Use and Design of Peer Evaluations for Bonus Allocations

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ABSTRACT

We conduct an experiment to investigate the use of peer evaluations for compensation purposes. Although organizations often rely on peer evaluations for incentive compensation, it is not well understood how peer feedback should be used and designed to ensure non-distorted evaluations and motivate effort provision. We study peer evaluations in form of bonus allocation proposals, allowing us to test our hypotheses with quantifiable data. We distinguish between a discretionary use (i.e., allocation by the manager) and a formulaic use (i.e., allocation by the team via the average) of self-including and self-excluding proposals. We find that, relative to self-including proposals, self-excluding proposals are less distorted, irrespective of use, but lead to more effort provision only under formulaic use. Under discretionary use, the benefits of self-excluding proposals are offset, as managerial biases enter bonus allocations. Our results are relevant for practitioners and researchers interested in incorporating peer evaluations into incentive compensation.

Keywords: peer evaluations, team-based compensation, mutual monitoring, mechanism design.
JEL Classifications: C92, D23, D86, D90, M40, M52

1. Introduction

Peer evaluations are common practice, because peers usually have better information about each other's actions than their superiors (via mutual monitoring). Organizations increasingly rely on peer evaluations for incentive compensation (Edwards and Ewen [1996], Appelo [2015], Deb, Li, and Mukherjee [2016]). As such, a burgeoning literature examines the use of peer evaluations in bonus pool arrangements (Arnold, Hannan, and Tafkov [2018, 2020], Dong, Falvey, Luckraz [2019], Abbink, Dong, and Huang [2022]). In these arrangements, an objective measure of group performance typically determines the size of the bonus pool, while subjective signals, such as peer evaluations, inform the allocation of the bonus pool among employees (Baiman and Rajan [1995], Rajan and Reichelstein [2006, 2009]).[1] Yet, it is not well understood how peer feedback should be used and designed to ensure non-distorted evaluations and motivate effort provision. Our study employs a bonus pool arrangement to compare the effectiveness of a discretionary use (i.e., managers keep discretion) and a formulaic use (i.e., managers commit to the average) of self-including and self-excluding peer evaluations in motivating employee effort.

Studying the use of peer evaluations for compensation purposes is important, as millennials and generation Zs, a growing share of the workforce, "embrace personal responsibility" and want their voices to be heard, especially as it pertains to their compensation (see Deloitte [2021]). The extent to which peer feedback is used for incentive compensation varies in practice and is subject to debate. In many organizations, managers elicit peer feedback but maintain discretion over the allocation of bonuses. For example, at Goldman Sachs and LivingSocial, employees provide peer evaluations that help managers set annual bonuses (e.g., Silverman and Kwoh [2012], Alexander [2022]). Similarly, at Crane, peer evaluations inform discretionary bonus pool allocations among subunit presidents. In other organizations, managers do not maintain discretion and, instead, commit to formulaically aggregating peer feedback to determine bonuses, effectively delegating incentive compensation to their employees. For instance, at Agility Scales, peer evaluations are directly entered into the bonus formula (Hannah [2019]). Similarly, Galbraith [1997] reports on a formulaic aggregation via the average of peer bonus pool allocation proposals at National City Bank (now Citybank). Google, Meta, Microsoft, and Zappos use peer-to-peer bonuses, enabling their employees to reward each other through peer assessments (e.g., Emmonds [2019]). Given these trends toward utilizing peer feedback for incentive compensation, it is critical to understand how peer evaluations should be used and designed to best motivate employee effort.

In line with prior work, we study peer evaluations in form of bonus pool allocation proposals (e.g., Arnold, Hannan, and Tafkov [2018, 2020]). The bonus pool arrangement lends itself to our research

[1] Survey evidence indicates that most US firms use bonus plans that are based on both firm profits and subjective signals of performance (Murphy and Oyer [2003], WorldatWork and Compensation Advisory Partners [2021a]).

question because it creates – like the public goods game [PGG] – opportunities for free riding (i.e., employees generate, with their efforts, a common pool that is shared among them). Yet, unlike the classic PGG, bonus pools are not necessarily evenly split. Rather, the allocation of the pool is based on subjective signals – here, peer allocation proposals – enabling a reward system that can limit free riding but also create incentives for employees to distort proposals in their own favor, similar to peer performance evaluations used for incentive pay.[2]

Within this setting, we compare a discretionary use (i.e., allocation by an impartial manager) and a formulaic use (i.e., allocation by the team via the average) of self-including proposals and self-excluding proposals. Self-including proposals allow employees to propose an allocation of the bonus pool among all team members including themselves, whereas self-excluding proposals prohibit self-allocations. Prior research does not compare discretionary use vs. formulaic use or self-including design vs. self-excluding design. In the accounting literature, Arnold, Hannan, and Tafkov [2018] study, in isolation, the combination of discretionary use and self-including design. They find that managers' bonus allocations lead to more effort provision when self-including proposals are made available to managers than when they are not. In the common pool literature in economics, Dong, Falvey, and Luckraz [2019] focus on the combination of formulaic use and self-excluding design. They find that a linear aggregation of self-excluding proposals leads to more effort provision than an even-split allocation. However, it remains unknown across the two literatures whether a discretionary use or a formulaic use of either self-including or self-excluding (peer) allocation proposals is better suited to motivate effort provision.

To address this gap, we first outline the monetary incentives underlying those different uses and designs within an analytical framework. The predictions of the analytical framework greatly vary with small changes in the assumptions, illustrating the need for an empirical investigation. Distinct from the analytical framework, we develop a hypothesis drawing on behavioral theories.

Our reasoning builds on the notion that employees provide more effort the more they expect their bonuses to be fair. We define bonuses as fair – and, similarly, proposals as non-distorted – if they reflect employees' relative contributions to the bonus pool. Whether bonuses will be fair depends on (i) employees' allocation proposals and (ii) the transformation of these proposals into bonuses. First, we argue that the self-excluding design leads to less distortion in proposals than the self-including design under both discretionary use and formulaic use. We expect employees to neglect incentives to distort self-excluding proposals, which arise under discretionary use but not under formulaic use (as will be described). Second, we argue that compared to formulaic use, managers' transformations of proposals into bonuses are more prone to bias when proposals are self-excluding than self-including. Specifically,

[2] A key feature of bonus pool arrangements, relative to other common pool arrangements, is that the reward system is self-funding, as reward and punishment solely materialize via the allocation of the pool (i.e., a zero-sum game).

we expect it to be more complex for managers to derive fair bonuses from self-excluding proposals than from self-including proposals. Therefore, we hypothesize that the positive effect of the self-excluding design, relative to the self-including design, on effort provision is less pronounced under discretionary use than under formulaic use.

To test this hypothesis, we conduct an incentivized laboratory experiment with business school students. We assign participants to groups of four – one manager and three employees – that stay together for a total of eight rounds, each consisting of three stages. Stage 1 is similar to a PGG in that employees choose costly effort contributions, which are linearly aggregated to form group output. A fixed percentage of group output determines the bonus pool. While the manager only observes group output, employees also observe individual contributions. In stage 2, each employee proposes an allocation of the bonus pool. In stage 3, the bonus pool is allocated among the three employees. Within this set-up, we manipulate – between-groups – the design in stage 2 (self-including vs. self-excluding) and use in stage 3 (formulaic vs. discretionary) of employees' allocation proposals. The self-including design allows employees to propose an allocation of the pool among all three employees, while the self-excluding design requires an allocation among the other two employees. Under formulaic use, the average of all proposals determines employees' final bonuses (i.e., allocation by the team), whereas, under discretionary use, the manager keeps full discretion over the final bonus allocation (i.e., allocation by the manager).

The results of the experiment support our hypothesis. We find that, under formulaic use, the self-excluding design leads to significantly more effort provision than the self-including design. Under discretionary use, this positive effect is significantly attenuated, such that we do not find a significant difference in effort provision between the self-including and self-excluding designs. Overall, the formulaic use of self-excluding proposals leads to more effort provision than each of the other three conditions. Perceptions of distributive fairness explain these differences in effort. Consistent with the behavioral theory underlying our hypothesis, the self-excluding design leads to less distortion in proposals than the self-including design, irrespective of use. However, under discretionary use, this effect is counteracted, as managerial biases enter the transformation of proposals into final bonuses more when proposals are self-excluding than self-including. That is, managers tend to allocate more (less) to low (high) contributors than suggested by the average of employees' proposals when the design is self-excluding than self-including.

Our study makes several contributions. First, we contribute to a burgeoning literature that examines the use of peer evaluations for incentive compensation (e.g., Deb, Li, and Mukherjee [2016], Arnold, Hannan, and Tafkov [2018, 2020]). Specifically, we advance the understanding of how different uses and designs of peer evaluations affect employee behavior. We find that the combination of formulaic use and self-excluding design results in the most favorable outcomes. Thus, organizations may consider limiting managers' discretion in setting bonuses and separating employees' self-evaluations from evaluations of their peers. In this vein, we also contribute to research on calibration committees, that hold managers accountable for their bonus allocations (e.g., Demeré, Sedatole, and Woods [2019], Grabner, Künneke, and Moers [2020]).

Second, our study bridges the literatures on bonus pools in accounting and common pools in economics, which – independent of each other – examine the different uses and designs of peer allocation proposals within bonus pool arrangements. While research in accounting focuses on a transfer of employees' private information about each other to an impartial manager who uses that information to allocate the bonus pool (Arnold, Hannan, and Tafkov [2018, 2020]), research in economics focuses on a self-governing use of this information, thereby enabling employees to allocate bonuses among themselves (e.g., Yang et al. [2018], Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022]). Our results demonstrate that the relative effectiveness of the two uses depends on the design of the allocation proposals.

Third, our study contributes to the broader management literature on delegation (Nagar [2002], Moers [2006], Graham, Harvey, and Puri [2015]) and answers calls for more research on the delegation of decision rights to teams rather than individuals (Fehrler and Janas [2021]). In that regard, we also add to analytical work on bonus pools in the accounting literature (Rajan and Reichelstein [2006, 2009]) by considering the delegation of the allocation decision to employees. Notably, the formulaic use of self-excluding proposals extends the solution of the moral hazard problem between manager and employees to the moral hazard problem among employees.

Fourth, we contribute to the accounting literature that examines how control design affects cooperation and fairness perceptions in firms (Coletti, Sedatole, and Towry [2005], Tayler and Bloomfield [2011], Maas and van Rinsum [2013], Cardinaels and Yin [2015]). Specifically, we create an understanding of how control choices relating to the use and design of peer evaluations – for bonus compensation – can enable cooperation within teams by establishing fair bonus pay.

In sum, our study delivers important insights to practitioners and researchers who consider the use of peer evaluations for compensation purposes. Our results also speak to teachers relying on student feedback to assess group work or class participation (Erez, Lepine, and Elms [2002]). The remainder of this paper is organized as follows. Section 2 reviews the literature and outlines the analytical framework and hypothesis development. Section 3 describes the experimental setting, design, and procedures. Section 4 summarizes the results, and Section 5 concludes.

2. Literature Review, Analytical Framework, and Hypothesis Development

2.1 BONUS POOL ARRANGEMENTS IN ACCOUNTING LITERATURE

Subjective information is omnipresent in performance appraisals and compensation systems. In principal-agent relationships, such non-verifiable information creates a moral hazard problem, as the principal could claim ex-post that the agents performed worse than they did, resulting in lower bonuses for agents and larger profits for the principal. Bonus pool arrangements eliminate this moral hazard problem (e.g., Baiman and Rajan [1995], Rajan and Reichelstein [2006, 2009]) in that the principal commits ex-ante to a formulaic determination of the size of the bonus pool, using an objective measure of group performance (e.g., a fixed percentage of profits). Because the bonus pool is only shared among the agents, the principal can credibly use subjective signals of individual performance to allocate the pool among the agents, thereby providing them with incentives to contribute effort (Ederhof, Rajan, and Reichelstein [2011]).

