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Power Play, Because of Pay? How Pay Transparency Affects Counterproductive Work Behaviors

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ABSTRACT: With social comparison theory as our theoretical foundation, how employees target one another based on the presentation of information that they see and evaluate, we explain how process pay transparency and outcome pay transparency affect the probability of counterproductive work behaviors from employees toward individuals (CWB-I) and organizations (CWB-O). We utilize field study data courtesy of Mendeley ("Pay Communication, Justice and Affect: The Asymmetric Effects of Process and Outcome Pay Transparency on Counterproductive Workplace Behavior," 2020) and select methods from SimanTov-Nachlieli and Bamberger (2021, 235) using SmartPLS. While three hypotheses failed to produce significant results, and the only hypothesis that produced significant results was not supported (process pay transparency negatively, not positively, related to counterproductive work behaviors directed at the organization), our final bootstrapped SEM fit our data for our saturated model (SRMR = 0.046 < 0.08, NFI = 0.915 > 0.9). Implications are discussed.

KEYWORDS: social comparison, pay communication, pay transparency, process pay transparency, outcome pay transparency, counterproductive work behaviors (toward organization and individuals)

Introduction

While there is established research on how pay transparency affects supervisees, the same does not hold true for supervisors, who are neglected in comparison (Wong, Cheng, Lam & Bamberger 2022, 3). There are continued rising concerns about wage gaps based on gender, inequality, and race, more researchers are now becoming interested in researching within the pay communication umbrella, and there is tension regarding which forms of pay transparency are helpful and hurtful at the individual, team, and organizational levels (Bamberger 2021, 1). Pay transparency forms have been touted as the most direct way to close gender pay gaps, but an issue has been brought up that specific end users, people, and organizations (i.e., business, government) who put research into practice do not create pay policies (Kulik 2020, 74). This is true despite Executive Order 13665. Trotter, Zacur & Stickney (2017) discuss how this order took effect in 2016, and how organizations cannot penalize employees for both the disclosure and discussion of compensation factors (529). Different forms of pay transparency have led to independent effects on employee outcomes (SimanTov-Nachliel & Bamberger 2021, 230). Organizational justice theory also describes phenomena regarding how the amount of pay openness practices outcomes affects counterproductive work behaviors (i.e.,, sexual harassment) (Marasi, Wall & Bennett 2016, 53). Social exchange theory postulates that the more an employee perceives they positively interact with another employee or their organization, the more likely they will feel that it is beneficial to continue a relationship (54). Therefore, if pay openness is received positively, employees will demonstrate outcomes such as organizational citizenship behaviors. Equity theory states, for example with pay transparency, that if employees feel that they are underpaid or their pay is not just, they will either withdraw positive behaviors and/or enact negative behaviors (54). Like but assumedly distinct from equity theory (Adams coined equity theory in 1965; Festinger coined social comparison theory in 1954), social comparison theory can describe how one evaluates then behaves *toward a specific target* in response to social information (Wood 1996, 521). We ask how forms of pay transparency, similarly and differently, affect counterproductive work behaviors at different organization levels? How can our findings lead to decreased CWBs as mediators toward insight on improving organizations' images and statistics? SimanTov-Nachliel & Bamberger state that there is little reason to explore the effect of process pay transparency on CWB-I because the CWB-I target in response to that is likely to be the organization putting the processes into effect versus a fellow employee (232), Lau, Au & Ho (2003), examining antecedents of CWBs, listed communication flow and policy-related characteristics as predictors to CWBs such as absenteeism (75). However, absenteeism is a construct that could be measured at both the individual and the unit level (Carpenter, Whitman & Amrhein 2021, 1501-1502). This, in tandem with the fact that individual and unit-level CWBs are not mutually exclusive (i.e., all their elements are not distinct to each other; they share some elements) (1501), provide rationale for us to explore what SimanTov-Nachliel & Bamberger (2021) have said and examine the relationship between process pay transparency at CWB-I (232). Bamberger (2021) stated that while there is plenty of research on the consequences of outcome pay transparency, the causal effects are not universally positive (beneficial to the employee from the employee's point of view) (para. 75). While he argued that his findings prove that outcome pay transparency itself could *itself* benefit female employees, outcome pay transparency could *adversely affect* other stakeholders, who could therefore, retaliate against said female employees, hurting them versus helping them. We propose opposing hypotheses to 1A and 1B to further differentiate process pay transparency and outcome pay transparency, with empirically thinking that if someone else has a higher salary, the chance of retaliation toward person could be higher versus someone with the same or lower pay. Therefore, we propose: *Hypothesis 1A.* Process pay transparency positively relates to counterproductive work behaviors directed at the organization. *Hypothesis 1B.* Process pay transparency negatively relates to counterproductive work behaviors directed at individuals. *Hypothesis 2A.* Outcome pay transparency negatively relates to counterproductive work behaviors directed at the organization. *Hypothesis 2B.* Outcome pay transparency positively relates to counterproductive work behaviors directed at individuals.

