Poster Formatting and Sample Proposal

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Body of the Proposal Document

- A summary with a maximum of 3,000 words.
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- Proposals should consist of a complete paper prepared for blind review.
- All poster sessions are 50 minutes.

SUBMISSION TYPE Poster

TITLE I-O Psychology's Decline in Effect-Size Magnitude Over Time

ABSTRACT

We examined the relation between effect size and publication year among primary sources in 52 meta-analyses. Findings indicate a negative relation (r = -.09) across I-O psychology topics, and a substantial decline in effect size between the earliest year (r = .28) and late phase (r = .14) of investigation.

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I-O Psychology's Decline in Effect-Size Magnitude Over Time

Research in an array of scientific disciplines has revealed a phenomenon labeled the *decline effect* (Lehrer, 2010). The phenomenon refers to a negative relation between effect size and publication year, indicating that once relatively strong effects appear to weaken over time as replication attempts are made or, put differently, that "the truth wears off" (Lehrer, 2010, p. 52). The effect is especially problematic for medical sciences, where falsely inflated effectiveness estimates could result in misguided decisions regarding treatment. A decline effect in I-O psychology would be similarly troublesome, as it would reflect a lack of finding replicability, upwardly biased meta-analytic estimates, and misguided practitioner decisions. Together, these forces can lead to a widening of the science-practice gap (Cascio & Aguinis, 2008). However, no systematic study of the decline effect has been conducted in I-O psychology.

Studies used as input to existing meta-analyses reveal apparent decline effects for popular I-O psychology phenomena. As examples, Judge, Thoresen, Bono, and Patton's (2001) metaanalytic estimate of more than five decades of the job satisfaction-job performance relation (r =.18; 95% CI = .17, .20; k = 312) is substantially smaller than the earliest included effect size (r =.68; Brody, 1945), a 74% decline. Similarly, Rhoades and Eisenberger's (2002) meta-analytic estimate of the perceived organizational support-in role performance relation (r = .16; 95% CI = .09, .23; k = 12), is less than half the magnitude of the earliest included effect size (r = .33; Eisenberger, Fasolo, & Davis-LaMastro, 1990), a 52% decline. While we present only two examples, these popular I-O psychology topics clearly exhibit alarming decline effects. Targeted studies of the decline effect have revealed its presence in the areas of ecology (Barto & Rillig, 2012; Jennions & Møller, 2002), medicine (Gehr, Weiss, & Porzsolt, 2006; Ioannidis & Lau, 2001; Pereria & Ioannidis, 2011), and mental health (Trikalinos et al., 2004). As examples, Jennions and Møller (2002) observed a small, significant negative relation between effect size and publication year (r = -.08) among studies used as input to 44 existing metaanalyses. Similarly, the effectiveness of the lipid-lowering drug Pravastatin has decreased at the rate of 3.2% every five years following its initial investigation in 1990 (Gehr et al., 2006). Extrapolating a linear trend from its first reported effectiveness of 33.0% lipid reduction in 1990, the drug could be expected to provide no benefit at all 29 years from now. But what has changed? Could it be that the human body responds differently to the drug over time? Or are research and publication processes to blame for the decline effect? Might the same decline effect exist in I-O psychology and, if so, what impact might it have on practice (e.g., employee selection tools)?

The purpose of the present study is to investigate the existence of the decline effect in I-O psychology research. We extract lists of primary sources used as input to 52 meta-analyses pertaining to common I-O psychology topics. We assess the relation between effect size and publication year within meta-analyses. In addition, we go beyond existing studies on the decline effect by investigating the pattern of decline over time. Specifically, we investigate whether the decline effect exhibits an increasing or decreasing pattern over time. We interpret our findings in light of explanations for the decline effect and present recommendations for the interpretation of research findings, meta-analytic methodology, and strategies for reducing the science-practice gap.

Paradigm Shifts and Newsworthiness Bias as Explanations for the Decline Effect

Kuhnian paradigm shifts are one explanation for the decline effect (Alatalo, Mappes, & Elgar, 1997; Simmons, Tomkins, Kotiaho, & Hunt, 1999). According to this view, paradigms gain strength with an increased number of adherents to a theoretical framework (i.e., a *protective belt*;

Lakatos, 1970), which together resist change in the form of rejecting contradictory evidence for publication. Indeed, several studies have indicated that manuscript reviewers rate submissions as less adequate when containing null or contradictory findings (e.g., Hubbard & Armstrong, 1997). As Simmons et al. (1999) noted, "the early phase of a paradigm change is characterized by a publication bias, a less critical approach to research, or both" (p. 593).