Survey evidence confirms that discretionary bonus pool arrangements are widely used in practice (e.g., Murphy and Oyer [2003], WorldatWork and Compensation Advisory Partners [2021a, b, c]). Moreover, several studies examine these arrangements in laboratory experiments (e.g., Fisher et al. [2005], Bailey, Hecht, and Towry [2011], Maas, van Rinsum, and Towry [2012], Arnold, Hannan, and Tafkov [2018, 2020], Arnold and Tafkov [2019], Majerczyk and Thomas [2021]). For example, Fisher et al. [2005] find that it is indeed beneficial when the principal (i) fixes the size of the bonus pool ex-ante and (ii) uses subjective signals of individual performance to allocate the bonus pool among the agents.

Extending this work, Arnold, Hannan, and Tafkov [2018, 2020] consider peer evaluations as subjective signals of individual performance, assuming agents are better informed about each other's performance than the principal (i.e., mutual monitoring). Specifically, they focus on self-including peer evaluations, allowing agents to also submit assessments of their own performance. Such a self-including design creates a new moral hazard problem, because agents benefit from distorting peer evaluations in their own favor, thereby weakening the incentive effects of bonus pool arrangements. Arnold, Hannan, and Tafkov [2018] operationalize peer evaluations as bonus pool allocation proposals sent to an uninformed principal. They find that, when self-including proposals are available, the principal's allocation leads to more effort provision than when such proposals are not available to the principal, suggesting that – while susceptible to opportunism – self-including proposals contain valuable information. Independent of this work in accounting, research in economics also examines the use of peer evaluations in bonus pool arrangements to address the free rider problem in the common pool and PGG literatures.

2.2 BONUS POOL ARRANGEMENTS IN ECONOMICS LITERATURE

In a classic PGG, the marginal benefit of contributing to the common pool is known ex-ante and calibrated such that it is optimal for all players, collectively, to contribute (i.e., cooperate) but for each player, individually, to free ride on the contributions of others. Experimental studies provide evidence that, in repeated PGGs, some players initially cooperate while others free ride; yet, over time, average contributions decline, as initial cooperators observe free riders and lower their contributions (e.g., Kim and Walker [1984], Andreoni [1988], Isaac and Walker [1988], Chaudhuri [2011]). This strategy of adapting one's own contributions based on the contributions of others is called *conditional cooperation* (Fischbacher, Gächter, and Fehr [2001]).

To address the free-rider problem in the PGG, prior studies consider punishment and reward systems that enable players – after the pool is evenly split – to punish and/or reward each other. Such systems reduce free riding and can sustain cooperation (e.g., Ostrom, Walker, and Gardner [1992], Fehr and Gächter [2000], Sefton, Shupp, and Walker [2007], Gächter, Renner, and Sefton [2008], Rand et al. [2009]). Different from bonus pool arrangements, the punishment and reward systems in these studies create social losses or gains.[3]

More recent studies in the common pool literature consider *self-funding* reward systems, where punishment and reward only materialize via the allocation of the pool, absent an initial even-split allocation. These reward systems differ from discretionary bonus pool arrangements solely in that the allocation right is not given to an impartial principal but directly to the agents who observe each other's contributions.[4] We categorize this stream of research into studies with self-including and self-excluding designs of peer allocation proposals.

Studies with *self-including* design typically examine the delegation of the allocation right to a single agent who allocates the pool among all agents including themself (e.g., van der Heijden, Potters, and Sefton [2009], Drouvelis, Nosenzo, and Sefton [2017], Karakostas et al. [2023]).[5] These studies find that bonus allocations by a single agent are not fully opportunistic as they lead to higher contributions than even-split allocations. Notably, one agent who allocates the entire pool has similar incentives (for distortion) as many agents who each allocate a share of the pool.

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[3] Punishment creates a cost for both the sender and the receiver of the punishment, leading to a social loss; similarly, social gains arise, as the cost incurred for rewarding is usually smaller than the reward received (Rand et al. [2009]).

[4] Stoddard, Walker, and Williams [2014] and Stoddard, Cox, and Walker [2021] consider a third-party allocator who benefits from contributions to the pool (i.e., principal). Their setting captures discretionary bonus pool arrangements but assumes that the principal perfectly monitors individual contributions.

[5] Interestingly, Karakostas et al. [2023] require the agent who allocates the bonus pool to contribute their entire endowment to the pool, which may create a sense of obligation by others to match that contribution. Furthermore, other design features (e.g., number of agents, aggregation function, etc.) also differ among those studies, making it challenging to compare them. Baranski [2016] extends the approach in those studies by allowing all agents to vote on the proposing agent's allocation, which is implemented if a majority accepts the proposal.

Studies with *self-excluding* design usually delegate the allocation right to all agents such that each agent allocates an equal, fixed share of the pool among all other agents excluding themself, rendering them indifferent about their allocation (Yang et al. [2018], Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022]). In an experiment, Dong, Falvey, and Luckraz [2019] find that such a formulaic use of self-excluding proposals outperforms even-split allocations. Galbraith [1997] describes a slightly different, but algebraically equivalent mechanism, which requires each agent to propose an allocation of the *entire* bonus pool among only other agents, where the average of all agents' proposals determines the final bonus allocation.[6]

Dong, Falvey, and Luckraz [2019] argue that the formulaic use of self-excluding proposals outperforms even-split allocations because bonuses better reflect agents' relative contributions to the pool. Similarly, Yang et al. [2018, 9968] refer to "payoff-based conditional cooperation" to explain that agents will contribute more, the more they expect their payoffs – from the pool – to reflect their relative contributions. Arnold, Hannan, and Tafkov [2018, 2020] use a similar line of reasoning to explain the effectiveness of the discretionary use of self-including proposals.

While these studies examine different uses and designs of allocation proposals in isolation, we are not aware of research that compares their effectiveness. As such, it is unknown how peer evaluations – here, bonus allocation proposals – should be used (formulaic vs. discretionary) and designed (self-including vs. self-excluding) to best motivate effort provision. Our study bridges this gap. In what follows, we outline the monetary incentives underlying those uses and designs with an analytical framework, before developing our hypothesis drawing on behavioral theories.

2.3 ANALYTICAL FRAMEWORK

The analytical framework captures a bonus pool arrangement that reflects the settings in Arnold, Tafkov and Hannan [2018, 2020], Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022], and our study. Specifically, we outline a three-stage game, describing the problem of a manager (principal), who can use subjective peer evaluations, to motivate $n > 2$ employees (agents), each with an endowment of $E > 0$, to contribute effort to group output.

In stage 1, each employee i independently chooses how much costly effort, e_i, to contribute, where $c_i = e_i$ is the cost of effort ($c_i'(e_i) = 1$) and $0 \leq e_i \leq E$. Employees' efforts are added and multiplied with productivity factor $M \geq 1$ to determine group output $G = M\sum_i(e_i)$. Thus, $M\,e_i$ represents employee i's

[6] At Agility Scales, employees can award each other – but not themselves – points, the value of which depends on firm profit and the total of points awarded (Hannah [2019]). Similarly, peer-to-peer bonus schemes represent the use of self-excluding peer recognition. A recent report suggests "74 percent of companies considered these schemes to be fundamental to a positive work environment, high performance and a great culture" (Emmonds [2019]).

individual performance.[7] The manager keeps portion θ of group output, where $0 < \theta \leq (M - 1)/M$. The remainder $(1 - \theta)$ forms the bonus pool $B = (1 - \theta)\, M \sum_i (e_i) = M_B \sum_i (e_i)$, such that $M_B \geq 1$ reflects the marginal increase of the bonus pool per unit of effort.

In stage 2, the manager only observes group output, whereas employees also observe each other's effort contributions (and, thus, individual performances).[8] To access employees' private information, the manager requests peer evaluations, asking each employee i to send an allocation proposal, p_i, with a proposed bonus, $p_{i,j} \geq 0$, for every employee j, where $\sum_j (p_{i,j}) = B$.[9]

Stage 3 determines the final bonus allocation, b, with a bonus of $b_i \geq 0$ for each employee i, such that the bonus pool, B, is allocated among all employees without residual, i.e., $\sum_i (b_i) = B$. Importantly, this requirement ($\sum_i (b_i) = B$) is a key feature of bonus pool arrangements, because it ensures (i) the manager's impartiality toward employees and (ii) the self-funding nature of the reward system (i.e., the bonus allocation is a zero-sum game without social losses or gains).

Within this setting, we differentiate between the self-including and self-excluding designs (stage 2) and the formulaic and discretionary uses (stage 3) of employees' allocation proposals. Different from the self-including design, the self-excluding design requires employees to propose a bonus of zero to themselves, i.e., $p_{i,j} = 0$ for $i = j$ (Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022]). Under formulaic use, the final bonus allocation is then determined via the average of all n employees' proposals, i.e., $b_i = \sum_k (p_{k,i})/n$. That is, each employee's proposal allocates an ex-ante fixed share, $1/n$, of the pool, such that the final bonus allocation is delegated to the employees. Under discretionary use, the manager keeps full control over the final bonuses. In sum, we differentiate between formulaic use and self-including design (condition [1]), formulaic use and self-excluding design (condition [2]), discretionary use and self-including design (condition [3]), and discretionary use and self-excluding design (condition [4]).

Next, we outline for each condition the requirement for multiplier M_B to *induce* full effort as a

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7 In line with prior work, we operationalize individual performance as a perfect multiple of effort, abstracting away noise in the relation between effort and individual performance (thereby ensuring optimal experimental control).

8 That is, like Arnold, Tafkov and Hannan [2018, 2020], Dong, Falvey, and Luckraz [2019], and Abbink, Dong, and Huang [2022], we assume mutual monitoring. This assumption also aligns with the team production literature (e.g, Che and Yoo [2001], Kvaloy and Olsen [2006], Alonso and Matouschek [2008]). Similarly, in the PGG literature, transparency about contributions is a standard feature in studies that (i) incorporate punishment or reward systems (see Fiala and Suetens [2017]) or (ii) examine the benefits of peer leadership (see Eichenseer [2023]).

9 Note that $\sum_j (p_{i,j}) = B$ is not a necessary requirement, as the manager can proportionally transform any proposal (e.g., peer evaluations elicited on Likert scales) to percentages such that the proposed bonuses add up to 100 percent. For example, consider a team of three employees and assume employee A evaluates as follows: A: 9 / B: 7 / C: 4. The corresponding percentages amount to: A: 45 percent (= 9/20) / B: 35 percent (= 7/20) / C: 20 percent (= 4/20). In line with prior research and without loss of generality, we require $\sum_j (p_{i,j}) = B$, as it ensures consistent scaling across all employees, which enables a formulaic use based on simple averaging and facilitates the manager's task.

dominant-strategy equilibrium – respectively *sustain* full effort as a Nash equilibrium.[10] To do so, we extend the analysis in Dong, Falvey, and Luckraz [2019] and apply backward induction (from stage 3), assuming individuals are self-interested.[11] First, we show that, when self-interests are *pure*, the requirement for multiplier M_B to induce (sustain) full effort is identical for all four conditions: $M_B \geq n$ ($M_B \geq n$).[12] Then, we relax the assumption that self-interests are *pure* and show that the requirement for multiplier M_B hinges on other-regarding preferences and beliefs about others' actions that otherwise self-interested individuals may adopt if they are indifferent.

Formulaic Use: Allocation by the Team (Conditions [1] and [2])

Under formulaic use, the bonus allocation in stage 3 is formulaically derived and, therefore, deterministic given employees' proposals in stage 2 and efforts in stage 1. Hence, the problem reduces to a two-stage game (i.e., stages 1 and 2).

In condition [1], each employee i receives a bonus of $b_i = \sum_k (p_{k,i})/n$ and strictly prefers to propose allocating the entire pool to themself ($p_{i,i} = B$), as b_i grows with i's self-allocation, $p_{i,i}$ ($b_i'(p_{i,i}) = 1/n > 0$). Thus, each employee i receives $b_i = B/n$ and will contribute effort, if the marginal benefit of effort $b_i'(e_i) = M_B/n$ weakly exceeds the marginal cost $c_i'(e_i) = 1$, resulting in the following requirement for multiplier M_B to induce (sustain) full effort: $M_B \geq n$ ($M_B \geq n$).