Analytical Approach

We utilize Study 1 from SimanTov-Nachlieli & Bamberger (2021, 235) *including measures and select methods*. This is a field study that involved employees being surveyed at two different points in time (T1 and T2), at the beginning and end of respective workweeks. The data is presented on a Microsoft Excel spreadsheet with 20 columns: four items for outcome pay transparency, four items for process pay transparency, six items for CWB-O, and six items for CWB-I. The spreadsheet is described with model 1 and 2 data, and further information in Appendix A after the references. The top of each column contains the measure name and item number (ex: pay_o_1, pay_p_1, cwb_o_1, cwb_i_1), then the cells below contain the scored responses per 321 validated participants. We will download SmartPLS, a structural equation modeling application compatible with both Mac OSX and Windows (SmartPLS 3, 2022, para. 1). Williams, Vandenberg & Edwards (2009) define structural equation modeling as "an analytical approach that simultaneously combines factor analysis and linear regression models for theory testing" (543). We consulted Gerpott, Lehmann-Willenbrock, Voelpel & Van Vugt (2019) for an example of an analytical approach (725-726). After importing the data onto SmartPLS, to perform a factor analysis, and inputting all our latent variables, indicators, and paths into a .splsm file, we performed calculations to output the PLSc algorithm, then we bootstrapped the data. Due to our SRMR being greater than 0.08 at 0.135, from looking at the (bootstrapped) outer loadings, we removed cwb_i_2 and cwb_i_4 from our model due to p-values greater than 0.05. After accounting for the first two indicators removed, we then removed the indicators with the highest outer VIF values per latent variable from our model (cwb_i_5, cwb_i_6, cwb_o_1, cwb_o_3, cwb_o_5, cwb_0_6, pay_o_1, pay_o_5, pay_p_2, pay_p_4). While SmartPLS reports VIF values equal to or above 3 as problematic, outer VIF values near and above 2.5 have been shown to be problematic, which is why we removed additional indicators (when possible) to ensure a best fit model with the data (Johnston, Jones & Manley 2018, 1968). For example, pay_o_2 and pay_o_3 had outer VIF values at 2.8 and 2.3 respectively, but a latent variable is strongly recommended to have at least two indicators (Bollen & Long, 1993; DuHamel et al. 2004, para. 22; Schumaker & Lomax 2004, 183). After deleting the given indicators, we ran our analysis again, bootstrapping the data with 4,999 subsamples (Henseler 2017, 17), to have the PLSc algorithm and bootstrap tabs appear.

