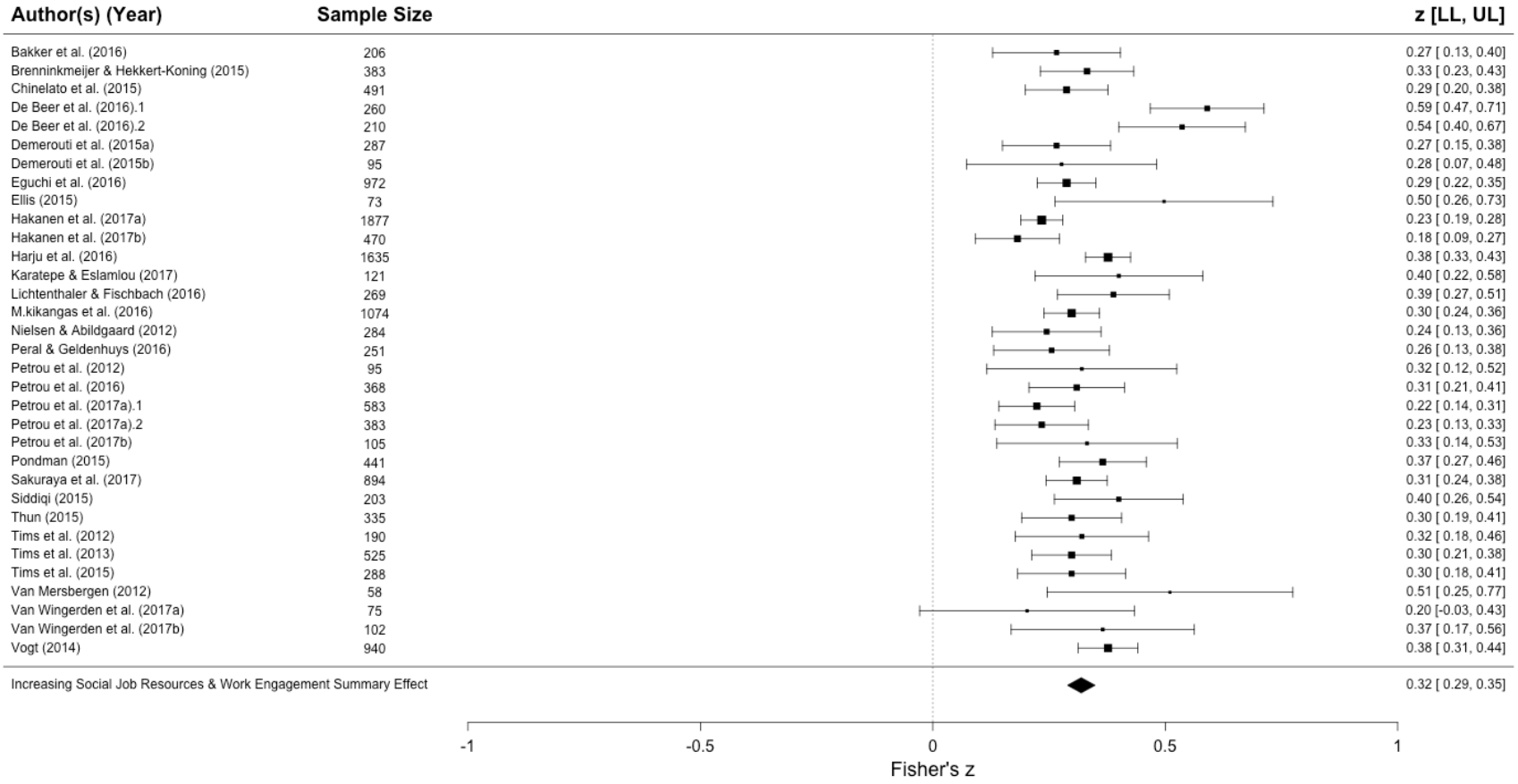

Figure C2. Forest plot depicting each effect size per study which contributed to the summary effect of increasing social job resources and work engagement. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

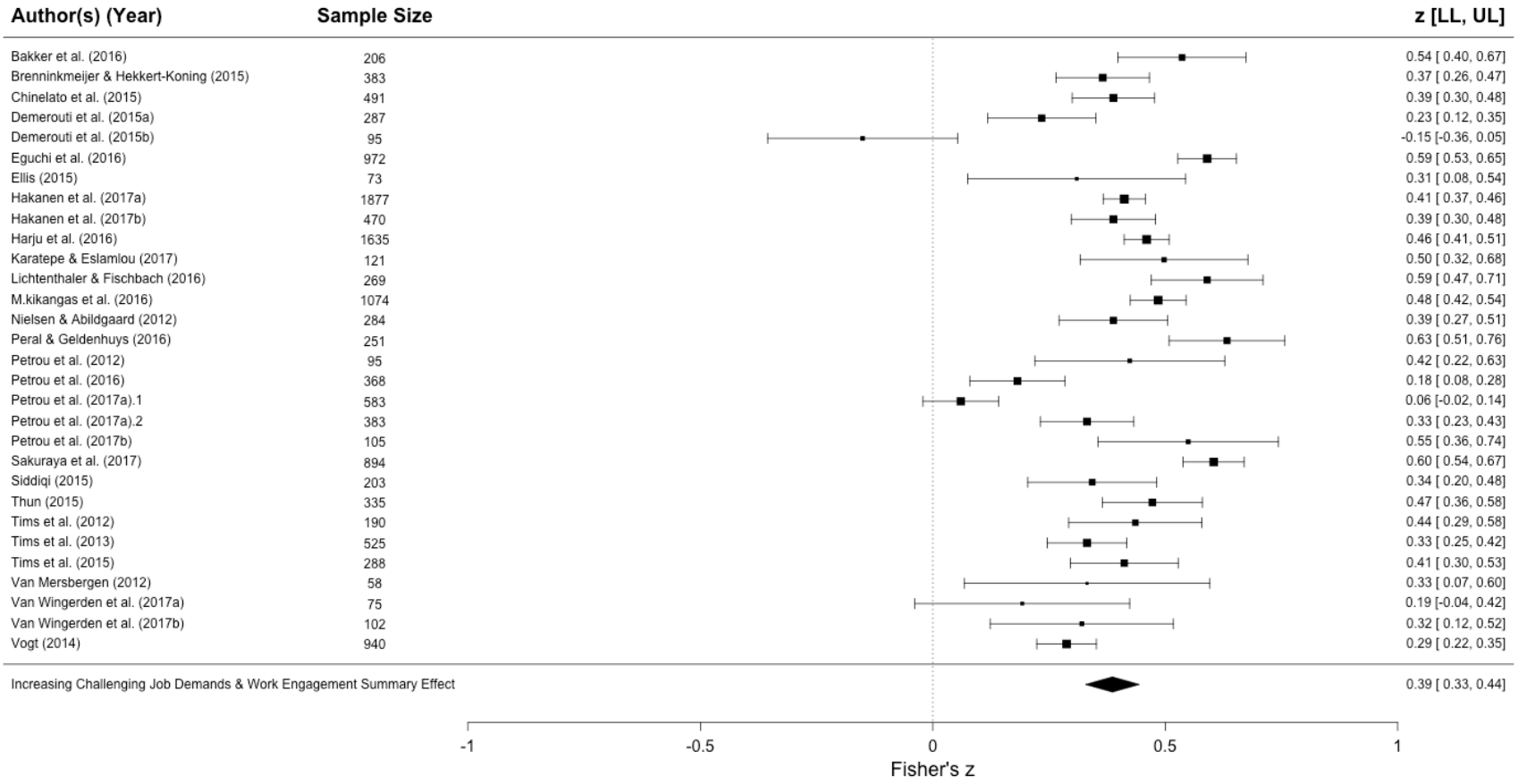

Figure C3. Forest plot depicting each effect size per study which contributed to the summary effect of increasing challenging job demands and work engagement. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