In condition [2], each employee i receives a bonus of $b_i = \sum_{k \neq i} (p_{k,i})/n$, where $b_i'(p_i) = 0$. Because p_i does not affect b_i, each employee is indifferent about their stage 2 proposal, such that any proposal, p_i, prescribes a dominant-strategy, subgame equilibrium in stage 2. Put differently, employees are impartial to their own proposals. Given *pure* self-interests, they randomly pick a proposal, such that – in expectation – all employees propose an even-split allocation among all other employees ($p_{i,j} = B/(n - 1)$ for $i \neq j$ and $p_{i,i} = 0$). Thus, each employee i receives a bonus of $b_i = B/n$, resulting in the same requirement for multiplier M_B in condition [2] as in condition [1].

To resolve the indifference in stage 2, Dong, Falvey, and Luckraz [2019] consider three *tie-breaking rules* that self-interested employees may adopt if they are otherwise indifferent about their proposals. Specifically, they consider (A) a concern for equality among others (i.e., even-split proposals), (B) a concern for equity among others (i.e., proportional proposals representing relative contributions to the

[10] In a full effort dominant-strategy equilibrium, it is best for each employee to provide full effort, irrespective of what others do, such that we refer to *inducing* full effort. In contrast, in a full effort Nash equilibrium, it is best for each employee to provide full effort, given all other employees provide full effort (i.e., no employee has an incentive to unilaterally deviate from full effort), such that we refer to *sustaining* full effort.

[11] While self-interests are not a useful assumption for making absolute predictions (as numerous PGG studies show), they may be a useful assumption for making relative predictions among different conditions.

[12] Note that, in our framework, both *purely* and *impurely* self-interested individuals first maximize their own payoffs. Our distinction only matters in case of indifference (i.e., individuals' own payoffs are not affected by their actions), in which case we assume that *purely* self-interested individuals choose randomly among available alternatives.

pool), and (C) a winner-takes-all approach (i.e., proposals allocating the entire pool to the highest contributor(s), in equal shares if several highest contributors exist). Table 1, Panel A shows, for each tie-breaking rule, the requirement for multiplier M_B to induce (sustain) full effort, as outlined by Dong, Falvey, and Luckraz [2019].

INSERT TABLE 1 ABOUT HERE

We focus on tie-breaking rule B, since it mirrors the presumption of a benevolent manager in analytical work on discretionary bonus pools (e.g., Baiman and Rajan [1995]). Moreover, prior research shows that individuals have concerns for truth-telling (e.g., Abeler, Nosenzo, and Raymond [2019]), which are – in our setting – identical to a concern for equity among others (e.g., Adams [1963, 1965], Lawler [1968]). As such, we define proposals to be *non-distorted* – and, similarly, bonuses to be *fair* – when they capture employees' relative contributions to the pool.[13] Table 1, Panel A depicts the requirement for multiplier M_B to induce (sustain) full effort given tie-breaking rule B: $M_B \geq n/(n - 1)$ (respectively, $M_B \geq n(n - 1)/(n(n - 1) - 1)$).

This requirement reflects an efficiency loss, as any value of M_B between 1 and $n/(n - 1)$ is insufficient, despite non-distorted proposals, to induce full effort. To illustrate the efficiency loss, consider one employee who contributes some effort and $(n - 1)$ employees who do not contribute any effort. The efficiency loss arises, as the sole contributor must allocate an *ex-ante fixed* share, $1/n$, of the pool among all other employees, such that only $n/(n - 1) \leq 1$ of the pool remains for the contributor. Thus, even if all proposals are non-distorted, bonuses will not necessarily be fair. Notably, the efficiency loss is transitive in that higher contributions result in larger bonuses, just not proportionally so (i.e., high contributors cross-subsidize low contributors).[14] Table 1, Panel B shows examples of the efficiency loss for $n = 3$ employees and $M_B = 1.5$.

Discretionary Use: Allocation by the Manager (Conditions [3] and [4])

Under discretionary use, the manager is indifferent about the allocation of the pool, such that any allocation prescribes a dominant-strategy, subgame equilibrium in stage 3. Hence, the requirement for

[13] We distinguish non-distorted proposals from fair bonuses since they differ for the self-excluding design, where a proportional transformation of proposals is needed, such that allocations to others reflect their relative contributions.
[14] This transitivity ensures that if all employees contribute equally, final bonuses will be fair (i.e., no efficiency loss). In general, the efficiency loss depends on employees' contributions (Dong, Falvey, and Luckraz [2019]). It is largest when only one employee contributes and decreases with increasing contributions of others. (Note that, if at least two employees provide some effort, the efficiency loss only materializes among those employees, while employees who do not contribute any effort will receive a fair bonus of zero.) Therefore, the requirement for M_B to *sustain* full effort – i.e., prevent unilateral deviations from full effort – is weaker than the requirement to *induce* full effort. Moreover, the efficiency loss, $n/(n – 1)$, decreases, as the number, n, of employees increases.

multiplier M_B to induce (sustain) full effort also depends on employees' beliefs about the manager's allocation, further adding complexity. If employees believe that the manager is *purely* self-interested and randomly chooses a bonus allocation, they will expect an even-split, $b_i = B/n$, resulting in the same requirement for M_B in conditions [3] and [4] as in condition [1].

If self-interests are not *pure* and employees believe that the manager takes the average of all proposals to derive final bonuses, discretionary use will perform equally well as formulaic use, resulting in the same requirement for multiplier M_B in condition [3] ([4]) as in condition [1] ([2]). In what follows, we illustrate that – relative to formulaic use – discretionary use has both upside and downside potential, depending on employees' beliefs about the manager's bonus allocation.

For example, condition [3] has upside potential relative to condition [1] in that the manager can treat self-including proposals as if they were self-excluding. Specifically, the manager can ignore employees' self-allocations and proportionally transform allocations to others such that they add up to the entire pool. If the manager takes the average of those transformed proposals to derive final bonuses, employees will have no reason to distort self-including proposals, resulting in the same requirement for M_B in condition [3] as in condition [2].

In contrast, condition [4] has downside potential relative to condition [2] in that the manager can treat self-excluding proposals as if they were self-including (to eliminate the efficiency loss). Specifically, the manager can derive fair bonuses – i.e., non-distorted self-including proposals – from any set of two non-distorted, self-excluding proposals, using the relative ratios of proposed bonuses in those proposals. Yet, in this case, employees have incentives to distort self-excluding proposals in the first place, as they no longer allocate an ex-ante fixed share of the bonus pool, resulting in the same requirement for M_B in condition [4] as in condition [1].[15]

Thus, beliefs about the manager's bonus allocation determine – irrespective of the design – whether employees have incentives to distort their proposals. We are not aware of a mechanism that induces truth-telling in stage 2 such that full effort is induced without efficiency loss in stage 1, thereby outperforming condition [2].[16] Recall that a key feature of bonus pool arrangements is the self-funding reward system,

[15] In essence, employees want to avoid that their own proposals allocate large shares of the pool to others and, thus, distort their proposals to preserve more of the pool for themselves. The optimal distortion strategy depends on which set of two proposals the manager uses to derive final bonuses. Overall, there are $n(n - 1)/2$ possible combinations that will result in the same solution of fair bonuses, if all n proposals are non-distorted. Yet, if at least one proposal is distorted, the $n(n - 1)/2$ solutions may differ. If the manager takes all proposals into consideration (e.g., by taking the average of all solutions), employees benefit from making proposals uninformative (e.g., by proposing even-split allocations), which is – in contrast to truth-telling – a Nash, subgame equilibrium in stage 2.

[16] While condition [2] *induces* truth-telling (proportional proposals) as a dominant-strategy, subgame equilibrium in stage 2, it merely induces full effort with efficiency loss in stage 1. Notably, it is possible to construct a mechanism that *sustains* truth-telling – assuming all other employees tell the truth – as a Nash, subgame equilibrium in stage 2, leading to full effort provision without efficiency loss in stage 1 (Battaglini [2002], Ambrus and Takahashi [2008]). Consider the self-including design and a bonus allocation based on 'agreeing' proposals. Specifically, if two or more

such that burning of the pool as a threat or use of the pool for costly verification are not feasible options. In sum, the predictions of the analytical framework greatly vary with small changes in the assumptions about human behavior, illustrating the need for a hypothesis drawing on behavioral theories and an empirical examination via an experiment.

2.4 HYPOTHESIS DEVELOPMENT

We argue that employees are more likely to provide effort, the more they expect bonuses to be fair. Our line of reasoning builds on the idea of payoff-based conditional cooperation (Yang et al. [2018]), suggesting that employees contribute more effort, the more their bonuses reflect their relative contributions to the pool. Prior research shows individuals are often willing to cooperate with others to pursue desirable group outcomes, even if they are better off defecting.[17] We expect the effectiveness of the different uses and designs of allocation proposals – in motivating effort – to depend on the extent to which employees believe they prevent defectors from taking advantage of cooperators, thereby ensuring fair bonuses. The fairness of bonuses depends on (i) employees' proposals and (ii) the transformation of these proposals into final bonuses.

First, irrespective of specific use, we argue that employees expect the self-excluding design to result in less distorted proposals than the self-including design. We suggest that employees see opportunities to benefit from distorting self-including proposals but not self-excluding proposals, regardless of use. Drawing on bounded rationality (Rubinstein [1998]), we argue that employees neglect possibilities – that arise under discretionary use but not under formulaic use – to benefit from (i) not distorting self-including proposals (in condition [3]) or (ii) distorting self-excluding proposals (in condition [4]). Thus, we predict that, irrespective of use, the self-excluding design leads to less distortion in proposals than the self-excluding design.

Second, we argue that – relative to formulaic use – managers' transformations of proposals into final bonuses are more prone to bias when proposals are self-excluding than self-including. We suggest that, under discretionary use, it is more complex for managers to derive fair bonuses from self-excluding proposals than from self-including proposals, even if they are non-distorted. Consider a pool of 180 that is

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employees propose the same allocation, the manager will allocate bonuses based on those agreeing proposals. If all employees tell the truth (i.e., non-distorted proposals), no employee will have an incentive to unilaterally deviate, as the manager will ignore the 'disagreeing' proposal. Thus, truth-telling can be *sustained*. Importantly, truth-telling is not a dominant strategy in stage 2, as the proposals of others matter. In fact, under this mechanism, any proposal will be a Nash, subgame equilibrium in stage 2, if all employees coordinate ('agree') on that proposal. Such coordination is complex, as each employee is interested in coordinating on a proposal that allocates more of the pool to themself.

[17] Thöni and Volk [2018] report that 61 percent of players in PGGs are conditional cooperators and only 19 percent are free riders, who always defect. Equity theory states that individuals care about the fair distribution of rewards (e.g., Adams [1963, 1965]). Similarly, a large body of work documents and formalizes non-standard preferences, like preferences for fairness and truth-telling (e.g., Rabin [1993], Fehr and Schmidt [1999], Bolton and Ockenfels [2000], Fehr and Gächter [2000], Charness and Rabin [2002], Abeler, Nosenzo, and Raymond [2019]).

allocated among employees A, B, C, and assume that the following allocation is fair: 30 / 60 / 90. If all employees provide non-distorted, *self-including* proposals, each proposal reflects that allocation. Yet, if all employees provide non-distorted, *self-excluding* proposals, the proposals will differ: A: 0 / 72 / 108; B: 45 / 0 / 135; C: 60 / 120 / 0. While the manager can derive the fair allocation from any set of two self-excluding proposals via the ratios of proposed bonuses, it is more complex than with self-including proposals.[18] Bol [2011] finds that complexity exacerbates managerial biases like centrality bias – i.e., assessing low (high) performers better (worse) than justified. Thus, we predict that (unintentional) managerial biases in final bonuses are more pronounced when proposals are self-excluding than self-including.

In sum, we expect (i) that the self-excluding design results in less distorted proposals than the self-including design, irrespective of use, and (ii) that, relative to formulaic use, discretionary use is more prone to managerial biases – in the transformation of proposals into final bonuses – when the design is self-excluding than self-including. Overall, we argue that the positive effect of the self-excluding design, relative to the self-including design, in establishing fair bonuses and, thus, motivating effort is weaker under discretionary use (i.e., allocation by the manager) than under formulaic use (i.e., allocation by the team).[19] We state the following hypothesis:

H1: The positive effect of the self-excluding design – relative to the self-including design – on effort provision is weaker under discretionary use (i.e., allocation by the manager) than under formulaic use (i.e., allocation by the team) of allocation proposals.