Simmons et al.'s (1999) example of the decline effect in sexual selection research indicates that 100% of published studies on *fluctuating asymmetry* during the early 1990s presented supportive evidence, compared to 36% in the late 1990s. According the Kuhnian account, negative attitudes toward contradictory evidence weaken as a particular research area matures (e.g., new explanations emerge), thereby resulting in increased publication of non-significant findings (Alatalo et al., 1997; Simmons et al., 1999).

Critically, a Kuhnian paradigm shift explanation would predict a relatively stable pattern of supportive findings during early phases of a research domain, followed by a marked increase in the publication of non-supportive findings (i.e., smaller effect sizes) in later phases. That is, if the *protective belt* (Lakatos, 1970) resists non-supportive evidence in the form of publication bias (i.e., allowing fewer publications with *negative* results; Simmons et al., 1999), then one should expect some duration of relative effect-size stability followed by a decline. We refer to this pattern as an *increasing decline*. Importantly, in the absence of a paradigm shift (i.e., its identification), one should nonetheless expect some degree of effect-size stability during relatively early phases of a research program.

A second explanation for the decline effect has been labeled *newsworthiness bias* (Hartshorne & Schachner, 2012), whereby counter-intuitive or unexpectedly strong initial findings are published and widely disseminated, followed by smaller effects in replication attempts. The

threat from newsworthiness bias is that falsely inflated effects become widely known and absorbed by consumers of science. As evidence for the problematic nature of newsworthiness bias, Ioannidis (2005) reported that papers cited more frequently are associated with lower levels of replication success. Thus, newsworthiness bias and its effect on research dissemination have the potential to distort our understanding of reality. Importantly, the newsworthiness bias explanation predicts a distinct decline effect pattern--a substantial decline followed by a relatively stable pattern of weaker effect sizes (a *decreasing decline*).

Further evidence for the decline effect has been demonstrated by Pereira and Ioannidis (2011), who updated 80 meta-analyses in medicine and found that relevant studies published up to five years after the original meta-analysis contained significantly smaller effects – approximately 85% in magnitude. In addition, Aguinis et al. (2011) observed a negative relation (r = -.04) between meta-analytic summary estimates and publication year (e.g., a meta-analytic estimate published in 1990 on relation a b is larger than a meta-analytic estimate published in 2000 on

relation c d). However, while this finding is informative, it does not provide information on whether effect sizes decline *within* research domains, as is required to test the existence of the decline effect (cf. Jennions & Moller, 2002). Indeed, Aguinis et al.'s (2011) finding may be explained by increased research attention to a more diverse set of I-O phenomena over time, some of which might be associated with smaller effect sizes. Provided that the decline effect has been observed across a wide array of scientific disciplines, we expect to find a similar reduction in I-O psychology research. Thus, we hypothesize the following:

Hypothesis 1. Effect size and publication year will be negatively related.

As described earlier, one explanation for the decline effect is *newsworthiness bias*, according to which an unexpectedly large or counter-intuitive initial finding captures the attention of consumers of science. Following this logic, the earliest year of reported effect sizes within each meta-analytic dataset should present with substantially larger effect sizes than later reports. In contrast, a Kuhnian paradigm shift explanation would predict a substantial decline that occurs in later phases of investigation. Thus, we hypothesize the following:

Hypothesis 2. The earliest inclusion year within meta-analyses will contain significantly larger effect sizes than those reported in subsequent years.

We investigate the decline of effect-size magnitude in I-O psychology by analyzing sources used as input to meta-analyses for the following three reasons: First, meta-analytic evidence is interpreted as having a higher degree of truth value than individual primary studies, and more frequently reaches practitioner audiences (Aguinis et al., 2011; Pereira & Ioannidis, 2011). Second, the extant meta-analytic databases are the result of detailed literature searches and contain evidence from a wide variety of journal sources spanning decades of research. Finally, our sample of 52 meta-analyses on a variety of workplace topics allows a high degree of generalizability to the field of I-O psychology.