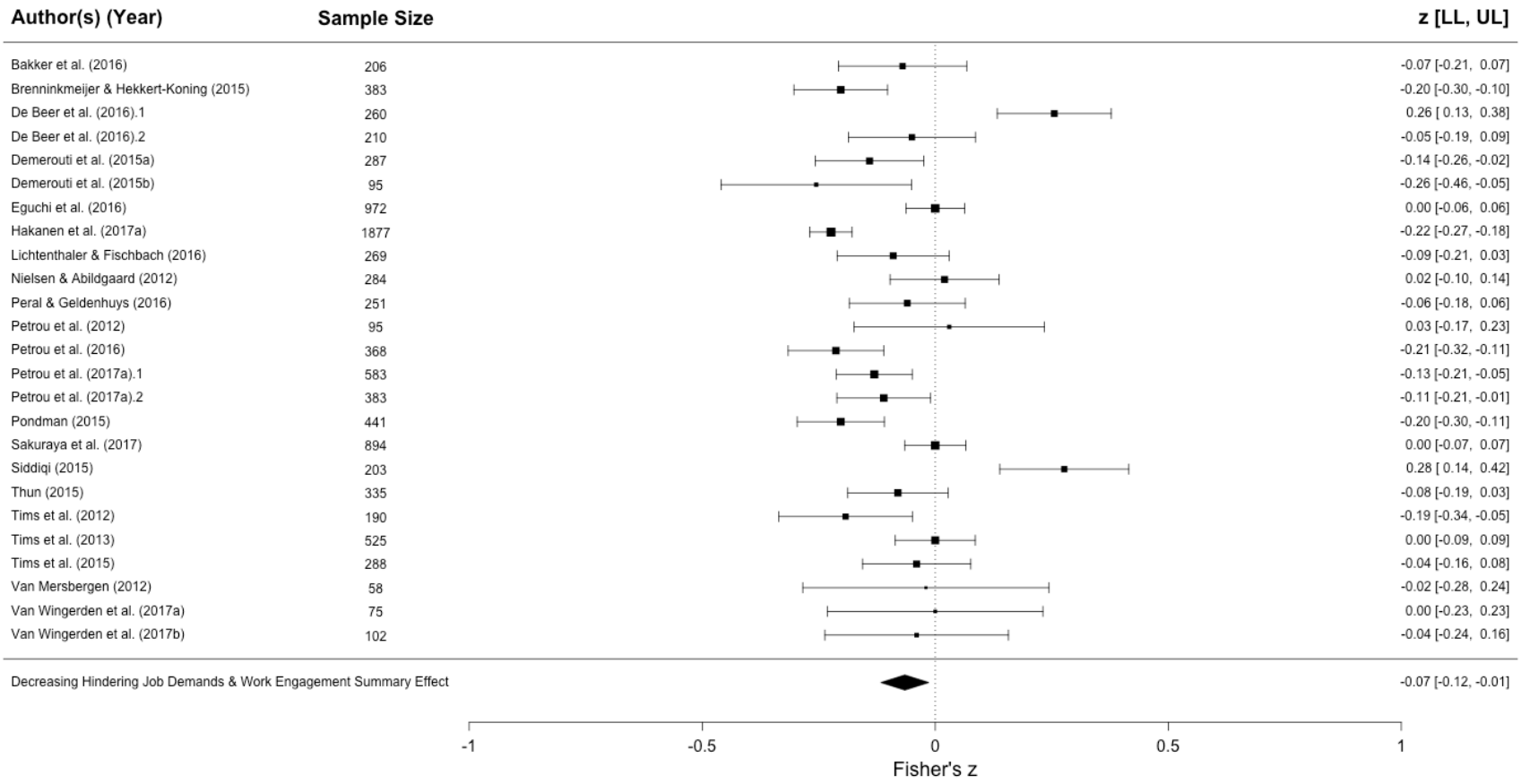

Figure C4. Forest plot depicting each effect size per study which contributed to the summary effect of decreasing hindering job demands and work engagement. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

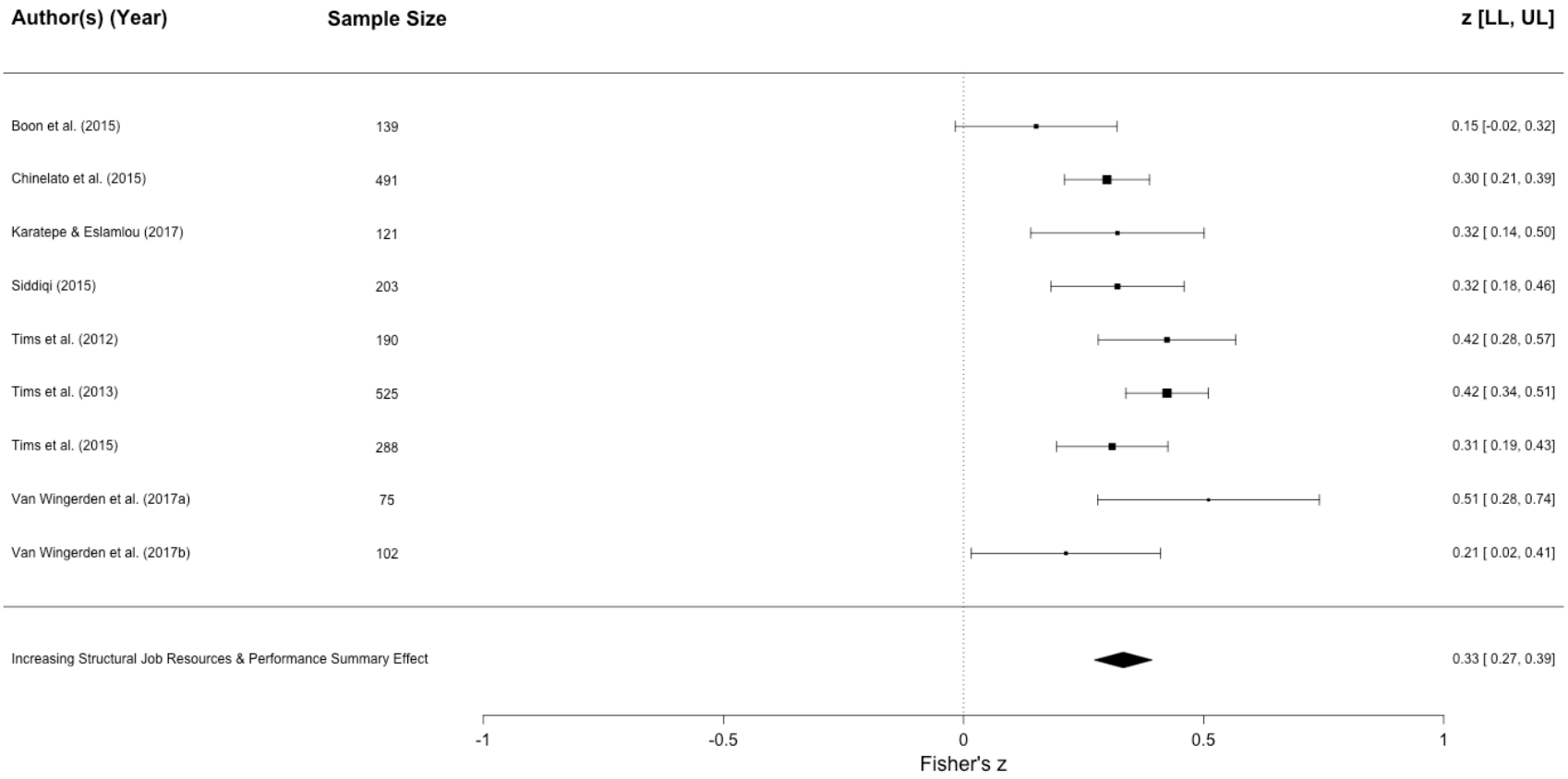

Figure C5. Forest plot depicting each effect size per study which contributed to the summary effect of increasing structural job resources and performance. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