3. Method

To test our hypothesis, we conduct a laboratory experiment that comprises eight rounds, each representing the three-stage game described in the analytical framework (see section 2.3).[20] We assign

[18] In the example, employee A proposes a bonus for B that is two thirds of C's bonus, and employee B proposes a bonus for A that is one third of C's bonus. Given that the bonuses must add up to 180 (= 1/3 b_C + 2/3 b_C + b_C), the fair bonuses can be derived (b_C = 90). The complexity underlying the self-excluding design increases, relative to the self-including design, as the number of employees, *n*, increases. Notably, because self-including proposals are more likely to be distorted than self-excluding proposals, there is more upside to deviating from the average of proposals. Furthermore, the efficiency loss arising from the average of non-distorted, self-excluding proposals (35 / 64 / 81) is relatively small (see B's bonus), given its transitivity and diminishing size, as contributions grow more similar.

[19] Note that when proposals are self-including, we expect formulaic use and discretionary use to result in similar effort provision. On the one hand, formulaic use may activate a sense of responsibility in employees and, thus, limit tendencies to distort self-including proposals. On the other hand, formulaic use may encourage more distortion in self-including proposals than discretionary use, as each proposal has an equal weight, such that employees may want to protect themselves more against defectors and, hence, distort proposals more heavily in their own favor.

[20] The experiment has been approved by the applicable university's Institutional Review Board. It was programmed using the software Lioness Lab (Giamattei, Yahosseini, Gächter, and Molleman [2020]). We assume a finite time horizon, which is reflective of practice in that the composition of teams often changes over time. Predictions of a framework with one round translate to a framework with a finite number of rounds (based on backward induction).

participants to groups consisting of one manager and three employees (i.e., $n = 3$), which remain grouped together throughout all eight rounds of the experiment.[21] We manipulate – between-groups – the design in stage 2 (*self-including* vs. *self-excluding*) and use in stage 3 (*formulaic* vs. *discretionary*) of employees' bonus pool allocation proposals.

3.1 EXPERIMENTAL SETTING AND PARAMETER CHOICES

In stage 1 of every round, each employee receives an endowment of $E = 40$ points, where each point is worth U.S. \$0.05. Employees simultaneously choose costly efforts $e_i \in \{0, 2, 4, \ldots, 40\}$, which must be even numbers to avoid rounding issues. Each point of effort increases group output by $M = 2$ points. The manager receives $\theta = 0.25$ of the output. The remaining 75 percent form the bonus pool. That is, each point of effort increases the bonus pool by $M_B = 1.5$ points.[22]

In stage 2 of every round, each employee proposes to the manager how to allocate the pool. Proposed bonuses, $p_{i,j} \geq 0$, must be multiples of three – to avoid rounding issues in stage 3 – and add up to the pool, $\sum_j(p_{i,j}) = B$. While the self-including design enables an allocation among all three employees, the self-excluding design requires an allocation among the other two employees such that $p_{i,i} = 0$. We make proposals private in that they are not available to other employees.[23]

In stage 3 of every round, the bonus pool is allocated among the three employees such that individual bonuses, $b_i \geq 0$, add up to the pool, $\sum_i(b_i) = B$. Under formulaic use (i.e., allocation by the team), the final allocation is calculated as the average of the three employees' proposals, $b_i = \sum_k(p_{k,i})/3$. Under discretionary use (i.e., allocation by the manager), the manager has full discretion over individual bonuses and decides how to use the proposals. Thus, in any given round, employee i earns $\Pi_i = 40 - e_i + b_i$, while the manager earns $\Pi_M = 20 + 0.5\sum_i(e_i)$.

At the end of every round, employees are informed of each other's bonuses and earnings in that round. This design choice aligns with Arnold, Hannan, and Tafkov [2018, 2020] as well as prior work on self-funding reward systems in the common pool literature (e.g., van der Heijden, Potters, and Sefton

[21] A team size of three employees is the smallest meaningful size for self-excluding proposals and provides the most stringent test of our hypothesis. Specifically, a smaller team size (a) increases the efficiency loss under formulaic use and self-excluding design, which biases against finding a positive effect of self-excluding proposals under formulaic use, and (b) reduces complexity in the manager's task under discretionary use and self-excluding design, which biases against the expected mitigating influence of discretionary use on the effect of the self-excluding design.

[22] We opt for clarity in the instructions with parameters that are cognitively easy to process. Moreover, a multiplier of $M_B = 1.5$ aligns with prior studies. Arnold, Hannan, and Tafkov [2018] choose $M_B = 1.8$, while Dong, Falvey, and Luckraz [2019] choose $M_B = 1.2$ and $M_B = 1.8$. Further, it corresponds to a marginal per capita return [MPCR] of 0.5 in PGGs, which aligns with an average MPCR of 0.46 as reported in the meta-analysis by Fiala and Suetens [2017].

[23] This design choice aligns with Arnold, Hannan, and Tafkov [2018, 2020] and reflects common business practice, as peer evaluations are typically not public. Notably, prior work in economics (Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022]) makes employees' proposals transparent. Therefore, our study contributes to that literature also by examining the effectiveness of formulaic use and self-excluding design when proposals are private. The (non-)transparency of proposals among employees does not affect the predictions of the analytical framework.

[2009], Dong, Falvey and Luckraz [2019], Karakostas et al. [2023]).[24]

3.2 PARTICIPANTS AND PROCEDURES

In April 2022, we ran our experimental sessions at a private U.S. university in the Southeast. In total, 200 BBA students participated in the study.[25] Each session lasted about 75 minutes with an average payment per participant of U.S. $20.46. We randomly assign participants to groups of four and, within each group, to the manager and employee roles. Further, we randomly assign each group to one of the four experimental conditions (and do so in a balanced way).

As participants enter the laboratory, they select a computer terminal, where all instructions are provided on the computer screen. Throughout the instruction phase, participants complete understanding questions that must be answered correctly (i.e., they have as many attempts as needed), ensuring their understanding. Once all participants within a group have completed the instruction phase, round 1 begins. After the final round, participants answer questions about the task, their decisions, and socio-demographic background. We sum participants' earnings across all rounds, convert them to U.S. dollars, and pay participants in cash, as they exit the laboratory.

4. Results

4.1 DESCRIPTIVE RESULTS AND HYPOTHESIS TEST

Our dependent variable of interest is *Effort*, which ranges from 0 to 40. Table 2 shows average *Effort* – per round and individual employee – for each condition. Under formulaic use (i.e., allocation by the team), average *Effort* – across all eight rounds – amounts to 19.646 for the self-including design and 27.444 for the self-excluding design, whereas under discretionary use (i.e., allocation by the manager), average *Effort* amounts to 19.744 for the self-including design and 19.667 for the self-excluding design. Figure 1, Panel A illustrates the results graphically.

INSERT TABLE 2 ABOUT HERE

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[24] Fiala and Suetens [2017] report that 11 percent of PGG experiments make payoffs transparent. They find that transparency of payoffs decreases contributions, while transparency of contributions increases contributions, with the former effect outweighing the latter. Transparency of payoffs likely decreases contributions, as players observe free riding to be individually beneficial. It is unclear whether this effect translates to our setting, where free riding (i.e., not providing any effort) may not be beneficial.

[25] In appreciation of students' decision to participate, they received partial course credit. Participation was voluntary, and alternative options to obtain partial credit were offered. Participants have an average age of 20 years, 36 percent identify as female, and 89 percent indicate that English is their primary language. Testing for randomization success, we do not find significant differences in age ($F_{Age\ (3,196)} = 1.60$, $p = 0.191$), gender ($F_{GenderID\ (3,196)} = 1.16$, $p = 0.326$), or primary language ($F_{Language\ (3,196)} = 1.13$, $p = 0.336$, all un-tabulated) among the four experimental conditions.

INSERT FIGURE 1 ABOUT HERE

We use regression analysis to test our hypothesis and cluster standard errors within teams to account for interdependence of observations (i.e., among the three employees per team across all eight rounds). Specifically, we regress *Effort* on indicator variables for the *Design* and *Use* of the allocation proposals and their interaction term. Table 3 depicts the results. Columns 1, 2, and 3 differ in the level of analysis: (1) decision level (i.e., one observation per round and employee), (2) employee level (i.e., one observation per employee – averaged across all eight rounds), and (3) team level (i.e., one observation per team – averaged across all three employees and all eight rounds). Clustering standard errors within teams accounts for interdependence of observations at the decision and employee levels (columns 1 and 2) and also implements robust standard errors at each level (columns 1 to 3). Our results are consistent across all three levels.[26]

INSERT TABLE 3 ABOUT HERE

The positive effect of *Design* (column 1: $\beta_1 = 7.799$, p = 0.009) shows that, under formulaic use, the self-excluding design leads to significantly more *Effort* than the self-including design.[27] The negative interaction effect ($\beta_3 = -7.876$, p = 0.041, one-tailed) supports the hypothesis that the positive effect of *Design* is significantly less pronounced under discretionary use than under formulaic use. Notably, this interaction effect completely offsets the positive effect of *Design* in our setting. That is, under discretionary use, *Effort* does not significantly differ between the self-including and self-excluding designs ($\beta_1 + \beta_3 = -0.077$, p = 0.982, un-tabulated).

The simple comparisons reported in Table 3 illustrate that condition [2], formulaic use and self-excluding design, leads to significantly more *Effort* than each of the other three conditions ([1], [3], [4]). Further, note that *Effort* does not significantly differ among those three conditions ($F_{(2, 49)} = 0.00$, p = 0.999, un-tabulated). In sum, our results support the hypothesis that the effect of the self-excluding design

[26] Note that coefficients in columns 1, 2a, and 3 are identical, as average *Effort* – per round and employee – does not depend on the level of analysis (i.e., decision, employee, or team). Because we cluster standard errors within teams, *t*-statistics (in parentheses) barely differ among columns 1, 2a, and 3 despite the divergent numbers of observations. Given its categorical nature, we also test whether the dependent variable *Effort* (0, 2, …, 40) is normally distributed, using the Shapiro-Wilk test. While the assumption of normality is rejected at the decision level (p < 0.001), it is not rejected at the employee level (p = 0.139) or team level (p = 0.741, all un-tabulated). Because the coefficients are identical across the three levels (in columns 1, 2a, 3), we conclude that measurement of *Effort* as categorical variable does not bias the coefficients. Similarly, the normality assumption for the error term is rejected at the decision level (p < 0.001) but not at the employee level (p = 0.432) or team level (p = 0.516, all un-tabulated).

[27] All tests are two-tailed, unless they relate to a directional prediction, in which case we report one-tailed tests.

– relative to the self-including design – on effort provision is weaker under discretionary use than under formulaic use.

To better understand the mechanism underlying this finding, we examine responses to four post-experimental questions [PEQs] capturing participants' perceptions of *Distributive Fairness* (in the allocation of bonuses).[28] Because employees give one response to each PEQ, we examine *Distributive Fairness* at the employee level. Table 3, column 2b depicts the results of regressing *Distributive Fairness* on indicator variables capturing our manipulations. Note that the pattern of results mirrors the pattern in column 2a. Further, the simple comparisons show that participants perceive significantly higher levels of *Distributive Fairness* under condition [2], formulaic use and self-excluding design, than under each of the other three conditions ([1], [3], [4]).

Column 2c illustrates the results of including *Distributive Fairness* as explanatory variable in the main regression model. We find a significantly positive effect of *Distributive Fairness* on *Effort* ($\beta_4 =$ 5.209, $p < 0.001$), while neither the effect of *Design* ($\beta_1 = 3.738$, $p = 0.117$) nor the interaction effect ($\beta_3 = -3.175$, $p = 0.366$) is statistically significant. Similarly, we no longer find significant simple comparisons, suggesting that perceptions of *Distributive Fairness* explain the differences in *Effort* among the four conditions. In sum, the results show that a formulaic use and self-excluding design is perceived to lead to fairer bonuses than any of the other three conditions, thereby potentially creating a stronger motivation for employees to contribute effort.[29]

4.2 SUPPLEMENTAL ANALYSES

To gain additional insight into the mechanisms underlying our results, we examine in more detail (i) employees' effort contributions in stage 1 (section 4.2.1), (ii) their allocation proposals in stage 2 (section 4.2.2), and (iii) the final bonus allocations in stage 3 (section 4.2.3).