Method

Sample

Using an existing database of meta-analytic findings as our guide (Aguinis et al., 2011), we collected all meta-analyses containing a table of included samples with effect size and publication year information for each sample. Table 1 presents a list of journal sources including the number of meta-analyses located within each journal from 1980-2012. We extracted effect size and publication year information from each meta-analysis, resulting in a database of 52 I-O related meta-analyses (e.g., job satisfaction, Judge et al., 2001; employee turnover; Griffeth et al., 2000) that together analyzed 2,615 samples with a total of 1,240,665 observations.

Coding Technique

First, we identified the single largest meta-analytic estimate (i.e., that associated with the greatest number of samples) within each meta-analysis, and extracted effect size, publication year, and sample size data for each meta-analytic dataset. Next, we converted all effect sizes to correlation coefficients (e.g., for those meta-analyses that reported *d* scores). Finally, we calculated the effect size-publication year correlation for each meta-analytic dataset.

Within each meta-analytic dataset, we estimated sample-weighted mean correlations for four meta-analytic inclusion periods: (a) first year, (b) early phase, (c) middle phase, and (d) late phase of investigation. We treat publication year as a proxy for research attention over time, with each *phase* representing one third of a meta-analysis' inclusion year range with the first year excluded. As an example, if a given meta-analysis used as input samples from 1978-2008, then we coded all samples from 1978 as the *first year*, all samples from 1979-1988 as the *early phase*, 1989-1998 as the *middle phase*, and 1999-2008 as the *late phase*. By splitting each meta- analysis' year range into thirds, we are able to investigate the progression of effect size from relatively early, middle, and recent samples in each meta-analysis. In addition, our approach allowed us to include all meta-analyses regardless of their inclusion year ranges. Finally, we chose to split yearly ranges into thirds because additional bins would have resulted in a substantial number of empty cells for the present analyses.

Results

Meta-analytic estimates for the effect size-publication year relation are shown in Table 2. We observed support for Hypothesis 1 with a small, statistically significant negative relation between effect size and publication year with the unweighted analytic approach (r = -.09, 95% CI = -.15, -.02) and the sample-weighted approach (r = -.08, 95% CI = -.13, -.03). Thus, in our sample of 52 meta-analyses in I-O psychology, effect sizes exhibit a decline effect over time.

To test Hypothesis 2, we analyzed sample-weighted mean correlation values from (a) the first year, (b) the early phase, (c) the middle phase, and (d) the late phase of each meta-analysis year range. We conduct meta-analytic tests for moderation using the Q_b statistic as an indicator of statistical significance across moderator levels (cf. Aguinis, Sturman, & Pierce, 2008). The omnibus test for the moderating effect of year phase on effect size was significant ($Q_b = 163.71, p < .01$). Specifically, effect sizes from the first year of meta-analytic year ranges (r = .28, 95% CI = .23, .33) were significantly larger than the early phase of the year range (r = .18, 95% CI = .14, .22) ($Q_b = 58.28, p < .01$), middle phase of the year range (r = .15, 95% CI = .11, .19) ($Q_b = 112.16, p < .01$), and late phase of the year range (r = .14, 95% CI = .11, .17) ($Q_b = 151.47, p < .01$). In addition, effect sizes from the early phase were significantly larger than those from the middle ($Q_b = 8.38, p < .01$) and late ($Q_b = 16.53, p < .01$) phases. However, effect sizes from the

middle and late phases did not differ significantly ($Q_b = 0.84, p > .05$).

Thus, as shown in Figure 1, we observed support for Hypothesis 2. Specifically, the

largest decline in effect-size magnitude is from the first year to the early phase of the metaanalysis year range (35% decline). The effect size decline then appears to decelerate between the early and middle phases (18% decline) and, finally, a nonsignificant decline between the middle and late phases (6% decline). Noteworthy is a staggering decline between the first year (r = .28) and late phase (r = .14) ($Q_b = 151.47$, p < .01), where effect-size magnitude declines by 50%.

Discussion

The decline in effect-size magnitude presents a serious cause for concern among I-O scientists and practitioners. For scientists, the decline effect raises the possibility that much of what we think is effective, especially during early phases of a given research program, could be demonstrated as ineffective in the future. For practitioners, the presence of a substantial decline effect highlights the possibility that much of what I-O psychologists recommend to practitioners could be false, resulting in a widening of the science-practice gap (Cascio & Aguinis, 2008). Further, some alternative explanations for such a decline suggest that pioneering authors may be engaging in questionable practices, including systematic data exclusion. In the present investigation, we provide the first empirical demonstration of the decline effect in I-O psychology. As shown in Table 2, effect size and publication year are negatively related. Importantly, in the present analyses, weighted (r = -.08) and unweighted (r = -.09) analyses result in the same substantive conclusion, indicating that variance in sample size does not account for the decline effect. In addition, as shown in Figure 1, we document a decreasing decline of effect size over time. The decline is especially problematic in light of standards for the validity of preemployment selection devices (e.g., $r_c = .30$; Mount & Barrick, 1995).