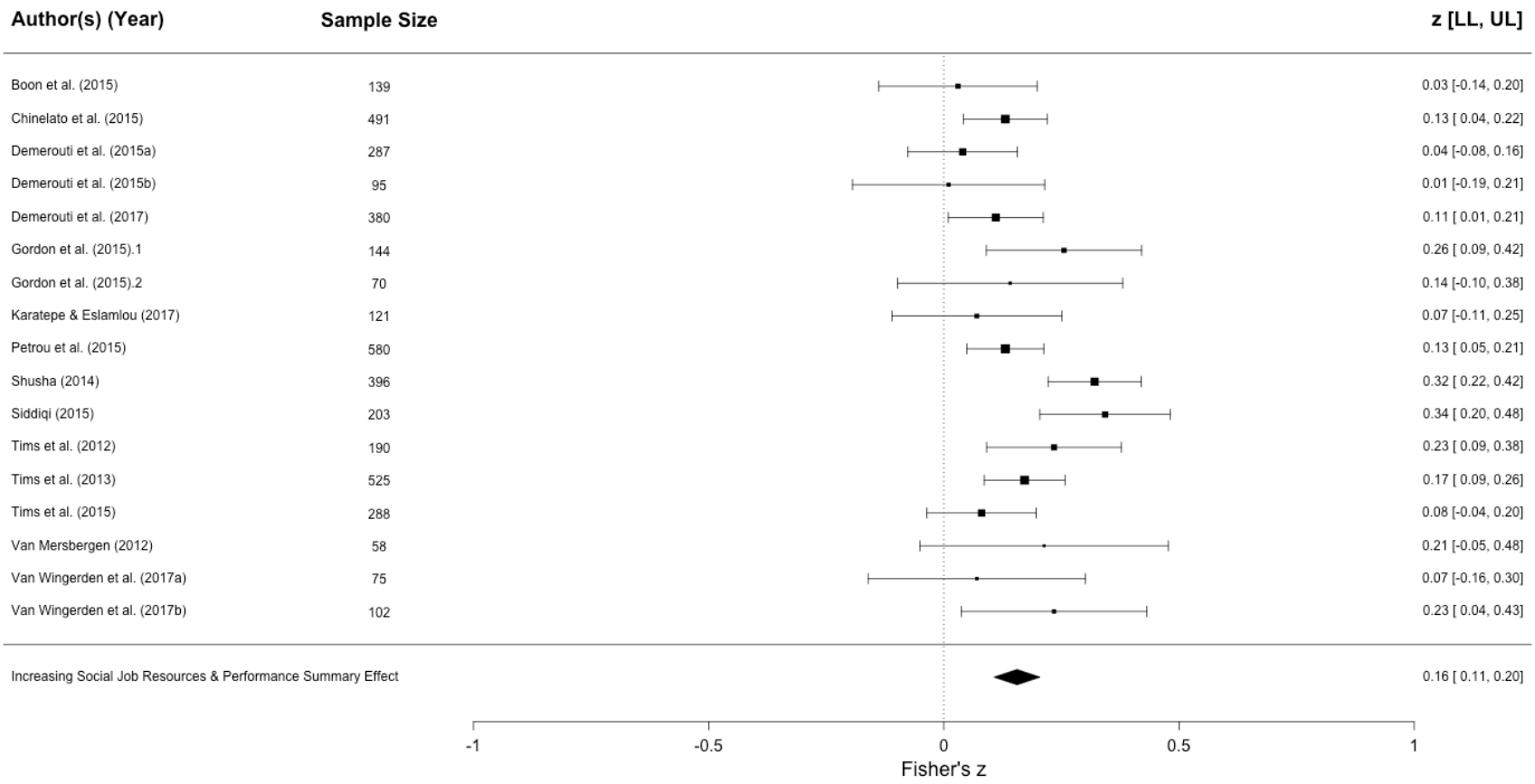

Figure C6. Forest plot depicting each effect size per study which contributed to the summary effect of increasing social job resources and performance. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

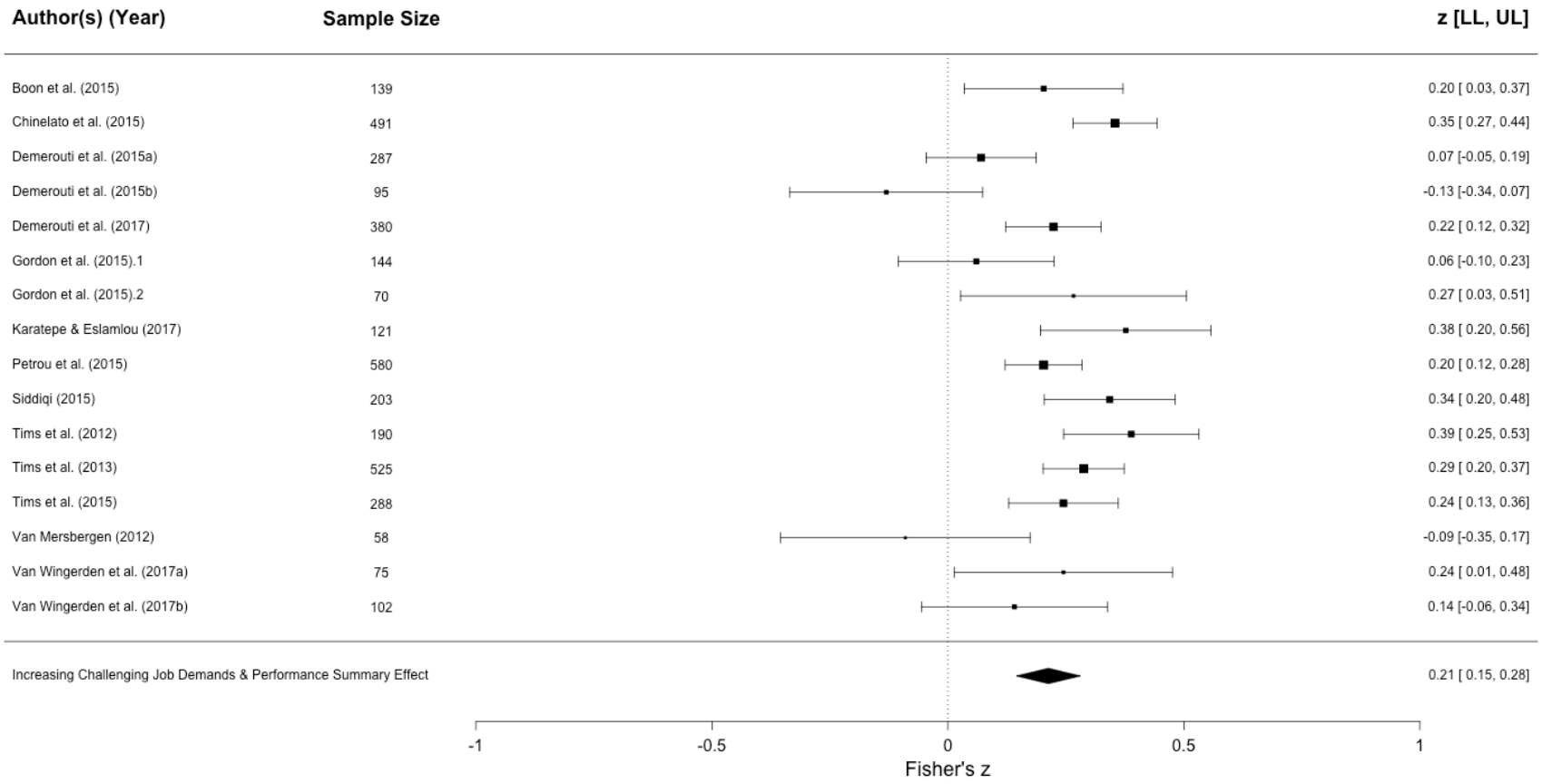

Figure C7. Forest plot depicting each effect size per study which contributed to the summary effect of increasing challenging job demands and performance. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