4.2.1 Employees' Effort Contributions (Stage 1)

Figure 1, Panel B illustrates, for each condition, how *Effort* evolves over time. In Round 1, we do not find significant differences in *Effort* among our conditions (un-tabulated). Over time, *Effort* quickly increases in condition [2], whereas, in conditions [1], [3], and [4], *Effort* initially remains stable but eventually decreases. Testing our hypothesis separately in each round, we find directional support after

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[28] We ask participants to indicate their agreement, on a Likert-scale from 1 (*strongly disagree*) to 7 (*strongly agree*), with the following four statements. To what extent … (1) "do your individual bonuses reflect your contributions," (2) "are your individual bonuses appropriate for the outputs you have generated," (3) "do your individual bonuses reflect your contributions to team output," and (4) "are your individual bonuses justified, given your performance?" A confirmatory factor analysis shows that the four PEQs load on one factor with eigenvalue of 3.210 (un-tabulated). We use the loadings of the four PEQs to create a variable that captures the factor *Distributive Fairness*.

[29] In four additional PEQs, participants also indicate that they perceive more procedural fairness under formulaic use than under discretionary use ($F_{(1,49)} = 6.11$, $p = 0.017$). While these perceptions do not directly translate into effort contributions in our setting, they may have long-term effects on organizational culture and employee involvement.

Round 1 and inferential support after Round 2 (un-tabulated).

Figure 2 shows histograms of employees' effort contributions for each condition and round. In Round 1, *Effort* is concentrated – in each condition – at 20, the center of the distribution, with only few observations at 0 and 40. Over time, effort contributions in condition [2] steadily shift toward 0, while effort contributions in conditions [1], [3], and [4] initially spread more equally but eventually shift toward 0.[30] Note that, despite these shifts toward the extremes, the majority of observations, in each condition and round, does not fall on either extreme. In sum, our results show that employees are more inclined in condition [2], formulaic use and self-excluding design, to increase their effort contributions over time compared to conditions [1], [3], and [4].

INSERT FIGURE 2 ABOUT HERE

4.2.2 Employees' Allocation Proposals (Stage 2)

Our theoretical reasoning purports that employees are more motivated to contribute effort the more they expect final bonuses to be fair, which critically depends on employees' allocation proposals in stage 2 (and the transformation of these proposals into final bonuses in stage 3, which we consider in the following sub-section). We predict that the self-excluding design leads to less distortion in proposals than the self-including design, irrespective of specific use.

Focusing first only on the self-including design, we find that employees propose to allocate significantly more to themselves than justified, both under formulaic use (by 17.146) and under discretionary use (by 10.635, both $p < 0.001$, at each level of analysis, one-tailed) – without significant difference between the two uses (all $p > 0.270$, un-tabulated). Overall, approximately 60 percent of all self-including proposals exhibit some degree of self-serving distortion.[31]

To compare the self-including and self-excluding designs, we create a measure capturing full distortion in each employee i's proposal: $Full\ Distortion_i = \sum_j |p_{i,j} - k_{i,j}|$, where – in any given round – $p_{i,j}$ denotes the bonus proposed by employee i for employee j, and $k_{i,j}$ denotes the corresponding non-distorted benchmark ($i, j \in \{A, B, C\}$, $p_{i,i} = k_{i,i} = 0$ for self-excluding design). Results in Appendix A illustrate that *Full Distortion* is significantly smaller when proposals are self-excluding than self-

[30] In the final round (i.e., Round 8), 56 percent of effort contributions in condition [2] are larger than 30, compared to only 14 percent, 18 percent, and 18 percent in conditions [1], [3], and [4] respectively; similarly, only 8 percent of effort contributions in condition [2] are smaller than 10, compared to 33 (46, 38) percent in condition [1] ([3], [4]).
[31] In 24 of the 600 self-including proposals, distortion is not possible due to a bonus pool of zero. Of the remaining 576 proposals, 352 (61 percent) exhibit some degree of self-serving distortion in that self-allocations are larger than justified by relative contributions (including 74 unjustified self-allocations of the entire pool), 52 (9 percent) exhibit altruism in that self-allocations are smaller than justified, and 172 (30 percent) exhibit non-distorted self-allocations.

including, under each use (both $p < 0.025$, at all three levels, one-tailed) – without significant difference between the two uses ($p > 0.370$, at all three levels).[32]

In addition, we create a measure that captures distortion in the average proposed bonus for each employee: $Distortion_i = \left|\sum_j (p_{j,i})/3 - 1.5\ e_i\right|$, where – in any given round – $\sum_j (p_{j,i})/3$ denotes the *Proposed Bonus* as average of proposed bonuses for employee i by all employees j, and 1.5 e_i denotes employee i's *Fair Bonus* ($i, j \in \{A, B, C\}$, $p_{i,i} = 0$ for self-excluding design). Table 4, Panel A shows average *Distortion* – per round and employee – for each condition. Panel B shows the results of regressing *Distortion* on the experimental variables. We find that the self-excluding design leads to significantly less *Distortion* than the self-including design, both under formulaic use (β_1 = -2.840) and under discretionary use ($\beta_1 + \beta_3$ = -3.135, both $p < 0.050$, at all three levels, one-tailed) – without significant difference between uses (β_3 = -0.294, $p > 0.850$).

INSERT TABLE 4 ABOUT HERE

To test our theory more directly, we examine the relation between effort contributions and average proposed bonuses. Absent any distortion, each unit of *Effort* contributed by employee i leads to a 1.5-unit increase in the *Proposed Bonus* for that employee. As such, we can also assess distortion by regressing *Proposed Bonus* on *Effort*: $Proposed\ Bonus_i = \alpha + \gamma\ Effort_i$. If $\gamma < 1.5$, proposals will exhibit cross-subsidization from high to low contributors in that proposed bonuses are, on average, lower (higher) than justified for high (low) contributors. Table 5 shows the results of regressing *Proposed Bonus* on *Effort* separately for each condition (columns 1 to 4) as well as differences in the relation between *Proposed Bonus* on *Effort* among the four conditions (column 5). Because the results are robust across the decision level (Panel A) and employee level (Panel B), we focus on the decision level (Panel A) below.[33]

INSERT TABLE 5 ABOUT HERE

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[32] Of all 1,176 proposals (excluding 24 which, due to a bonus pool of zero, have no distortion), 22 percent (225) are non-distorted. This percentage does not significantly differ among conditions ($p = 0.757$, un-tabulated). Given the proportional transformation needed and the requirement to use multiples of three, it is often impossible to submit a non-distorted, self-excluding proposal. Thus, we also assess the percentage of proposals with *Full Distortion* of six or less (where six is the next smallest *Full Distortion* for self-including proposals). The percentage of proposals with *Full Distortion* of six or less is significantly larger ($p < 0.001$) for the self-excluding design (53 percent) than the self-including design (32 percent) – without a significant difference between the two uses ($p > 0.315$, un-tabulated).

[33] At the team level, the coefficient of *Effort* γ is by default 1.5, as the average of all bonuses allocated within a team is exactly 1.5 times the average of efforts contributed. Further, we observe that, at the employee level, γ is – in each condition – larger than at the decision level, as several employees are low contributors in some rounds (with higher proposed bonuses than justified) and high contributors in other rounds (with lower proposed bonuses than justified).

In all four conditions (columns 1 to 4), we observe cross-subsidization in average proposed bonuses from high to low contributors (i.e., $\gamma_0 < 1.5$). Importantly, this cross-subsidization is significantly more pronounced for the self-including design than the self-including design both under formulaic use (column 5a: γ_1 = 0.275, p = 0.006, one-tailed) and under discretionary use ($\gamma_1 + \gamma_3 = 0.312$, p = 0.001, one-tailed, un-tabulated) – without significant difference between the two uses ($\gamma_3 = 0.037$, p = 0.798). That is, irrespective of use, we find less cross-subsidization in average proposed bonuses with the self-excluding design than with the self-including design.

4.2.3 Final Bonus Allocations (Stage 3)

Next, we assess the transformation of proposals into final bonuses in stage 3. We predict that – relative to formulaic use – managers' transformations of proposals into final bonuses are more prone to bias for the self-excluding design than the self-including design.

To test this prediction, we create a measure that captures, for each employee i, the extent to which the final bonus is unfair: $Unfairness_i = |b_i - 1.5\ e_i|$, where – in any given round – b_i denotes employee i's *Final Bonus*, and 1.5 e_i denotes employee i's *Fair Bonus* ($i \in \{A, B, C\}$). Table 6, Panel A shows average *Unfairness* – per round and individual employee – for each condition. Under formulaic use, average *Unfairness* in final bonuses (Table 6, Panel A) equals, by design, average *Distortion* in proposed bonuses (Table 4, Panel A). Thus, we focus only on discretionary use, where *Unfairness* and *Distortion* may differ – for any given employee – due to managers' use of discretion in setting bonuses. We find that, under discretionary use, *Unfairness* exceeds *Distortion* less for the self-including design (10.673 vs. 9.147) than for the self-excluding design (11.279 vs. 6.013). Table 6, Panel B shows the regression results of this within-comparison (between *Unfairness* and *Distortion*), where a positive effect of *Within* reflects bias in managers' transformations of proposals into final bonuses (i.e., *Unfairness* exceeds *Distortion*). Although not significantly different for the self-including design ($\beta_2 = 1.526$, p > 0.200), *Unfairness* is significantly larger than *Distortion* for the self-excluding design ($\beta_2 + \beta_3 = 5.263$, p < 0.010), illustrating that managers' transformations are significantly more prone to bias when proposals are self-excluding than self-including ($\beta_3 = 3.737$, p < 0.055, at all three levels, one-tailed).[34]

INSERT TABLE 6 ABOUT HERE

To better understand how managers transform proposals into final bonuses, we also assess the

[34] Of all 615 bonuses under discretionary use (i.e., excluding 9 bonuses that are zero due to a bonus pool of zero), 145 (24 percent) do not differ from the average proposal. Importantly, when proposals are self-including, managers' transformations are similarly often harmful (45 percent: *Unfairness* in bonuses exceeds *Distortion* in proposals) and beneficial (42 percent: *Unfairness* in bonuses is smaller than *Distortion* in proposals); whereas, when proposals are self-excluding, managers' transformations are more frequently harmful (48 percent) than beneficial (18 percent).

relation between *Effort* and *Final Bonus* and compare it to the relation between *Effort* and *Proposed Bonus*. Any difference in the relations can be attributed to managers' transformations. Table 7 shows the regression results for the two relations and each discretionary use condition separately (columns 1 to 4) as well as differences among these relations (column 5).

INSERT TABLE 7 ABOUT HERE

Again, we focus on the decision level (Panel A). For the self-including design, the strength of the relation between *Effort* and *Final Bonus* (column 1: $\gamma_0 = 0.990$) and the strength of the relation between *Effort* and *Proposed Bonus* (column 3: $\gamma_0 = 1.001$) do not significantly differ (column 5: $\gamma_2 = -0.011$, p $= 0.885$). That is, managers' transformations do not add systematic bias when proposals are self-including. In contrast, for the self-excluding design, the strength of the relation between *Effort* and *Final Bonus* (column 2: $\gamma_0 = 1.025$) is significantly weaker (column 5: $\gamma_2 + \gamma_3 = -0.288$, p $= 0.002$) than the strength of the relation between *Effort* and *Proposed Bonus* (column 4: $\gamma_0 = 1.313$). This result illustrates that managers' transformations exacerbate cross-subsidization from high to low contributors for the self-excluding design but not for the self-including design. Thus, managers' transformations add centrality bias (Bol [2008, 2011]) when proposals are self-excluding but not when they are self-including, as shown by the three-way interaction term (column 5: $\gamma_3 = -0.277$, p $= 0.012$, one-tailed).

