Non-binding Goals in Teams: A Real Effort Coordination Experiment

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Abstract

Non-binding (wage-irrelevant) goals are easy to implement and ubiquitous in practice. These goals have been shown to improve individual performance, but it remains to be seen if such goals are effective in team production when there is production complementarity among workers. In this paper, we investigate the impact of non-binding goals, set by a manager, on a team of workers with "weak-link" production technology. Participants in our lab experiment act as either team workers or managers. A manager can set a non-binding goal for the team production, which is determined by the minimum (or weak-link) performance of its workers. Our experimental hypotheses are based on a model where goals act as references point for workers' intrinsic motivation to complete the task. Consistent with our model we find evidence that team production does increase when managers are able to set goals and that this effect is strongest when goals are challenging but attainable for weak-link workers. However, we also find evidence that many managers persistently assign goals that are too challenging for weak-link workers, resulting in suboptimal team production, lower profits and higher wasted performance (performance above the weak-link level). We discuss the implications of these results and conclude that even though goals are effective motivators in teams some managers have difficulty overcoming personal biases when setting goals.

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1. Introduction

Setting a goal that does not directly impact a worker's earnings is a ubiquitous motivational tool; a manager may have an informal celebration if an early deadline is met, send a congratulatory message when the project is completed, or keep a running tally of the number of days with no workplace accidents to encourage safety. Under standard utility theory, these goals, commonly called non-binding goals, should have no impact on output and, hence, managers should not use them to motivate workers. However, non-binding goals are seen everywhere in practice, and evidence from psychology (Deci 1971; Frey and Jegen 2001; Kamenica 2012) and managerial economics (Heath et al. 1999, Goerg and Kube 2012, Gómez-Miñambres 2012, Corgnet et al. 2015, 2018) show that non-binding goals can be very effective motivators. Typically, a non-binding goal can increase individual performance by 10% to 30% in human-subject experiments. Furthermore, non-binding goals are particularly attractive tools for managers, as these goals are costless to implement. There is limited research on the impact of goals in teams, especially in more complex production settings, though evidence from operations management (Doerr et al. 1996, Linderman et. al 2006) suggest that binding and non-binding goals can improve output for pull production and Six Sigma teams. Still, it is unclear whether non-binding goals will be effective in production settings with complementarities, where team production depends on all workers exerting effort. For example, in project management, all team members must meet the deadline to avoid late delivery. In software development, large software suites are coded in pieces, and all developers must ensure their portion of the code is bug-free before shipping the final product. In these settings, managers may only be able to set one goal for the whole team, due to fairness concerns or unobservability of individual worker performance. When the goal is not individualized for each worker, and the team production technology depends on all workers, it is unclear whether non-binding goals are still effective.

Therefore, we look to answer the following questions: (1) can non-binding goals increase production in teams? And if so, (2) what goal should managers set to maximize production? In this paper, we show that non-binding goals are powerful enough to motivate a team of workers to increase production, even when significant production complementarities exist. However, managers often set suboptimal goals for teams. We define a production setting where teams, consisting of one manager and three workers, must coordinate to increase team production; team production and monetary payoffs for everyone are determined by the minimum performance of all workers (i.e., the weak-link). To capture the effect of non-monetary incentives on the team, we allow managers to assign a non-binding goal for team production. We use the weak-link production technology as a strong test for non-binding goals; if non-binding goals are effective in a team setting with the highest degree of complementarity, these goals should be even more effective for teams with less complementarity, where team production also depend on worker performance above the minimum.

Our research is motivated by extensive evidence of team coordination failure in weak-link production settings, with individual effort rapidly falling to the minimum level (see Camerer 2003, Devetag and Ortmann 2007 for review). In particular, we contribute to the literature by studying how non-binding, seemingly payoff-irrelevant, goals affect team production with weak-link technology. From a theoretical standpoint, we modify the standard weak-link coordination game (Van Huyck et al. 1990) by assuming that workers have two sources of motivation: a standard monetary motivation that depends on the team production and a non-monetary motivation that depends on whether the individual's performance is above or below the goal. As a result, a worker's utility not only depends on the standard monetary payoffs and cost of effort but also on whether he achieved the goal or not. In other words, even if producing more than the weak-link does not entail monetary rewards, it does provide non-monetary satisfaction for those workers whose individual performance is above the goal. We show that when non-binding goals are present, the solution of the game is characterized by two types of workers: a group of low ability workers who match what the weak-link worker does; and a group of high ability workers who choose to produce above the weak-link level to garner the intrinsic utility associated with goal attainment. Importantly, we also show that in order to maximize team production, a manager must set a goal that it is challenging but attainable for the weak-link worker and that the optimal goal minimizes high ability workers' wasted performance (performance above the weak-link level), minimizing the spread of performance among team members.