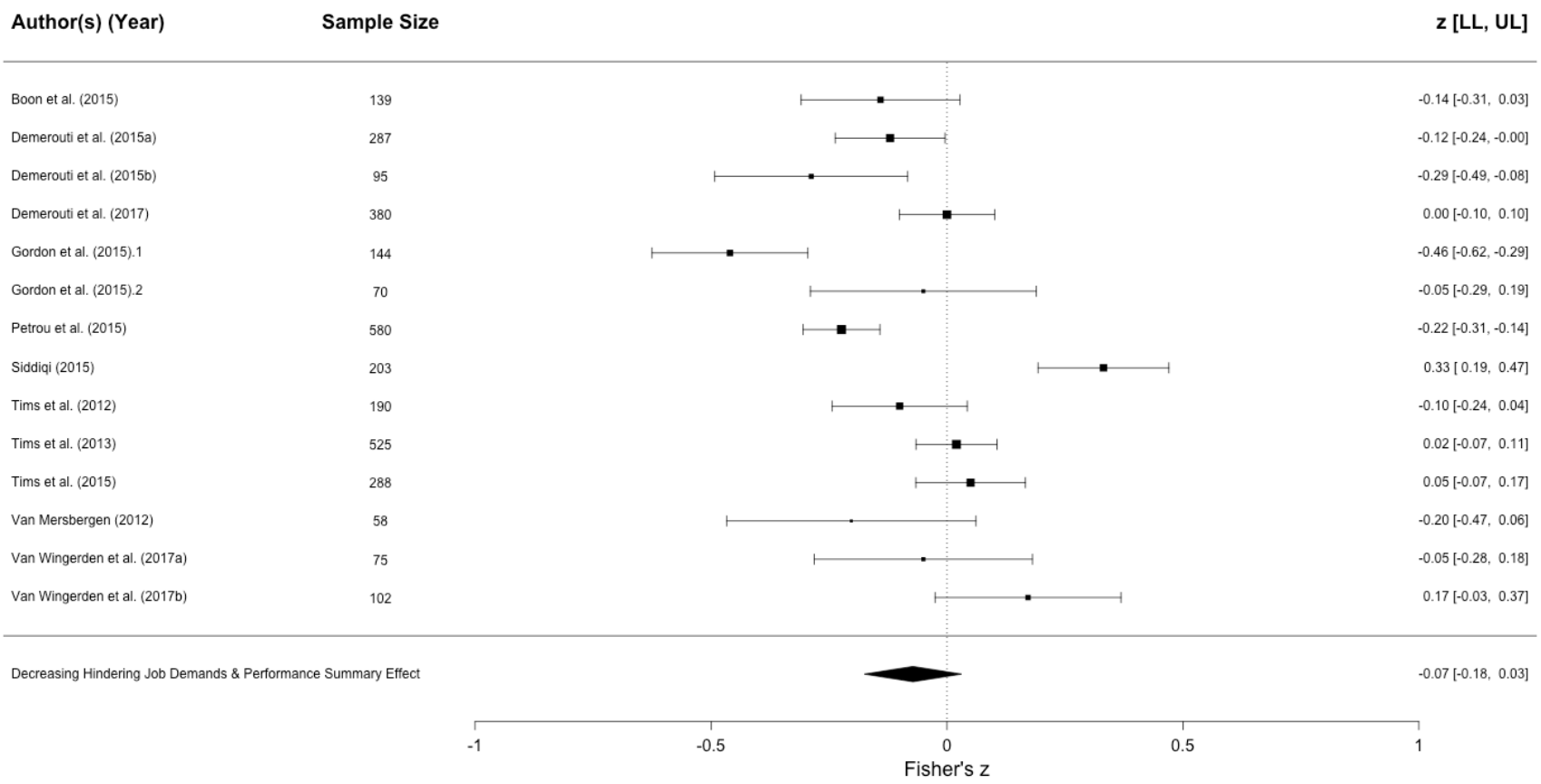

Figure C8. Forest plot depicting each effect size per study which contributed to the summary effect of decreasing hindering job demands and performance. *z* = Fisher's *z*; [*LL*, *UL*] = lower limit and upper limit of the 95% confidence interval.

Appendix D

Table D1

Results of the Single Exploratory Moderator Analyses on the Relationship Between Job Crafting, Work Engagement, and Performance Separated by Job Crafting Practice

Moderator	k	$Q_B(df)$	b	95% CI *LL*	95% CI *UL*	τ^2	$Q_E(df)$	I^2	R^2
Increasing Social Job Resources & Work Engagement									
Culture	33	4.75(1)*				0.0035	77.44(31)***	59.49%	10.65%
Collectivistic[a]	7		(.379***)	(.318)	(.441)				
Individualistic vs. Collectivistic	26		(-.077*)	(-.146)	(-.008)				
Increasing Challenging Job Demands & Work Engagement									
Culture	30	7.07(1)**				0.0165	179.99(28)***	87.47%	22.87%
Collectivistic[a]	5		(.541***)	(.416)	(.665)				
Individualistic vs. Collectivistic	25		(-.185*)	(-.322)	(-.049)				
Region	30	5.83(1)*				0.0174	194.02(28)***	88.09%	18.45%
Non-Western[a]	6		(.513***)	(.398)	(.629)				
Western vs. Non-Western	24		(-.160*)	(-.289)	(-.030)				
Country	30	11.88(1)***				0.0140	170.13(28)***	85.82%	34.62%
Netherlands[a]	13		(.282***)	(.205)	(.359)				
Other vs. Netherlands	17		(.174***)	(.075)	(.273)				
Constructs	30	24.87(2)***				0.0095	124.36(27)***	80.74%	55.65%
Seeking Challenges[a]	8		(.211***)	(.129)	(.293)				
ICHJD vs. Seeking Challenges	21		(.243***)	(.147)	(.339)				

Moderator	k	$Q_B(df)$	b	95% CI *LL*	95% CI *UL*	τ^2	$Q_E(df)$	I^2	R^2
Increasing Job Demands vs. Seeking Challenges	1		(.121)	(-.216)	(.457)				
Decreasing Hindering Job Demands & Work Engagement									
Culture	25	13.29(1)***				0.0071	79.57(23)***	71.48%	45.05%
Collectivistic[a]	6		(.062)	(-.019)	(.142)				
Individualistic vs. Collectivistic	19		(-.175***)	(-.269)	(-.081)				
Region	25	13.29(1)***				0.0071	79.57(23)***	71.48%	45.05%
Non-Western[a]	6		(.062)	(-.019)	(.142)				
Western vs. Non-Western	19		(-.175***)	(-.269)	(-.081)				
Country	25	4.11(1)*				0.0111	132.94(23)***	79.80%	14.75%
Netherlands[a]	13		(-.118***)	(-.188)	(-.048)				
Other vs. Netherlands	12		(.100*)	(.003)	(.197)				
Increasing Structural Job Resources & Performance									
Medium	9	4.12(1)*				0.0015	9.57(7)	26.24%	54.53%
conference	1		(.151)	(-.034)	(.336)				
journal vs. conference	8		(.200*)	(.007)	(.392)				
Quality	9	5.08(1)*	(.068*)	(.009)	(.127)	0.0014	8.43(7)	23.81%	57.64%
Increasing Social Job Resources & Performance									
Culture	17	13.35(1)***				0.0002	19.33(15)	3.65%	96.81%
Collectivistic[a]	3		(.284***)	(.209)	(.359)				
Individualistic vs. Collectivistic	14		(-.155**)	(-.237)	(-.072)				

Moderator	k	$Q_B(df)$	b	95% CI *LL*	95% CI *UL*	τ^2	$Q_E(df)$	I^2	R^2
Percentage Women	17	5.57(1)*	(.002**)	(.000)	(.004)	0.0016	17.74(14)	27.25%	54.98%
Constructs	17	7.45(3)†				0.0022	19.95(13)†	33.18%	57.43%
Seeking Resources[a]	6		(.113***)	(.047)	(.180)				
Increasing Job Resources vs. Seeking Resources	1		(.100)	(-.188)	(.387)				
ISOJR vs. Seeking Resources	9		(.043)	(-.043)	(.129)				
Relational Crafting vs. Seeking Resources	1		(.207**)	(.057)	(.358)				
Increasing Challenging Job Demands & Performance									
Region	16	5.91(1)*				0.0078	35.89(14)**	62.45%	38.90%
Non-Western[a]	3		(.356***)	(.230)	(.483)				
Western vs. Non-Western	13		(-.176*)	(-.317)	(-.034)				
Country	16	4.77(1)*				0.0093	38.56(14)***	66.45%	27.42%
Netherlands[a]	11		(.169***)	(.095)	(.242)				
Other vs. Netherlands	5		(.144*)	(.015)	(.273)				
Tenure	16	4.18(1)*	(-.016*)	(-.032)	(-.001)	0.0123	28.44(8)***	76.98%	29.19%
Constructs	16	16.13(2)***				0.0034	23.64(13)*	42.97%	73.74%
Seeking Challenges[a]	6		(.135***)	(.062)	(.208)				
ICHJD vs. Seeking Challenges	9		(.163***)	(.068)	(.257)				
Increasing Job Demands vs. Seeking Challenges	1		(-.225)	(-.522)	(.071)				