In sum, the supplemental analyses support our theory that (a) the self-excluding design leads to less distortion in employees' proposals than the self-including design, irrespective of use, and that (b) managers' bonus allocations under discretionary use introduce more bias – relative to formulaic use – when proposals are self-excluding than self-including.

5. Conclusions

This study examines how the design and use of peer evaluations for incentive compensation affects employees' motivation to contribute effort to group outcomes. Focusing on a mutual monitoring setting, we study peer evaluations in form of bonus allocation proposals and compare formulaic use against discretionary use and self-including design against self-excluding design. These uses and designs have been examined – independent of each other and in isolation – in the bonus pool literature in accounting (Arnold, Hannan, and Tafkov [2018, 2020]) and the common pool literature in economics (e.g., Dong, Falvey, and Luckraz [2019], Abbink, Dong, and Huang [2022]). Yet, we are not aware of research comparing the effectiveness of these different uses and/or designs in motivating employee effort. Our study fills this gap, thereby building a bridge between the bonus pool literature in accounting and the common pool literature in economics.

After outlining the monetary incentives underlying the different uses and designs with an analytical framework, we develop a hypothesis drawing on behavioral theories. Consistent with this hypothesis, the results of our experiment show a positive effect of the self-excluding design, relative to the self-including design, on effort provision under formulaic use (i.e., allocation by the team), which is mitigated under discretionary use (i.e., allocation by the manager). We also provide evidence for the mechanisms underlying this finding. First, the self-excluding design leads to less distortion in proposals – i.e., better reflects relative contributions to the pool – than the self-including design both under formulaic use and under discretionary use, suggesting that employees neglect complex possibilities of how the manager could use discretion to derive fair bonuses. Second, the positive effect of the self-excluding design is counteracted, as managerial biases enter the transformation of proposals into final bonuses, under discretionary use, more when proposals are self-excluding than self-including. Taken together, final bonuses best reflect relative contributions to the pool under formulaic use and self-excluding design, resulting in more effort provision than any of the other three conditions. Put differently, the combination of formulaic use and self-excluding design incorporates subjective peer evaluations best into reward systems and, thus, provides employees with the strongest incentives to contribute effort.

Our results illustrate that the proper use and design of subjective peer evaluations can help inform bonus allocations and, thus, enable organizations to benefit from employees' information advantage. Our findings suggest that organizations may want to (i) limit self-interested behaviors by separating employees' self-evaluations from assessments of their peers and (ii) also limit managerial biases by reducing managers' discretion in the allocation of rewards. As such, our study contributes to research on calibration committees (Demeré, Sedatole, and Woods [2019], Grabner, Künneke, and Moers [2020]). We also extend prior work on bonus pools (Baiman and Rajan [1995], Rajan and Reichelstein [2006, 2009]) in that the formulaic use of self-excluding proposals extends the solution of the moral hazard problem between manager and employees to the moral hazard problem among the employees. Importantly, our study provides a theoretical and empirical underpinning for the increasingly popular practice of peer-to-peer bonus schemes. These schemes not only promote employee involvement within organization but also, when used and designed effectively, can play a critical role in shaping organizational culture.

Overall, we create an understanding of how peer feedback used for compensation purposes can enable cooperation by establishing fair bonuses. Accordingly, our findings have important implications for practitioners and researchers interested in the use and design of peer evaluations for incentive compensation.

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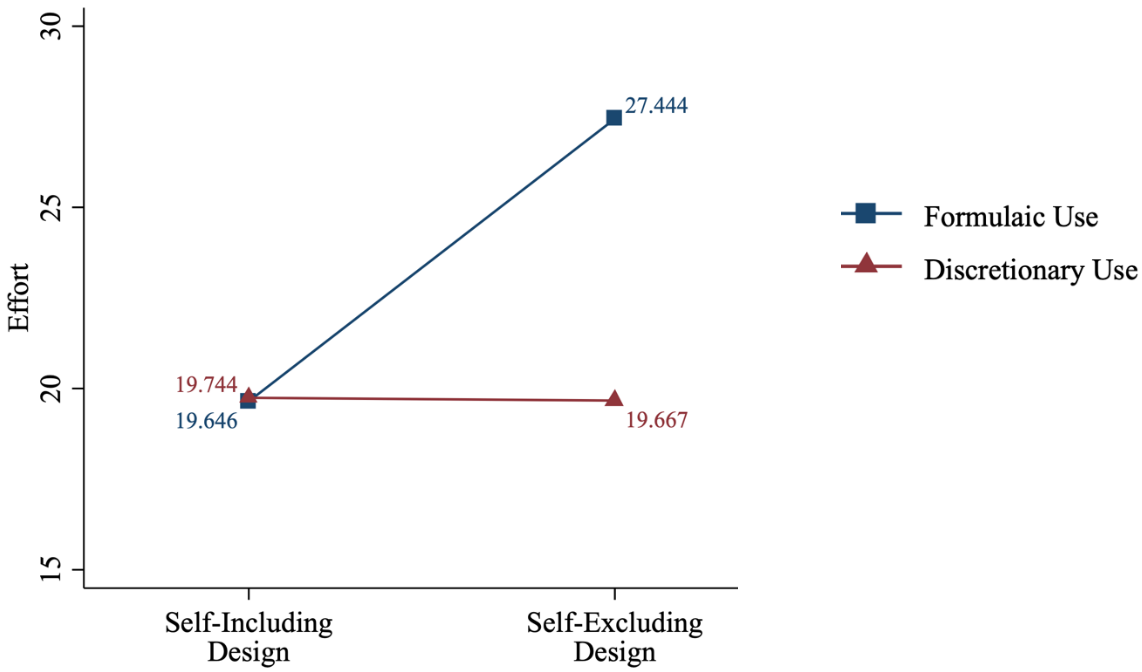
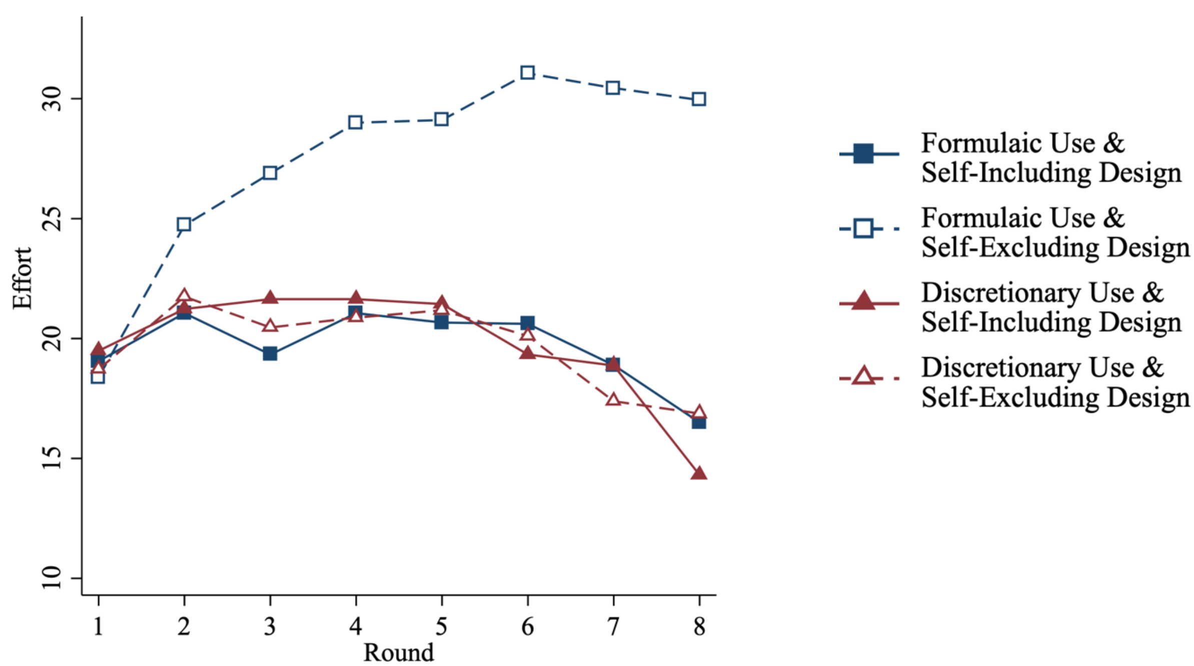
Figure 1: Effort

Panel A: Effort Averaged Across All Eight Rounds

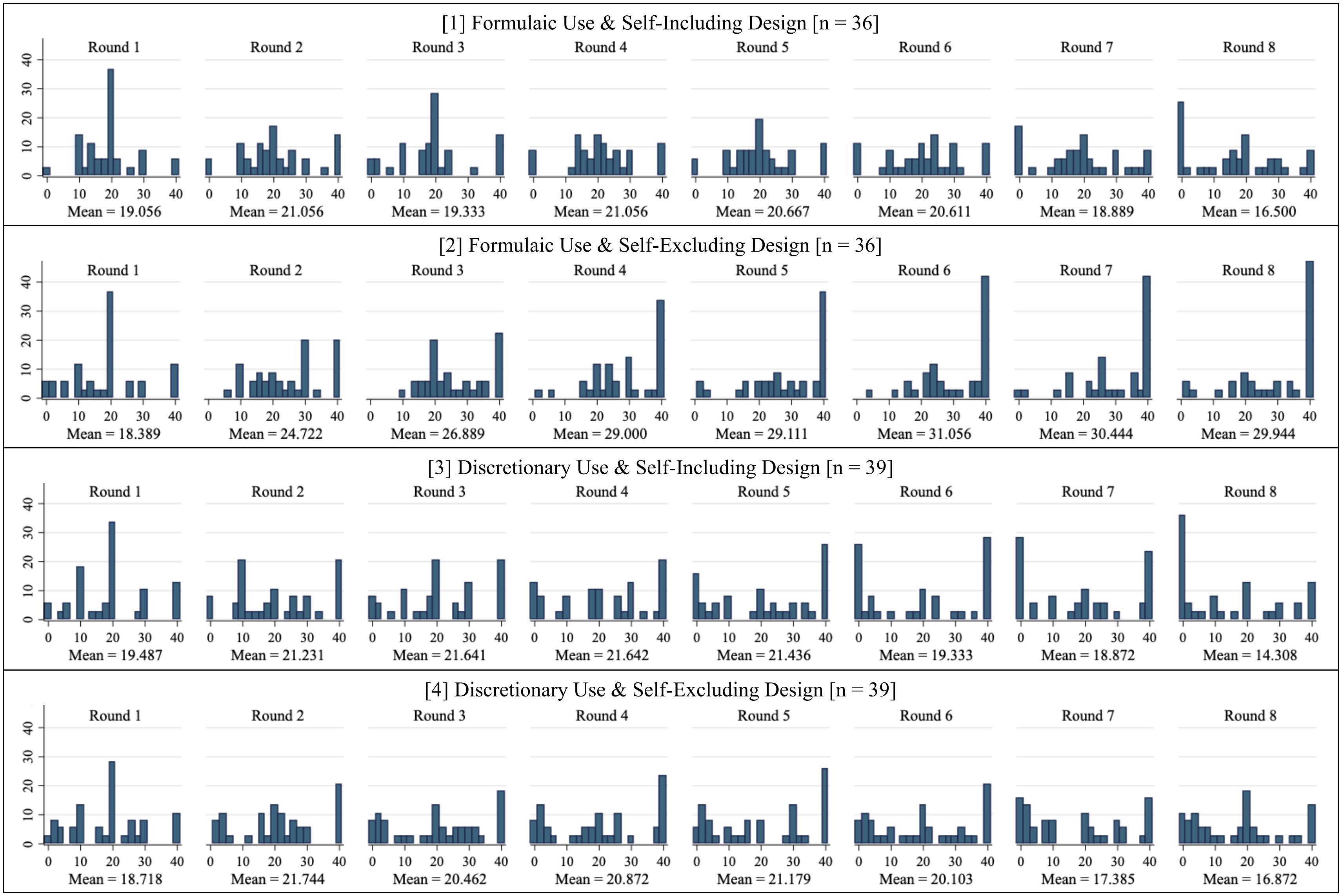


Panel B: Effort Over Time



Panel A shows average *Effort* – per round and employee – under formulaic use (i.e., allocation by the team) in blue squares and under discretionary use (i.e., allocation by the manager) in red triangles for both the self-including design and the self-excluding design.
Panel B shows, for each round, average *Effort* – per employee – under formulaic use (i.e., allocation by the team) in blue squares and under discretionary use (i.e., allocation by the manager) in red triangles for both the self-including design (filled markers) and the self-excluding design (unfilled markers). Figure 2 provides descriptive results.