To our knowledge, we are the first paper to theoretically and experimentally examine the impact of non-binding goals on team production with weak-link complementarity. We design a weak-link coordination game using a real effort laboratory experiment, and we allow managers to set a non-binding goal for team production. We chose to use a laboratory experiment so that we can make causal inferences about the efficacy of non-binding goals, as well as measure and control for heterogeneity in worker ability. Consistent with our predictions, we find that when managers are able to set goals for the team, team production increases by 19.8% on average and, as our model predicts, the positive effect of goal setting is especially strong when goals are challenging but attainable for the weak-link worker, whose performance determines team production. However, we also find that managers do not always set profit-maximizing goals for the team, indicating that managers may be setting goals for other reasons. In particular, we find evidence that managers often disregard the weak-link worker's ability, which leads some managers to assign unreasonably difficult goals for the weak-link worker. Finally, consistent with our theoretical results we provide evidence that managers who assign unreasonable goals for the weak link do not only generate lower team production but also higher wasted performance; this is, in part, because goals that are too difficult for the weak-link are more motivational for higher ability workers.

1.1. Connection to the Literature

Our research sits at the intersection of the goal-setting and the coordination in teams literature, which are well-studied topics in psychology, managerial economics, and recently in operations management. In this section, we highlight the streams of literatures most relevant to our paper and detail our contributions. In the goal-setting literature, the motivational effect of wage-irrelevant goals has been studied at length in psychology (Locke and Latham 2002 for review). Psychologists have focused on the motivational and cognitive aspects of goals stressing that goals should be S.M.A.R.T. (Specific, Measurable, Attainable, Relevant and Time-based). More recently, non-binding goals have been studied in managerial economics and proven to be effective motivators for individual workers (Heath et al. 1999; Goerg and Kube 2012; Gómez-Miñambres 2012; Smithers 2015; Corgnet et al. 2015; Corgnet et al. 2018). Rather than relying upon the monetary consequences of their actions, the goals considered in this literature appeal to the intrinsic motivation of workers (Deci 1971, Frey and Jegen 2001, Kamenica 2012). While a growing number of papers in economics and management have documented the effectiveness of various forms of non-monetary incentives on individual workers, including performance goals (Wu et al., 2008; Goerg and Kube, 2012; Gómez-Miñambres, 2012; Corgnet et al., 2015; Corgnet et al., 2018), personal goals in self-control setting (Ainslie, 1992; Hsiaw, 2013), status incentives (Charness et al., 2014), symbolic rewards (Kosfeld and Neckermann, 2011), delegation (Fehr et al., 2013), autonomy (Falk and Kosfeld, 2006) or trust (Dickinson and Villeval, 2008), little is known about the effectiveness of non-monetary incentives in teams. Contrary to the existing literature on goal setting, we focus on a team environment where the success or failure of a project relies on the performance of the weakest link. This is similar to an assembly line context that Doerr et al. (1996) studies, analyzing the impact of binding goals under push vs. pull production policies. The authors find that these incentives have a positive impact on output under pull production. Our results show that non-binding goals also have a positive effect on team production. However, the goals that we consider are non-binding and hence cheaper and easier to implement in practice.

Our research is also motivated by extensive evidence of team coordination failure in weak-link games, with effort rapidly falling to the minimum level (see Camerer 2003, Devetag and Ortmann 2007 for review). The study of weak-link (or minimum-effort) games is common in the economics and operations literature (Van Huyck et al. 1990, Weber 2006, Brandts et al. 2011, Hyndman et al. 2014, Shokoohyar et al. 2017), as these games apply to many different production environments. Almost all of these studies are “abstract effort” experiments in the sense that they use the concept of induced valuation to create individual cost of effort (Smith 1976); if a subject selects effort level x then they pay a certain amount $c(x)$ in experimental earnings. Furthermore, most of these experiments also induce symmetric costs of effort across the experimental subjects.[1] These studies find that with large groups (three or more subjects) coordination outcomes often converge to the least-efficient equilibrium (see Van Huyck et al. 1990, Knez and Camerer 1994, Brandts et al. 2011). External influences, such as pre-game communication or intergroup competition, can induce better outcomes (Van Huyck et al. 1990, Cooper et al. 1992, Bornstein et al. 2002).