Moderator	*k*	$Q_B(df)$	*b*	95% CI *LL*	*UL*	τ^2	$Q_E(df)$	I^2	R^2
Decreasing Hindering Job Demands & Performance									
Culture	14	7.24(1)**				0.0192	56.47(12)***	80.28%	39.89%
Collectivistic[a]	1		(.332*)	(.027)	(.637)				
Individualistic vs. Collectivistic	13		(-.444***)	(-.752)	(-.135)				
Region	14	7.24(1)**				0.0192	56.47(12)***	80.28%	39.89%
Non-Western[a]	1		(.332*)	(.027)	(.637)				
Western vs. Non-Western	13		(-.436**)	(-.753)	(-.118)				
Constructs	14	8.84(2)*				0.0183	42.91(11)***	77.46%	42.72%
DHIJD[a]	7		(.043)	(-.073)	(.159)				
Decreasing Job Demands vs. DHIJD	2		(-.117)	(-.371)	(.137)				
Reducing Demands vs. DHIJD	5		(-.274**)	(-.455)	(-.094)				

Note. Values in parentheses are Fisher's *z*-values. *k* = number of studies in subgroups; $Q_B(df)$ = Omnibus test of moderators with df degrees of freedom; b = regression coefficient of the moderator; CI = confidence interval; *LL* = lower limit; *UL* = upper limit; τ^2 = estimated amount of residual heterogeneity; $Q_E(df)$ = Omnibus test for residual heterogeneity with df degrees of freedom; I^2 = percentage of true residual heterogeneity between studies; R^2 = amount of explained heterogeneity between studies; ISOJR = increasing social job resources; ICHJD = increasing challenging job demands; DHIJD = decreasing hindering job demands. $Q_B(df)$, τ^2, $Q_E(df)$, I^2, and R^2 are based on Fisher's *z*-values.
[a] Reference Group.
† $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Appendix E

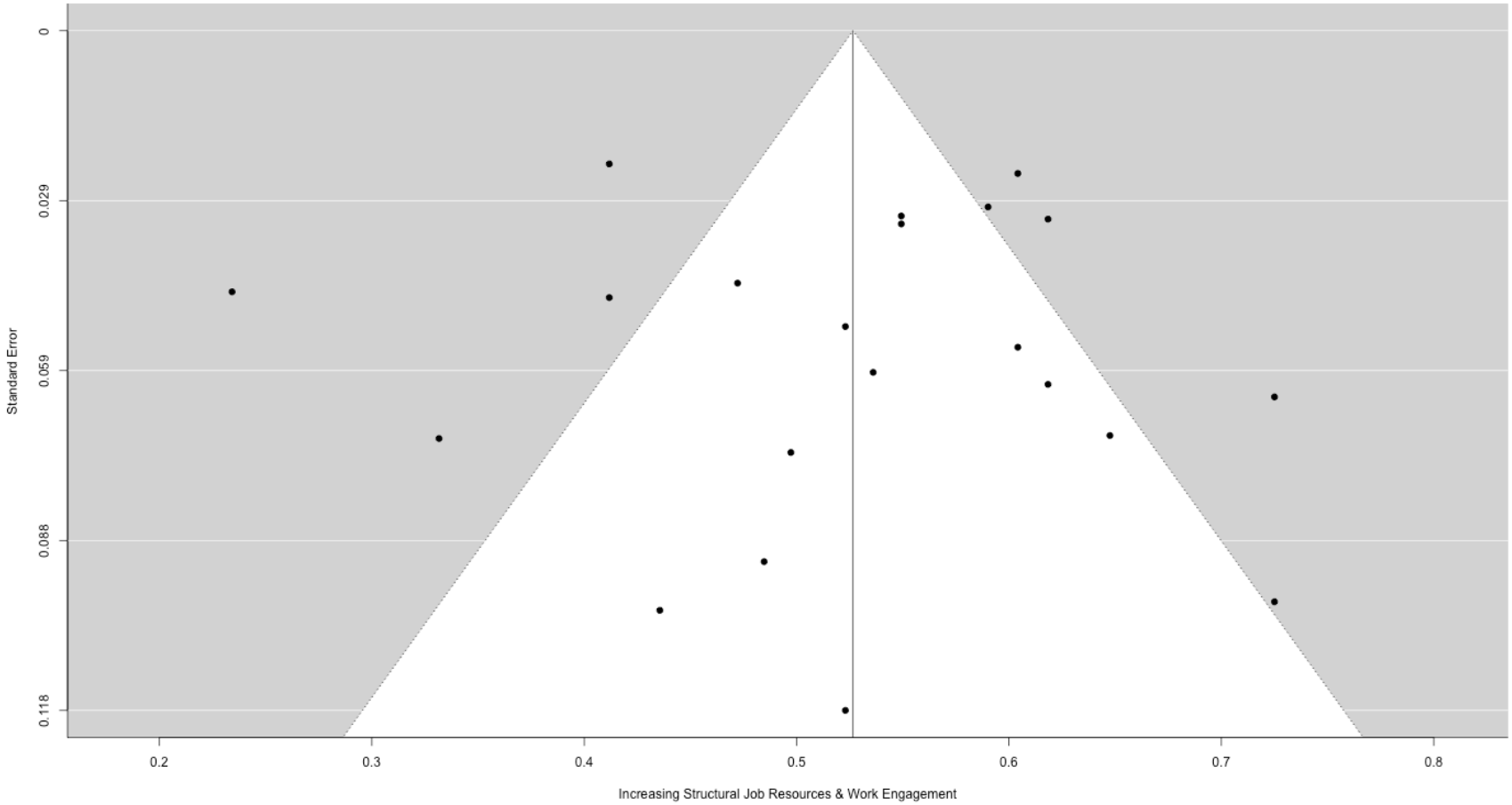

Figure E1. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing structural job resources and work engagement.

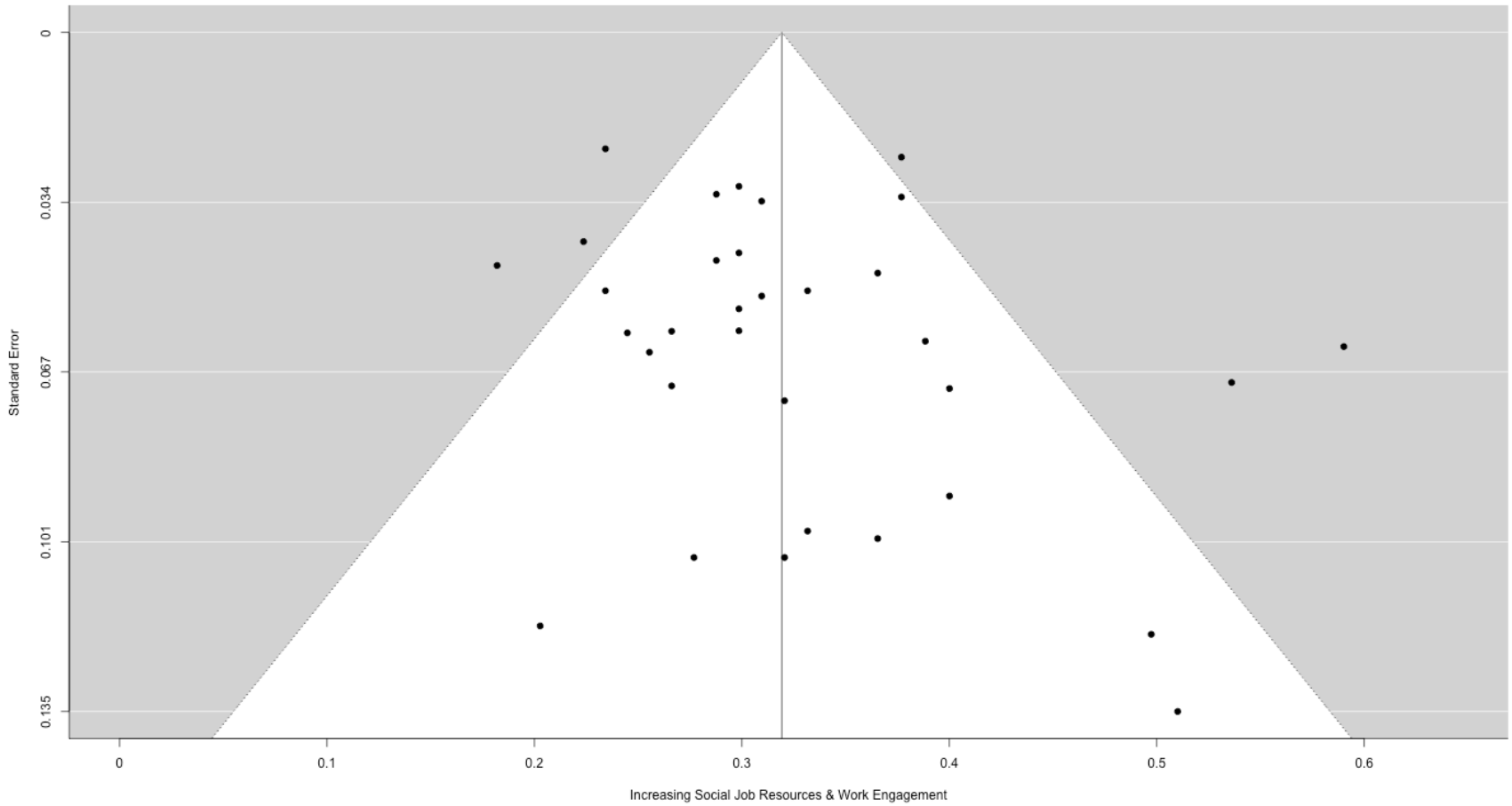

Figure E2. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing social job resources and work engagement.