Figure 2: Effort Histograms



This figure illustrates, for each condition and round, histograms of *Effort* – i.e., the percentages with which each effort contribution (from 0 to 40) occurs.

Table 1: Formulaic Use and Self-Excluding Design (Condition [2])

Panel A: Three Tie-breaking Rules (based on Dong, Falvey, and Luckraz [2019])

Stage 3: Allocation	Deterministic bonus allocation: average of proposals (from stage 2)		
Stage 2: Proposals	Each proposal prescribes a dominant-strategy, subgame equilibrium (i.e., employees are indifferent)		
	Tie-breaking rule A: Even-split proposals	Tie-breaking rule B: Non-distorted proposals (truth-telling)	Tie-breaking rule C: Winner-takes-all proposals
Stage 1: Effort Requirement for M_B to ...			
a) induce full effort as a dominant-strategy, subgame equilibrium	$M_B \geq n$	$M_B \geq \frac{n}{n-1}$	$M_B \geq \frac{n}{n-1}$
b) sustain full effort as a Nash, subgame equilibrium	$M_B \geq n$	$M_B \geq \frac{n\,(n-1)}{n\,(n-1)-1}$	$M_B \geq 1$

Panel B: Efficiency Loss with Tie-breaking Rule B (n = 3 employees and M_B = 1.5)

EXAMPLE 1

Employee	A	B	C	Bonus Pool
Effort	40	0	0	60
(%)	100%	0%	0%	
Proposal	to A	to B	to C	
by A	–	30	30	
by B	60	–	0	
by C	60	0	–	
Bonus	40.0	10.0	10.0	
(%)	66.7%	16.7%	16.7%	

EXAMPLE 2

Employee	A	B	C	Bonus Pool
Effort	40	20	0	90
(%)	67%	33%	0%	
Proposal	to A	to B	to C	
by A	–	90	0	
by B	90	–	0	
by C	60	30	–	
Bonus	50.0	40.0	0.0	
(%)	55.6%	44.4%	0.0%	

EXAMPLE 3

Employee	A	B	C	Bonus Pool
Effort	40	20	20	120
(%)	50%	25%	25%	
Proposal	to A	to B	to C	
by A	–	60	60	
by B	80	–	40	
by C	80	40	–	
Bonus	53.3	33.3	33.3	
(%)	44.4%	27.8%	27.8%	

EXAMPLE 4

Employee	A	B	C	Bonus Pool
Effort	40	40	20	150
(%)	40%	40%	20%	
Proposal	to A	to B	to C	
by A	–	100	50	
by B	100	–	50	
by C	75	75	–	
Bonus	58.3	58.3	33.3	
(%)	38.9%	38.9%	22.2%	

Panel A illustrates, for formulaic use and self-excluding design (condition [2]), the requirement for multiplier M_B to induce full effort as a dominant-strategy equilibrium, respectively sustain full effort as a Nash equilibrium, in stage 1 (via backward induction), for each of the three different tie-breaking rules (see Dong, Falvey, and Luckraz [2019]). Panel B illustrates, for formulaic use and self-excluding design (condition [2]), four examples of the efficiency loss when proposals are non-distorted (i.e., tie-breaking rule B). Note that bonuses are transitive (relative to efforts) and the bonus of employee A – whose effort is always 40 – increases, as the other two employees contribute more effort.

Table 2: Effort – Descriptive Results

	Self-Including Design			Self-Excluding Design		
Formulaic Use (Allocation by the Team)		19.646			27.444	
	(10.883)	(7.674)	(7.026)	(11.412)	(7.931)	(7.549)
	[n = 288]	[n = 36]	[n = 12]	[n = 288]	[n = 36]	[n = 12]
Discretionary Use (Allocation by the Manager)		19.744			19.667	
	(14.349)	(8.644)	(7.864)	(13.725)	(10.487)	(9.761)
	[n = 312]	[n = 39]	[n = 13]	[n = 312]	[n = 39]	[n = 13]

This table shows average *Effort* – per round and employee – under formulaic use (i.e., allocation by the team) and discretionary use (i.e., allocation by the manager) for both the self-including design and the self-excluding design. For each condition, standard deviations are depicted in parentheses at three levels with the respective numbers of observations in brackets (left: decision level with one observation per round and employee; middle: employee level with one observation per employee averaged across all eight rounds; right: team level with one observation per team averaged across all three employees and all eight rounds).

Table 3: Effort – OLS Regression Results

	(1) *Effort*	(2a) *Effort*	(2b) *Distributive Fairness*	(2c) *Effort*	(3) *Effort*
Design (β_1)	7.799***	7.799**	0.780***	3.738	7.799***
	(2.71)	(2.68)	(3.03)	(1.60)	(2.62)
Use (β_2)	0.098	0.098	-0.096	0.597	0.098
	(0.03)	(0.03)	(-0.32)	(0.26)	(0.03)
Design × *Use* (β_3)	-7.876** †	-7.876** †	-0.902**	-3.175	-7.876** †
	(-1.77)	(-1.76)	(-2.50)	(-0.91)	(-1.72)
Distributive Fairness (β_4)				5.209***	
				(7.47)	
Constant (β_0)	19.646***	19.646***	-0.105	20.194***	19.646***
	(10.00)	(9.91)	(-0.47)	(12.18)	(9.70)
# Observations	1,200	150	150	150	50
# Teams	50	50	50	50	50
F_{Model}	3.32**	3.26**	10.60***	17.01***	3.12**
R^2	0.0636	0.1274	0.1602	0.3742	0.1523
Simple Comparisons between Conditions: [2] *Formulaic Use & Self-Excluding Design* versus …					
[1] *Formulaic Use & Self-Including Design*	7.799***	7.799**	0.780***	3.74	7.799**
	(2.71)	(2.68)	(3.03)	(1.60)	(2.62)
[3] *Discretionary Use & Self-Including Design*	7.701**	7.701**	0.875***	3.14	7.701**
	(2.57)	(2.55)	(3.80)	(1.33)	(2.50)
[4] *Discretionary Use & Self-Excluding Design*	7.778**	7.778**	0.988***	2.58	7.778**
	(2.31)	(2.28)	(4.96)	(0.95)	(2.24)

This table shows the results of regressing *Effort* and *Distributive Fairness* on indicator variables for the *Design* and *Use* of the allocation proposals and their interaction term. *Design* takes a value of 0 for the self-including design and a value of 1 for the self-excluding design. *Use* takes a value of 0 for formulaic use (i.e., allocation by the team) and a value of 1 for discretionary use (i.e., allocation by the manager). Columns 1, 2 (a, b, c), and 3 differ in the level of analysis, as illustrated by the number of observations (see # Observations): (1) decision level (i.e., one observation per round and employee), (2) employee level (i.e., one observation per employee – averaged across all eight rounds), and (3) team level (i.e., one observation per team – averaged across all three employees and all eight rounds). The table also shows comparisons between condition [2], *Formulaic Use & Self-Excluding Design,* and condition [1], *Formulaic Use & Self-Including Design*, condition [3], *Discretionary Use & Self-Including Design*, condition [4], *Discretionary Use & Self-Excluding Design*, respectively.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a †, in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (reported in parentheses) are obtained using standard errors clustered within teams (see # Teams).

Table 4: Distortion (in Proposed Bonus)

Panel A: Distortion – Descriptive Results

	Self-Including Design			Self-Excluding Design		
Formulaic Use (Allocation by the Team)		<u>7.514</u>			<u>4.674</u>	
	(9.073) [n = 288]	(5.223) [n = 36]	(5.034) [n = 12]	(6.630) [n = 288]	(3.417) [n = 36]	(2.950) [n = 12]
Discretionary Use (Allocation by the Manager)		<u>9.147</u>			<u>6.013</u>	
	(9.363) [n = 312]	(5.342) [n = 39]	(4.992) [n = 13]	(6.914) [n = 312]	(3.184) [n = 39]	(2.660) [n = 13]

Panel B: Distortion – OLS Regression Results

	(1) *Distortion*	(2) *Distortion*	(3) *Distortion*
Design (β_1)	-2.840** †	-2.840** †	-2.840** †
	(-1.74)	(-1.73)	(-1.69)
Use (β_2)	1.634	1.634	1.634
	(0.84)	(0.83)	(0.81)
Design × *Use* (β_3)	-0.294	-0.294	-0.294
	(-0.13)	(-0.13)	(-0.13)
Constant (β_0)	7.514***	7.514***	7.514***
	(5.34)	(5.29)	(5.18)
# Observations	1,200	150	50
# Teams	50	50	50
F_{Model}	3.05**	2.99**	2.87***
R^2	0.0411	0.1290	0.1557
Simple Effects of …			
Design when *Use* = 1 ($\beta_1 + \beta_3$)	-3.135** †	-3.135** †	-3.135** †
	(-2.06)	(-2.04)	(-1.99)
Use when *Design* = 1 ($\beta_2 + \beta_3$)	1.339	1.339	1.339
	(1.22)	(1.22)	(1.19)

Panel A shows average *Distortion* in (average) proposed bonuses – per round and employee – under formulaic use (i.e., allocation by the team) and discretionary use (i.e., allocation by the manager) for both the self-including design and the self-excluding design. For each condition, standard deviations are shown in parentheses at three levels with the respective numbers of observations in brackets (left: decision level; middle: employee level; right: team level). Panel B shows the results of regressing *Distortion* on indicator variables for the *Design* and *Use* of the allocation proposals and their interaction term. *Design* takes a value of 0 for the self-including design and a value of 1 for the self-excluding design. *Use* takes a value of 0 for formulaic use (i.e., allocation by the team) and a value of 1 for discretionary use (i.e., allocation by the manager). Columns 1, 2 (a, b, c), and 3 differ in the level of analysis, as illustrated by the number of observations (see # Observations): (1) decision level, (2) employee level, and (3) team level. Panel B also shows simple effects of *Design* and *Use* when the other variable takes a value of 1.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a †, in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (reported in parentheses) are obtained using standard errors clustered within teams (see # Teams).