Specifically, true score correlations might eventually decline to levels deemed unacceptable by current standards.

Implications for Meta-analytic Methodology

The present findings highlight the importance of considering the novelty of a relation when conducting meta-analyses. Specifically, meta-analytic estimates are at risk for upward bias as a result of the decline effect. Indeed, as Gehr et al. (2006) noted, "Should the reported effect size... change with time, the result of a meta-analysis would depend on when it was performed. Thus, the validity of a meta-analysis could be impaired" (p. 26). Following this logic, Pereira and Ioannidis (2011) estimated that between 16-37% of meta-analytic results are "false positives – a value that many clinicians and statisticians may find 'alarmingly high'" (p. 1066).

Meta-analysts should consider observation novelty as a potential moderator of their relations of interest. While several meta-analysts attempt to do this by estimating the relation between effect size and publication year, this approach may be inadequate because a steep decline exists between initial investigation year and the first third of the meta-analytic year range. As another alternative, meta-analysts might consider trimmed estimates or recursive cumulative meta-analytic techniques, which provides information on the relative change in effect size estimate as new effect sizes are added (Ioannidis & Lau, 2001).

Implications for Practice

Practitioners in I-O psychology have a history of attention-switching between research fads – an obsession with the "newest findings" (Campbell, 2012). The present findings explain practitioners' need to switch between fads and act as a cautionary note regarding new evidence. Specifically, the present findings indicate that effectiveness estimates associated with the "newest findings" are inflated approximately 100%. Curiously, a poetic caution provided by Wherry (1975) in the context of theory construction appears to apply equally well decades later to the decline effect in I-O psychology, "Models are fine and statistics are dandy, But don't choose too quickly just cause they're handy, Stick to a model that's been through the mill, Don't try something new just for the thrill, A new shiny model is full of allure, But making it work is no sinecure" (pp. 16-17).

Thus, our findings shed light on the science-practice gap. If practitioners are constantly seeking out the newest findings, they are likely to receive alarmingly upwardly biased

effectiveness estimates. One potential solution to reducing the science-practice gap is thus to urge practitioners against the uncritical adoption of new techniques. While this approach would require some degree of attitude change on the part of practitioners, the science-practice gap itself would decline if practitioners insisted on information regarding a given technique's replicability.

Limitations and Future Research Directions

One limitation of the present study lies in a lack of temporal specification for paradigm shifts. Indeed, identifying the particular point at which paradigm shifts occur is problematic, although it has occurred in other fields (e.g., Simmons et al., 1999). We urge, however, that regardless of the particular point at which a paradigm shift occurs, a paradigm shift explanation would nonetheless predict relative stability during the early phase of a relation's investigation. The present results indicate the opposite – that the largest decline in effect size occurs directly after the *first year* of investigation, an observation incompatible with a paradigm shift explanation of effect size decline. We present alternative explanations with examples and future research directions in Table 4. We will engage in discussions with SIOP attendees many potential explanations for the decline in effect-size magnitudes in I/O psychology.

Conclusion

In the present investigation, we investigate the decline in effect-size magnitude in I-O psychology research. We observed a small, significant negative relation between effect size and publication year, indicating that effect sizes in I-O psychology decline over time. In addition, we document a decreasing pattern of decline, with the largest decline between the first year of publication and the early phase of investigation. Thus, our study findings support a newsworthiness bias account of effect size decline over time. We presented steps that can be taken by meta-analysts and practitioners to reduce concerns about the decline effect.