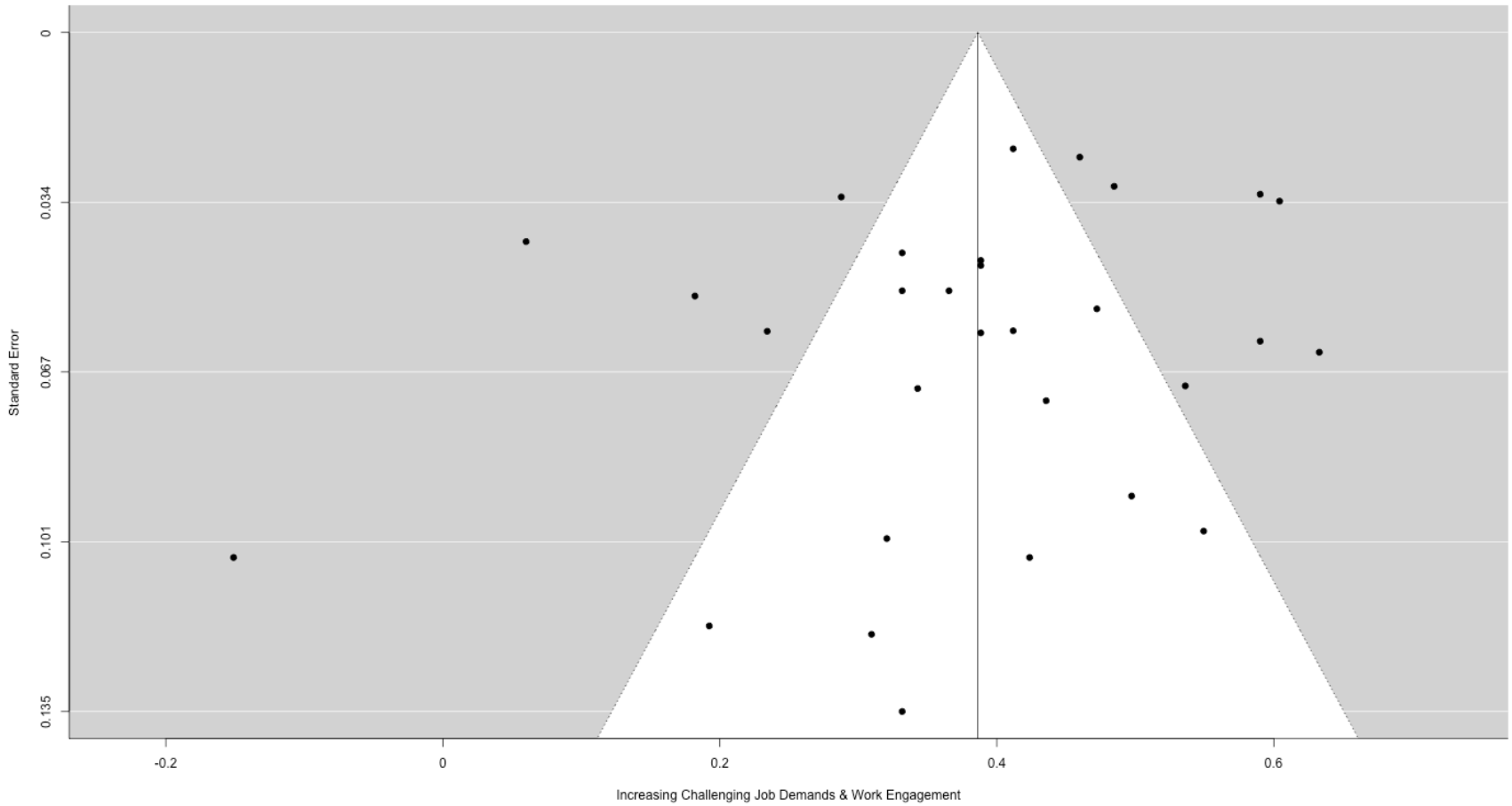

Figure E3. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing challenging job demands and work engagement.

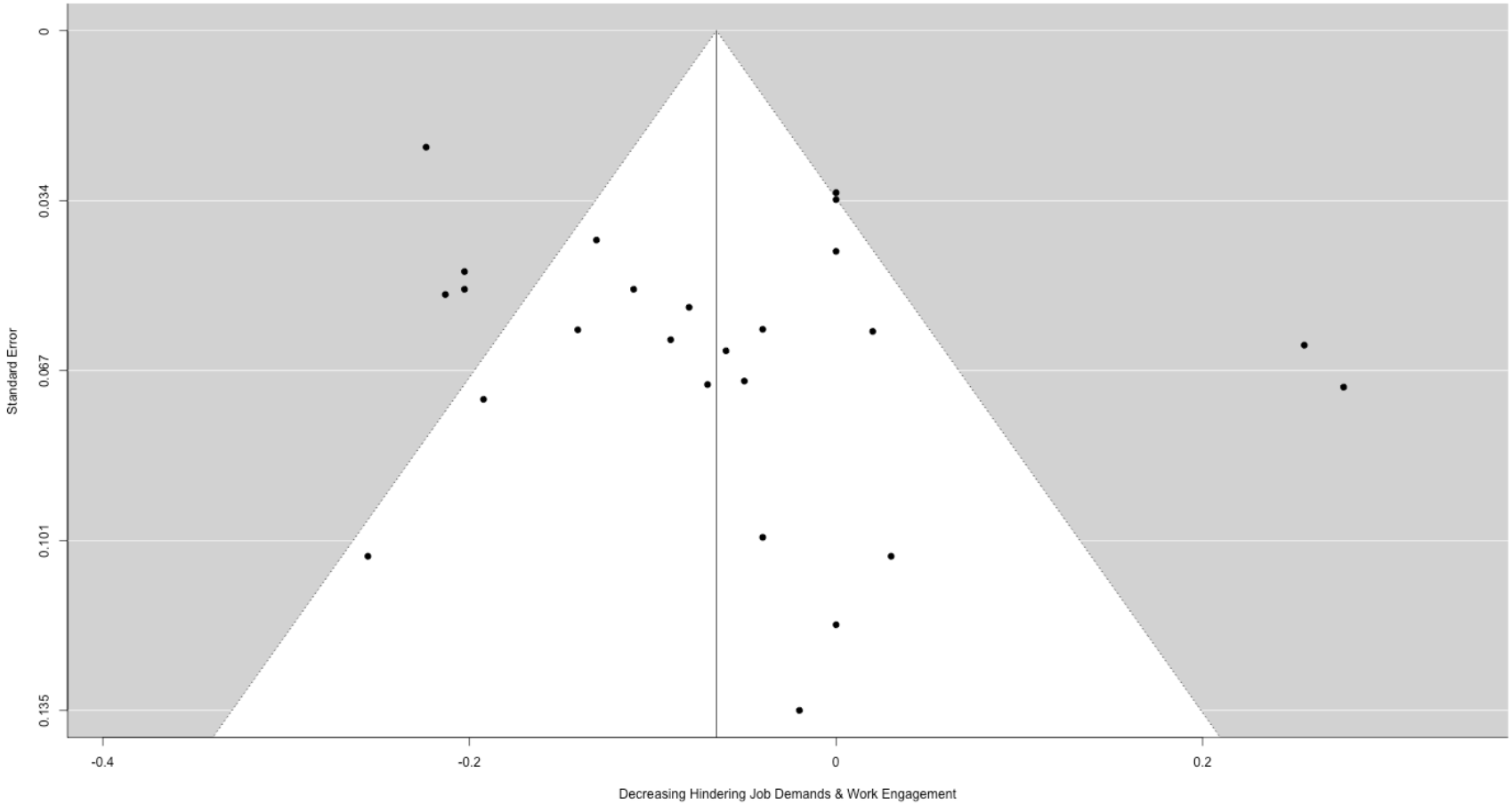

Figure E4. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of decreasing hindering job demands and work engagement.