Results

Researchers struggle to choose between reporting saturated or measurement model results ("Note of Caution" 2022, para. 27). The saturated model is the standard when determining how a structural equation model fits with data (Raykov, Lee, Marcoulides & Chang 2013, 1055). Benitez-Amado, Henseler & Castillo (2017) examined the standardized root mean squared residual (SRMR): "the square root of the sum of the squared differences between the model-implied correlation matrix and the empirical correlation matrix") (6; Henseler 2017, 23; Henseler et al. 2014). Benitez-Amado, Henseler & Castillo (2017) also examined the unweighted least squares discrepancy (d_{ULS}), and geodesic discrepancy (d_G), measures of "how strongly the empirical correlation matrix differs from the model-implied correlation matrix" for the saturated model to determine if their data supported their model (6; Henseler 2017, 22; Henseler et al. 2014). Our SRMR is 0.046, our d_{ULS} is 0.077, our d_G is 0.027, our chi-square is 45.485, and our NFI is 0.915 greater than 0.9 (Henseler, Hubona & Ray 2015, 10) under the PLS Algorithm. After bootstrapping, our SRMR is 0.081. While some have said the SRMR should be less than 0.08, the value was validated in green by SmartPLS, and others have cited the value can be less than 0.09 and 0.1 to be validated (Hu & Bentler 1999, 27; "Note of Caution" 2022, para. 11). The SRMR was also less than the corresponding HI_{95} (95% quantile of bootstrap discrepancies) value of 0.087. Our d_{ULS} is 0.237, less than the corresponding HI_{95} value of 0.270, and our d_G is 0.166, less than the corresponding HI_{95} value of 0.209. Therefore, from the saturated model perspective, we have demonstrated that our model is an excellent fit with the data and accept. Benitez-Amado, Henseler & Castillo (2017), similarly, reported SRMR, d_{ULS}, and d_G values less than the corresponding HI_{95} values, and demonstrated that their data aligns with the composites and factors in their measurement model (6). Regarding our hypotheses, since the p-values for both hypotheses with outcome pay transparency at the antecedent (2A, 2B), and the path from process pay transparency to CWB-I (1B) are greater than 0.05; the paths are not significant, and these hypotheses are not supported. The path coefficients were 0.031, -0.055, and -0.009 respectively. For Hypothesis 1A, for the path from process pay transparency to CWB-O, while the p-value is less than 0.05, the path coefficient is negative (-0.221), not positive as hypothesized. Therefore, while the path is significant, this hypothesis is also not supported.

Discussion and Conclusion

Using social comparison theory, we explained how two different forms of pay transparency, outcome pay transparency and process pay transparency influence the targeting of organizations and individual employees with counterproductive work behaviors. The only significant result we found, despite it being contrary to our hypothesis, is that process pay transparency decreases the likelihood of counterproductive work behaviors toward and organization. Considering the global sample SimanTov-Nachlieli & Bamberger (2021) found from multiple organizations (235), we can that external validity is high. They also found discriminant validity regarding the outcome pay transparency and process pay transparency constructs, the two were still highly correlated (237), and each of these had outer VIF values over 3 that needed to be removed, versus CWB-O and CWB-I which did not have an outer VIF values above or equal to 2.5. Therefore, there could be construct validity and collinearity concerns regarding differentiating process pay transparency and outcome pay transparency that should be addressed in future studies. In addition, to enhance statistical conclusion validity, we recommend re-examining the questions associated with assessing process pay transparency and outcome pay transparency, considering the number of indicators that needed to be removed in part due to high outer VIF values but primarily to appropriately find a best fit model for our data. Due to the nature of a field study, causality also cannot be assured between variables (239). Stuber (2020) wrote about an organization called Buffer, a tech company that creates tools for managing social media accounts (para. 4), and has all employees' names, positions, and salaries published online (para. 5). Therefore, Buffer from the observer perspective has high outcome pay transparency. From January 2013-Feburary 2020, while Buffer has more female employees, there is still a gender wage gap (para. 26). They state one way that could close the gap is hiring and retaining women in senior roles and technical positions (para. 33). However, most women leave the tech industry after 2-5 years. Over 200 women with over 10 years of tech experience cited verbal and sexual harassment as the top reasons (para. 37). Despite Buffer clarifying on job descriptions that applicants do not need to meet all criteria to apply, women typically apply to jobs they meet 100% of qualifications for, versus men (60%) (38). CWBs have been shown to tarnish company image (Abdul Rahim, Shabudin & Mohd Nasurdin 2016, 117), and (communication of) company images have been shown to influence positive organizational attraction and recruitment, and curb employee shortages (Mohammed 2019, ii, 2). We believe managers being transparent to any degree about outcomes and providing little context on processes is detrimental: prioritizing transparency about processes (pay, etc.), how they were developed, and their purposes can decrease the probability of counterproductive work behaviors toward an organization, which can possibly curb a negative organizational image and therefore enhance recruitment *and* retention of new employees. Our research, in a young field, takes steps to reflect on possible advantages of disadvantages of differentiating pay transparency forms, establishes a link between communicating pay processes and reducing CWB toward an organization, and proposes future consequents to verify and directions toward retaining underrepresented employees.

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