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Journal Source	Number of Meta-analyses
Journal of Applied Psychology	17
Personnel Psychology	8
Psychological Bulletin	5
Journal of Occupational and Organizational I	Psychology 4
Journal of Organizational Behavior	3
Journal of Vocational Behavior	3
Academy of Management Journal	2
Journal of Personality and Social Psychology	2
Organizational Behavior and Human Decisio	n Processes 2
Academy of Management Review	1
Human Relations	1
Industrial and Labor Relations Review	1
Industrial Relations	1
Journal of Business Research	1
Journal of Occupational Psychology	1
Total	52

Journals Included in Meta-analysis Search

Table 2

Meta-analyzed Relation	k	N	mean r	SDr	95% CI lower	95% CI upper
Publication year with effect size						
Unweighted	52	52	-0.09	0.24	-0.15	-0.02
Weighted by k	52	2,615	-0.08	0.19	-0.13	-0.03
Sample size with effect size						
Unweighted	52	52	-0.08	0.20	-0.13	-0.02
Weighted by k	52	2,615	-0.05	0.15	-0.09	-0.01
Publication year with sample size						
Unweighted	52	52	0.07	0.21	0.02	0.13
Weighted by k	52	2,615	0.08	0.17	0.04	0.13

Relations among Publication Year, Sample Size, and Effect Size

Note. k: number of meta-analyses; N: number of observations; mean r: mean correlation; SDr: standard deviation of r; 95% CI: 95% confidence interval for r.

Table 3

	k	Ν	mean <i>r</i>	SDr	95% CI lower	95% CI upper	Qb
Primary Source Publication Year Phase							163.71**
First Year	84 ²	10,629	.28	.17	.23	.33	
Early Phase of Year Range	589 ²	13,938	.18	.15	.14	.22	
Middle Phase of Year Range	912 ¹	16,605	.15	.13	.11	.19	
Late Phase of Year Range	1,030 ²	27,475	.14	.13	.11	.17	
First Year vs. Early Phase							58.28**
First Year vs. Middle Phase							112.16**
First Year vs. Late Phase							151.47**
First Phase vs. Middle Phase							8.38**
First Phase vs. Late Phase							16.53**
Middle Phase vs. Late Phase							0.84

Effect Size by Meta-analyses' Primary Source Publication Year Phase

Note. k: number of meta-analyses; N: number of observations; mean r: sample size-weighted correlation; SDr: standard deviation of r; 95% CI: 95% confidence interval for r; Q_b : χ^2 based test for significance of moderation. ¹Based on 51 meta-analyses. ²Based on 52 meta-analyses. *p < .05. *p < .01.

Table 4

Alternative Explanations for the Decline Effect, Examples, and Future Research Directions

Alternative Explanation for Decline Effect	Example	Future Research Direction
Increased construct refinement	Brayfield and Rothe's (1951) measure of job satisfaction contains 18 items, some of which relate to employee engagement and interest level. More recent job satisfaction facet approaches have emerged, with a narrower construct space for "overall job satisfaction." Thus, earlier measures may explain additional criterion variance, later considered contamination, resulting in larger effect sizes.	Future decline effect studies might control for measures used by investigating the decline effect within a sample of effect sizes relying on the same measures.
Decreased reliability	Over time, researchers adopt shortened versions of popular measures (e.g., job satisfcation; perceived organizational support). All else being equal, shorter scales are associated with lower, although still <i>acceptable</i> , reliability coefficients. This being the case, zero-order relations might be larger with an older form containing a greater number of items.	Future decline effect studies might investigate decline in effect sizes corrected for reliability.

Alternative Explanation for Decline Effect	Example	Future Research Direction
Increased range restriction	If work conditions have improved over time, there may be fewer dissatisfied employees. Thus, effect sizes with job satisfaction might decrease due to range restriction.	Future decline effect studies might investigate decline in effect sizes corrected for range restriction.
Changing nature of work	In contrast to earlier decades, employees might place less emphasis on compensation characteristics (e.g., pay), and more emphasis on autonomy-related characteristics (e.g., telecommuting). Variance in employee emphases could cause some effect sizes to exhibit a decline effect.	Future decline effect studies might investigate relations for which no moderating effect of time is expected (e.g., work motivation \rightarrow job performance; turnover intention \rightarrow turnover)
Author effects	Early reports might be upwardly- biased from authors and colleauges who champion original measures. Over time, as researchers in other labs report findings, effect sizes might exhibit a decline effect.	Future decline effect studies might compare effect sizes obtained from different research "groups" over time.
Regression to the mean	Unusually large (small) effects are reported initially, after which reported effects are smaller (larger), approaching the true score value.	Regression to the mean might be ruled out logically because some effects would be expected to increase over time, and others would be expected to decrease over time.



Primary Source Publication Year Phase

Figure 1. Effect Sizes as a Function of Meta-analytic Year Phase