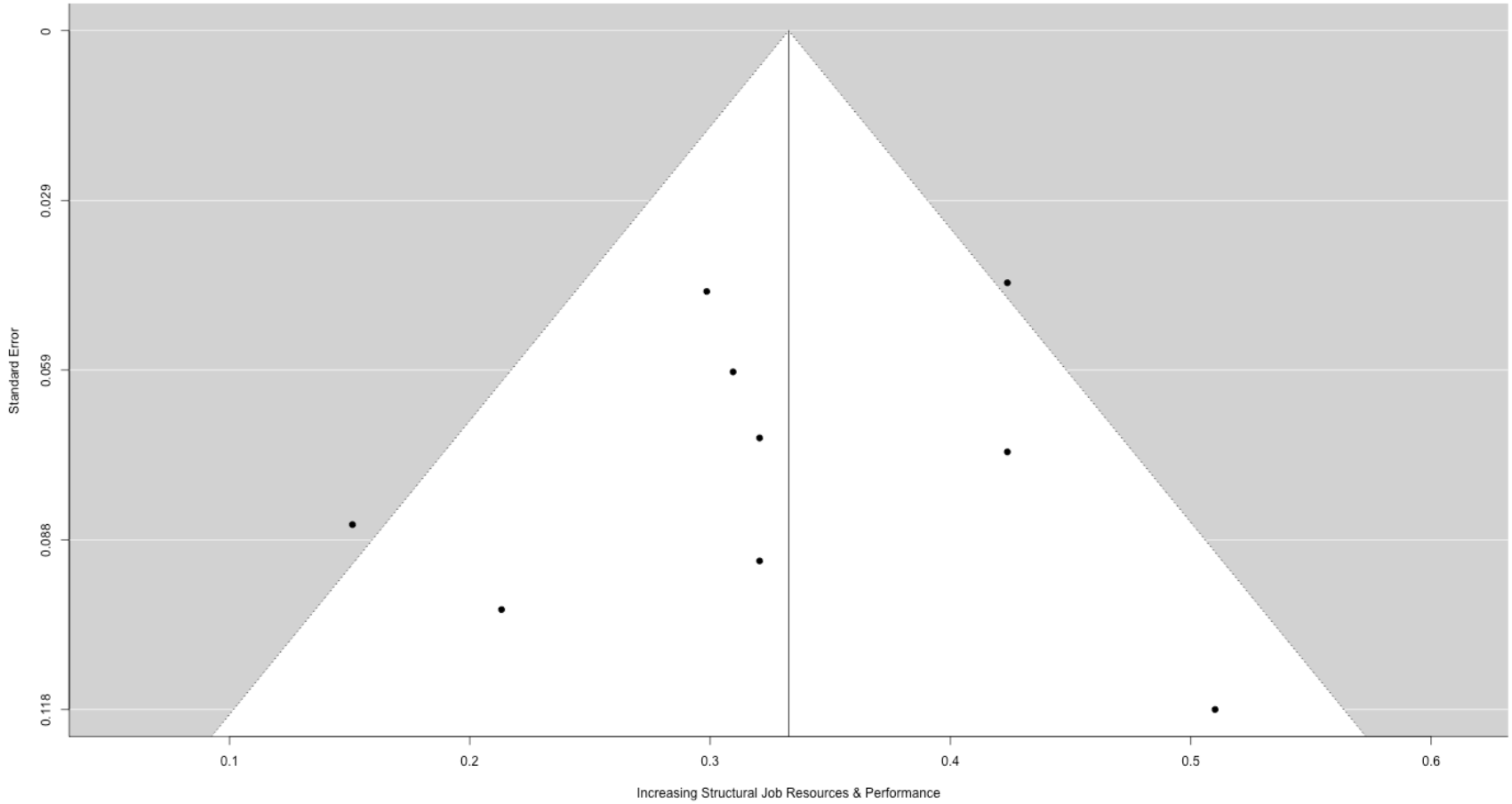

Figure E5. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing structural job resources and performance.

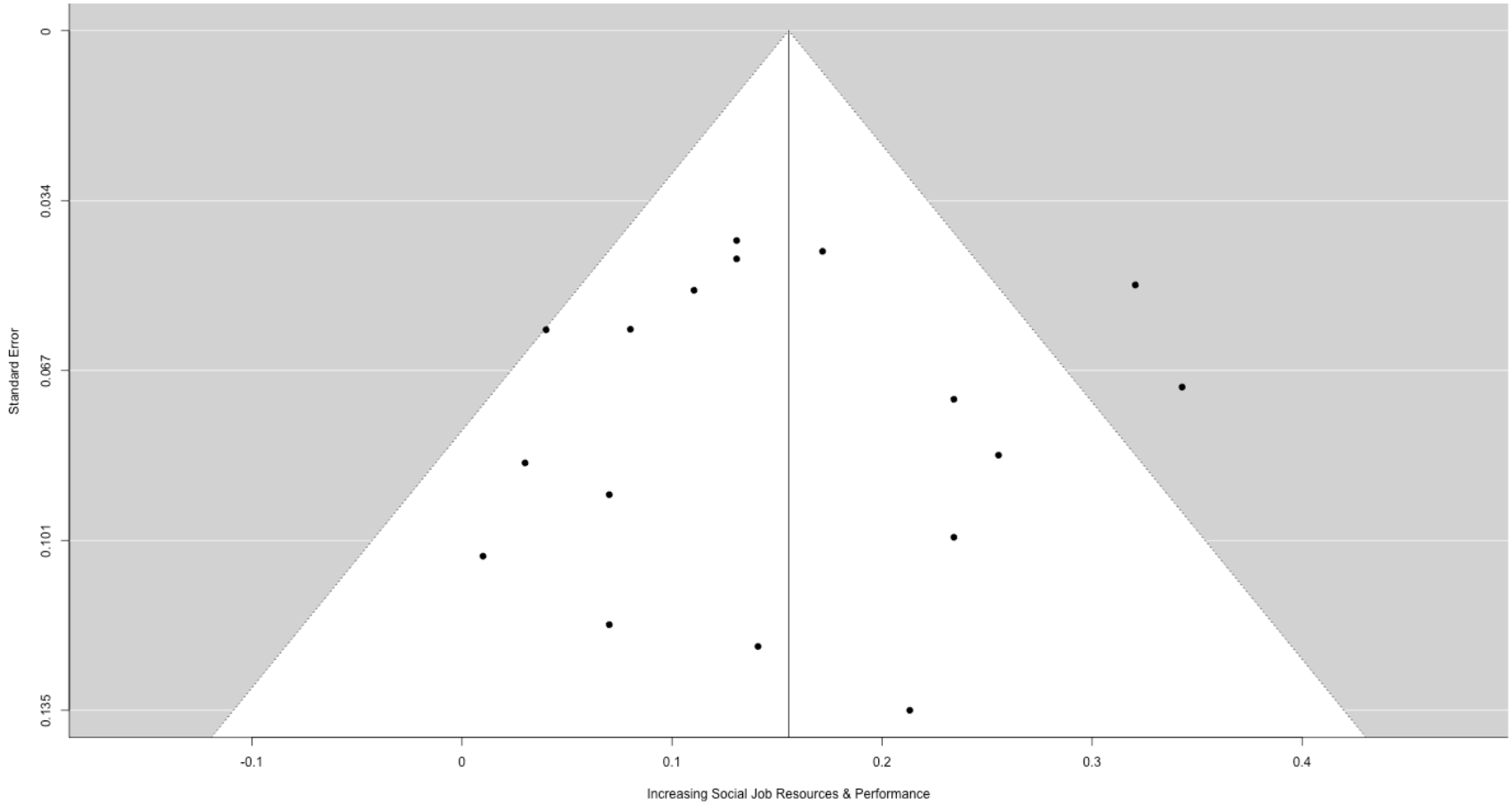

Figure E6. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing social job resources and performance.