Table 5: Proposed Bonus – OLS Regression Results

Panel A: Proposed Bonus – Decision Level [n = 1,200]

	Formulaic Use		Discretionary Use		All Conditions	
	Self-Including	Self-Excluding	Self-Including	Self-Excluding		
	(1) *Proposed Bonus*	(2) *Proposed Bonus*	(3) *Proposed Bonus*	(4) *Proposed Bonus*	(5a) *Proposed Bonus*	(5b) *Proposed Bonus*
Effort (y_0)	1.066*** (10.62)	1.341*** (31.11)	1.001*** (11.96)	1.313*** (24.63)	1.066*** (10.97)	1.024*** (15.94)
Effort × *Design* (y_1)					0.275*** † (2.60)	0.315*** † (4.36)
Effort × *Use* (y_2)					-0.064 (-0.51)	
Effort × *Design* × *Use* (y_3)					0.037 (0.26)	
Design (α_1)					-4.159 (-1.62)	-5.615*** (-3.61)
Use (α_2)					1.315 (0.46)	
Design × *Use* (α_3)					-2.011 (-0.64)	
Constant (α_0)	8.531*** (3.47)	4.372*** (4.48)	9.846*** (6.21)	3.676*** (3.78)	8.531*** (3.59)	9.382*** (6.83)
# Observations	288	288	312	312	1,200	1,200
# Teams	12	12	13	13	50	50
F_{Model}	112.87***	967.83***	143.11***	606.63***	329.76***	624.44***
R^2	0.5356	0.7891	0.6316	0.8074	0.7269	0.7260

Panel B: Proposed Bonus – Employee Level [n = 150]

	Formulaic Use		Discretionary Use		All Conditions	
	Self-Including	Self-Excluding	Self-Including	Self-Excluding		
	(1) *Proposed Bonus*	(2) *Proposed Bonus*	(3) *Proposed Bonus*	(4) *Proposed Bonus*	(5a) *Proposed Bonus*	(5b) *Proposed Bonus*
Effort (y_0)	1.223*** (6.50)	1.479*** (54.79)	1.259*** (14.38)	1.490*** (19.26)	1.223*** (6.66)	1.244*** (13.68)
Effort × *Design* (y_1)					0.256*[†] (1.38)	0.245***[†] (2.44)
Effort × *Use* (y_2)					0.036 (0.18)	
Effort × *Design* × *Use* (y_3)					-0.025 (-0.11)	
Design (α_1)					-4.861 (-1.24)	-4.773** (-2.31)
Use (α_2)					-0.684 (-0.17)	
Design × *Use* (α_3)					0.295 (0.07)	
Constant (α_0)	5.440 (1.38)	0.579 (0.81)	4.756*** (3.14)	0.189 (0.13)	5.440 (1.41)	5.043*** (2.77)
# Observations	36	36	39	39	150	150
# Teams	12	12	13	13	50	50
F_{Model}	42.30***	3001.85***	206.83***	370.98***	8180.24***	549.73***
R^2	0.7151	0.9689	0.7895	0.9191	0.8819	0.8818

This table shows the results of regressing *Proposed Bonus* (i.e., the average of proposed bonuses for an employee) on *Effort*. Columns 1, 2, 3, and 4 display the results separately for each condition. Column 5 (a, b) illustrates the corresponding differences among conditions and, thus, includes indicator variables for the *Design* and *Use* of the allocation proposals and their interaction term. *Design* takes a value of 0 for the self-including design and a value of 1 for the self-excluding design. *Use* takes a value of 0 for formulaic use (i.e., allocation by the team) and a value of 1 for discretionary use (i.e., allocation by the manager). Panels A and B differ only in the level of analysis, as illustrated by the number of observations (see # Observations): (A) decision level and (B) employee level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a [†], in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (in parentheses) are obtained using standard errors clustered within teams (see # Teams).

Table 6: Unfairness (in Final Bonus)

Panel A: Unfairness – Descriptive Results

	Self-Including Design			Self-Excluding Design		
Formulaic Use (Allocation by the Team)		<u>7.514</u>			<u>4.674</u>	
	(9.073) [n = 288]	(5.223) [n = 36]	(5.034) [n = 12]	(6.630) [n = 288]	(3.417) [n = 36]	(2.950) [n = 12]
Discretionary Use (Allocation by the Manager)		<u>10.673</u>			<u>11.276</u>	
	(12.807) [n = 312]	(7.149) [n = 39]	(6.701) [n = 13]	(16.196) [n = 312]	(9.481) [n = 39]	(8.959) [n = 13]

Panel B: Unfairness & Distortion – Within-Comparison (Discretionary Use Only)

	(1) *Unfairness & Distortion*	(2) *Unfairness & Distortion*	(3) *Unfairness & Distortion*
Design (β_1)	-3.135** †	-3.135** †	-3.135** †
	(-2.04)	(-2.02)	(-1.98)
Within (β_2)	1.526	1.526	1.526
	(1.28)	(1.27)	(1.25)
Design × *Within* (β_3)	3.737** †	3.737* †	3.737* †
	(1.72)	(1.70)	(1.67)
Constant (β_0)	9.147***	9.147***	9.147***
	(6.73)	(6.68)	(6.68)
# Observations	1,248	156	52
# Teams	26	26	26
F_{Model}	7.01***	6.89***	6.62***
R^2	0.0288	0.0867	0.1028
Simple Effects of …			
Design when *Within* = 1 ($\beta_1 + \beta_3$)	0.603	0.603	0.603
	(0.20)	(0.20)	(0.20)
Within when *Design* = 1 ($\beta_2 + \beta_3$)	5.263***	5.263***	5.263***
	(2.88)	(2.86)	(2.80)

Panel A shows average *Unfairness* in final bonuses – per round and employee – under formulaic use (i.e., allocation by the team) and discretionary use (i.e., allocation by the manager) for both the self-including design and the self-excluding design. For each condition, standard deviations are shown in parentheses at all three levels with the respective numbers of observations in brackets (left: decision level; middle: employee level; right: team level). Panel B shows the results of regressing a variable (DV) capturing either *Unfairness* in final bonuses or *Distortion* in proposed bonuses on indicator variables for the *Design* of the allocation proposals, the *Within* comparison between *Unfairness* and *Distortion*, and their interaction term. *Design* takes a value of 0 for the self-including design and a value of 1 for the self-excluding design. Within takes a value of 0 when the DV captures *Distortion* and a value of 1 when the DV captures *Unfairness*. Columns 1, 2, and 3 differ in the level of analysis, as shown by the number of observations (see # Observations): (1) decision level, (2) employee level, and (3) team level. Panel B also shows simple effects of *Design* and *Within* when the other variable takes a value of 1.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a †, in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (reported in parentheses) are obtained using standard errors clustered within teams (see # Teams), accounting also for interdependence of observations regarding the *Within* comparison between *Unfairness* and *Distortion*.

Table 7: Final Bonus and Proposed Bonus – OLS Regression Results (Discretionary Use Only)

Panel A: Final Bonus and Proposed Bonus – Decision Level [n = 1,200]

	Self-Including	Self-Excluding	Self-Including	Self-Excluding	Within Comparison
	(1) *Final Bonus*	(2) *Final Bonus*	(3) *Proposed Bonus* [from Table 4]	(4) *Proposed Bonus* [from Table 4]	(5) *Final Bonus & Proposed Bonus*
Effort (y_0)	0.990*** (8.77)	1.025*** (9.86)	1.001*** (11.96)	1.313*** (24.63)	1.001*** (12.19)
Effort × *Design* (y_1)					0.312*** † (3.20)
Effort × *Within* (y_2)					-0.011 (-0.15)
Effort × *Design* × *Within* (y_3)					-0.277** † (-2.42)
Design (α_1)					-6.170*** (-3.38)
Within (α_2)					0.221 (0.15)
Design × *Within* (α_3)					5.445** (2.13)
Constant (α_0)	10.067*** (5.34)	9.342*** (3.72)	9.846*** (6.21)	3.676*** (3.78)	9.846*** (6.33)
# Observations	312	312	312	312	1,248
# Teams	13	13	13	13	26
F_{Model}	76.90***	97.28***	143.11***	606.63***	
R^2	0.4731	0.3630	0.6316	0.8074	0.5473

Panel B: Final Bonus and Proposed Bonus– Employee Level [n = 150]

	Self-Including	Self-Excluding	Self-Including	Self-Excluding	Within Comparison
	(1) *Final Bonus*	(2) *Final Bonus*	(3) *Proposed Bonus* [from Table 4]	(4) *Proposed Bonus* [from Table 4]	(5) *Final Bonus & Proposed Bonus*
Effort (y_0)	1.346*** (20.90)	1.316*** (16.52)	1.259*** (14.38)	1.490*** (19.26)	1.259*** (14.54)
Effort × *Design* (y_1)					0.231**† (2.00)
Effort × *Within* (y_2)					0.087* (1.73)
Effort × *Design* × *Within* (y_3)					-0.262**† (-2.40)
Design (α_1)					-4.567** (-2.16)
Within (α_2)					-1.718* (-1.77)
Design × *Within* (α_3)					5.158** (2.21)
Constant (α_0)	3.038** (2.71)	3.628* (2.16)	4.756*** (3.14)	0.189 (0.13)	4.756*** (3.17)
# Observations	39	39	39	39	156
# Teams	13	13	13	13	26
F_{Model}	436.75***	272.93***	206.83***	370.98***	
R^2	0.8981	0.7835	0.7895	0.9191	0.8505

This table shows, for discretionary use, the results of regressing *Final Bonus* (columns 1 and 2) and *Proposed Bonus* (columns 3 and 4) on *Effort*. Columns 1 and 3 display results for the self-including design, and columns 2 and 4 display results for the self-excluding design. Column 5 displays the corresponding differences among columns and, therefore, includes indicator variables for the *Design* and *Within* comparison. *Design* takes a value of 0 when proposals are self-including and a value of 1 when proposals are self-excluding. *Within* takes a value of 0 when the dependent variable captures the *Proposed Bonus* and a value of 1 when it captures the *Final Bonus*. Panels A and B differ in the level of analysis, as illustrated by the number of observations (see # Observations): (A) decision level and (B) employee level.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a †, in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (reported in parentheses) are obtained using standard errors clustered within teams (see # Teams), accounting also for interdependence of observations regarding the *Within* comparison.

Appendix A: Table A: Full Distortion (in Proposals)

Panel A: Full Distortion – Descriptive Results

	Self-Including Design			Self-Excluding Design		
Formulaic Use (Allocation by the Team)		42.625			14.489	
	(53.741) [n = 288]	(40.625) [n = 36]	(39.812) [n = 12]	(26.015) [n = 288]	(12.727) [n = 36]	(10.148) [n = 12]
Discretionary Use (Allocation by the Manager)		33.558			17.114	
	(40.186) [n = 312]	(27.605) [n = 39]	(19.692) [n = 13]	(27.403) [n = 312]	(13.995) [n = 39]	(10.788) [n = 13]

Panel B: Full Distortion – OLS Regression Results

	(1) *Distortion*	(2) *Distortion*	(3) *Distortion*
Design (β_1)	-28.136*** †	-28.136*** †	-28.136** †
	(-2.45)	(-2.43)	(-2.38)
Use (β_2)	-9.067	-9.067	-9.067
	(-0.74)	(-0.73)	(-0.71)
Design × *Use* (β_3)	11.693	11.693	11.693
	(0.90)	(0.89)	(0.87)
Constant (β_0)	42.625***	42.625***	42.625***
	(3.83)	(3.80)	(3.72)
# Observations	1,200	150	50
# Teams	50	50	50
F_{Model}	4.99***	4.90***	4.69***
R^2	0.0830	0.1652	0.2123
Simple Effects of …			
Design when *Use* = 1 (β_1 + β_3)	-16.443*** †	-16.443*** †	-16.443*** †
	(-2.72)	(-2.69)	(-2.64)
Use when *Design* = 1 (β_2 + β_3)	2.625	2.625	2.625
	(0.65)	(0.64)	(0.62)

Panel A shows average *Full Distortion* in employees' proposals – per round and employee – under formulaic use (i.e., allocation by the team) and discretionary use (i.e., allocation by the manager) for both the self-including design and the self-excluding design. For each condition, standard deviations are shown in parentheses at three levels with the respective numbers of observations in brackets (left: decision level; middle: employee level; right: team level). We capture *Full Distortion* – in employee i's proposal – as the sum of absolute deviations of the proposed bonuses from the non-distorted benchmarks. For the self-including design, the non-distorted benchmark ($k_{i,j}$) is the fair bonus (1.5 e_j): $k_{i,j}$ = 1.5 e_j, whereas for the self-excluding design, the non-distorted benchmark is derived as a proportional transformation of the fair bonus: $k_{i,j} = e_j / \sum_{j\neq i}(e_j)\ 1.5 \sum_j(e_j)$ for $\sum_{j\neq i}(e_j) \neq 0$ or $k_{i,j} = 1.5\ e_i / 2$ for $\sum_{j\neq i}(e_j) = 0$. Panel B shows the results of regressing *Full Distortion* on variables for the *Design* and *Use* of allocation proposals and their interaction term. *Design* takes a value of 0 for the self-including design and a value of 1 for the self-excluding design. *Use* takes a value of 0 for formulaic use (i.e., allocation by the team) and a value of 1 for discretionary use (i.e., allocation by the manager). Columns 1, 2 (a, b, c), and 3 differ in the level of analysis, as illustrated by the number of observations (see # Observations): (1) decision level, (2) employee level, and (3) team level. Panel B further shows the simple effects of *Design* and *Use* when the other variable takes a value of 1.

*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, referring to two-tailed tests, unless marked with a †, in which case they refer to one-tailed tests based on a directional prediction. All *t*-statistics (reported in parentheses) are obtained using standard errors clustered within teams (see # Teams).