Coordination is growing topic of research in operations management as well, as coordination failure can arise in team production environments such as supplier capacity allocation and project management. For example, Gerchak & Wang (2004) model how a set of suppliers coordinate when choosing production quantities to support assembly operations for a common customer. Argyres (1999) discusses the difficulty of coordination for the four suppliers of the B-2 Bomber program and the challenges to on-time delivery from a project management perspective. Experimentally, studies have examined coordination outcomes in two-player newsvendor games (Hyndman et al. 2014), project management games where effort accumulates over stages (Shokoohyar et al. 2017), and group selection games where subjects decide whether to pay a membership fee (Fan et al. 2016). Again, these studies focus on abstract effort, which may not capture important psychological effects from the act of working (such as intrinsic motivation) that can affect coordination outcomes.

Real effort tasks (such as adding rows of numbers or counting coins) may more closely match actual team production, where the cost of effort is not symmetric among team members, and they have the added challenges that players' cost functions and the “optimal” coordination level are not directly observable. There are only a few real effort coordination experiments in the literature. Bortolotti et al.’s (2009) coordination experiment consists of assigning subjects to teams and having them sort and count coins worth 1, 2, 5, and 10 Euro cents within a time limit. The objective is to minimize the number of counting errors. As in our experiment, the task is individual but the payoff to a team is the minimum of all team members. The authors find that subjects eventually coordinate at the efficient level of 0 errors from all members. The second real effort coordination experiment was conducted by Vranceanu et al. (2013). The authors use the task of counting 7s in a block of random numbers - correctly reporting the number of 7s in a block generates one unit of output. Subjects are paired and individual profit is a function of the minimum output as well as individual breaks taken, thought of as the opportunity cost of working.

[1] Brandts et al. (2007) experimentally study the effect of leadership on workers with asymmetric costs in an abstract effort coordination game. Without leadership, the authors find that asymmetric costs exacerbate coordination failure.

Higher-performing individuals can also punish their lower-performing counterpart. The study finds that team performance is not lower than individual performance, suggesting high levels of cooperation in pairs, and that the ability to sanction does not significantly improve team production.

The real effort activity in our experiment consists of a simple yet tedious slider task activity, first used by Gill and Prowse (2012) where individual effort is highly correlated with individual performance. Instead of relying on peer pressure or exogenously given goals, we consider the effect of non-binding goals set by managers whose payoff depends on the team production. Thus, we contribute to the literature by introducing non-binding goals as a potential mechanism to improve coordination for a group of workers facing high levels of strategic complementarity. Our findings indicate that (1) non-binding goals can meaningfully improve team production, though the level of the goal is important, and (2) real effort coordination outcomes can significantly differ from abstract effort coordination outcomes.[2]

The paper proceeds as follows. In §2 we introduce our theoretical framework, and we model the potential impact of goals on worker performance and team production. §3 describes the experimental environment, procedures and hypotheses. Main results are presented in §4, and §5 concludes.

2. Model

In this section, we develop a model of a weak-link coordination game where workers have asymmetric cost functions and intrinsic motivation. We use our model to establish our experiment hypotheses.

2.1. Setup

In our model, one manager is in charge of a team of *n* workers who must complete the project at hand. The effort of worker i is given by $y_i \in \mathbb{R}_+$ and we denote by $\mathbf{y} = [y_1, \ldots, y_n]$ to be the vector of possible effort levels. We assume that a worker's performance in the project only depends on his exerted effort. Therefore, we use the terms effort and performance interchangeably in this paper.[3] We assume workers have different increasing, twice differentiable and strictly convex cost of effort functions, $c(y; \theta_i)$. We interpret parameter θ_i as worker's *i* ability level, with $\theta_i \in [\underline{\theta}, \overline{\theta}]$. Without loss of generality we assume

[2] Using a voluntary contribution mechanisms design, Dutcher et al. (2015) find that abstract and real effort lead to identical contributions to a group account. This indicate that results of experiments that use an abstract cost of contributions to a public good might be as field relevant as real-effort experiments. However, as the authors indicate, these results might not generalize to different settings. Our results are in line with previous finding in the weak-link literature where real-effort seems to motivate workers more than abstract effort does. We propose in our theoretical framework one possible reason for this: when effort is real, workers might derive a non-monetary satisfaction from undertaking the task itself.