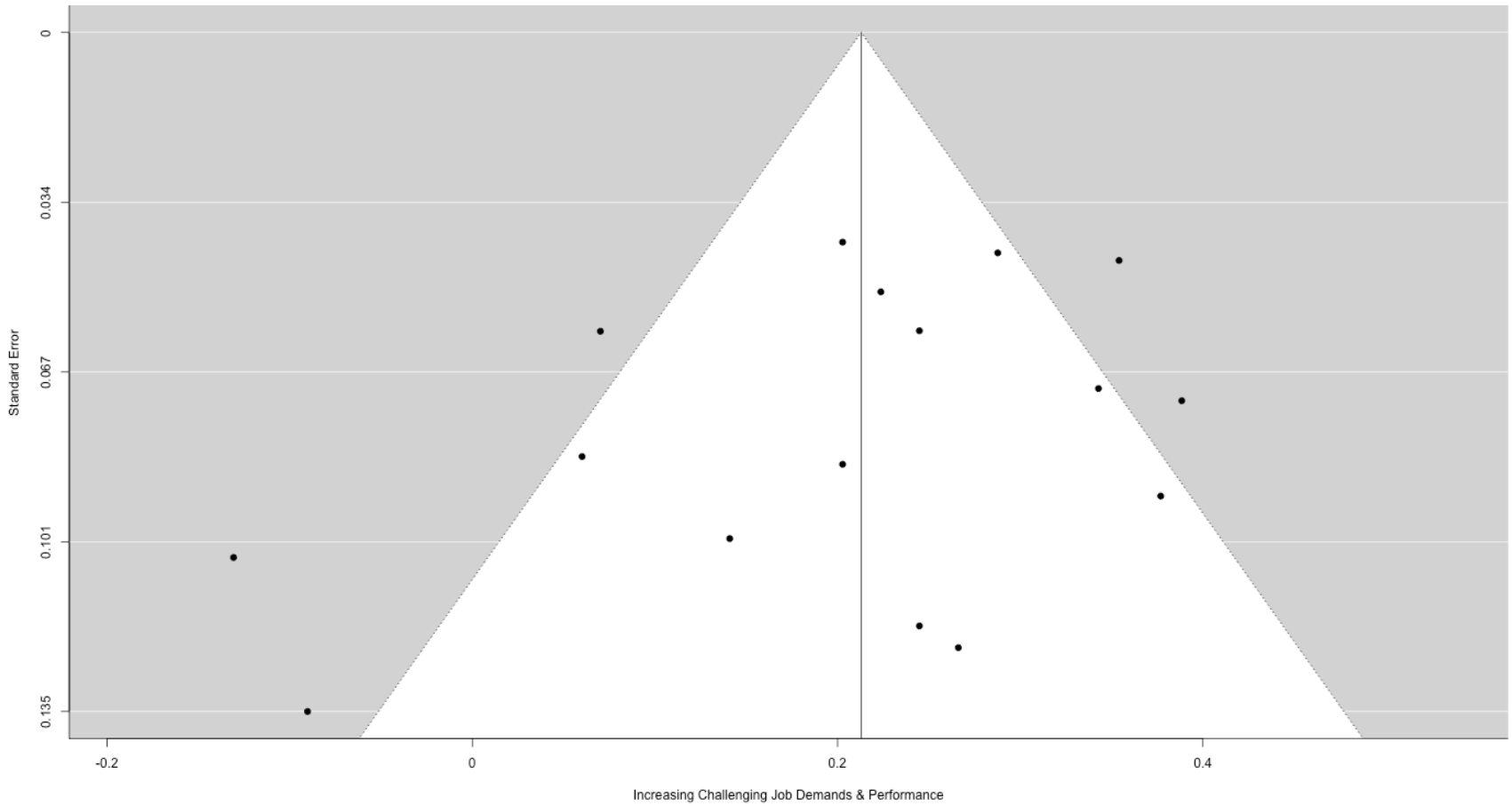

Figure E7. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of increasing challenging job demands and performance.

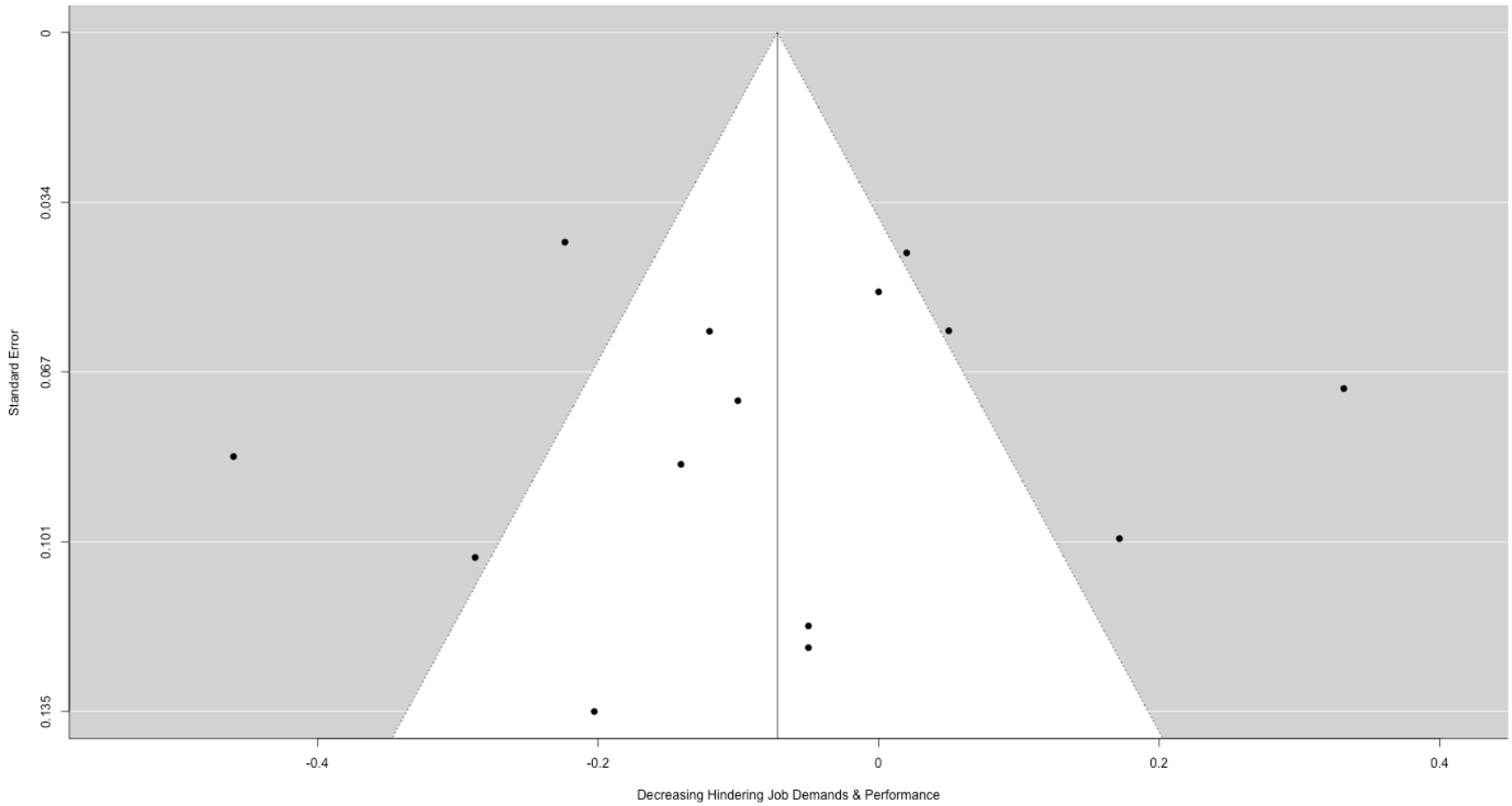

Figure E8. Funnel plot depicting the precision (standard error) of each effect size as a function of the effect size per study which contributed to the summary effect of decreasing hindering job demands and performance.