[3] Our results will not be significantly different if we consider a model with variability of performance given the effort, discussed in the online appendix.

that $\theta_1 \leq \theta_2 \leq \cdots \leq \theta_n$, so that θ_1 is the ability of the weak-link worker. We abstract away from moral hazard concerns by assuming that ability is common knowledge to manager and workers. We further assume that $c(0; \theta_i) = 0$ for all θ_i, and that

$$c_y(y; \theta_n) \leq c_y(y; \theta_{n-1}) \leq \cdots \leq c_y(y; \theta_1),$$

where $c_y(y; \theta_i)$ is the partial derivative of $c(y; \theta_i)$ with respect to y.

Team production $M(\mathbf{y})$ is determined by the lowest performance of all workers so that $M(\mathbf{y}) = \min(y_1, \ldots, y_n)$. For simplicity, we assume that all n workers as well as the manager receive identical monetary payoffs based on $M(\boldsymbol{y})$, so that the monetary payoffs are given by $A \cdot M(\mathbf{y})$, where $A > 0$ reflects the profitability of the team production and it hence determines the magnitude of the monetary team incentives. Workers may also be motivated by non-binding goals assigned by the manager. We formalize this effect by considering a goal-dependent, non-monetary value function $v(y_i - g)$, which satisfies the following prospect theoretic properties (Kahneman and Tversky 1979):

(i) $v(0) = 0$ (*goal as reference point*);

(ii) $v'(\cdot) > 0$ (*increasing in production given a goal*);

(iii) For all $x > 0$, $-v(-x) = \lambda v(x)$ where $\lambda > 1$ (*goal-induced loss aversion*);

(iv) $v''(x) > 0$ for all $x < 0$ (*convexity for goal-induced losses*), and;

(v) $v''(x) < 0$ for all $x > 0$ (*concavity for goal-induced gains*).

where $v'(\cdot)$ and $v''(\cdot)$ denote the first and second derivative of $v(\cdot)$ respectively. Our non-monetary utility function is motivated by experimental and field evidence showing that wage-irrelevant goals serve as reference points in a manner which is consistent with prospect theory (Heath et al. 1999). Properties (iv) and (v) capture a prospect theory principle commonly known as "diminishing sensitivity", the idea that outcomes have a smaller marginal impact when they are more distant from the reference point. Diminishing sensitivity not only gives the value function its characteristic S-shape but it has also been found to be the core explanation of the motivational effect of goals as reference points (Wu et al. 2008). Property (iii) captures loss aversion the property whereby losses loom larger than gains.[4] Similar specifications have also been considered by other authors in economics and management literatures (Dalton et al. 2016; Corgnet et al. 2015; Corgnet et al. 2018).

Overall, a worker's payoff, π_i^w, is the sum of his monetary gains and non-monetary utility minus the cost of effort:

[4] In particular, we follow a simple and tractable specification of loss aversion known as "constant loss aversion" introduced by Tversky and Kahneman (1991).

$$\pi_i^w(y_i, y_{-i}, g, A; \theta_i) = A \cdot M(\mathbf{y}) + v(y_i - g) - c(y_i; \theta_i)$$

Note that we assume that a worker's non-monetary utility function, $v(y_i - g)$, is determined by his individual performance relative to the goal.[5] Therefore, while a worker's monetary payoff only depends on the team production (as in the standard weak-link game), the worker gets an additional non-monetary payoff when his performance meets or exceeds the goal. The last effect represents the satisfaction that a worker gets from his individual performance regardless of team production, in other words, from doing his part of the project.

Finally, we assume the manager's payoff, π^m, only depends on the production of the team project:

$$\pi^m(\mathrm{A}, \mathbf{y}) = A \cdot M(\mathbf{y})$$

Thus, the manager incurs no cost of effort, as she does not participate in production, and her only objective is to maximize the team production by choosing a non-binding goal g that maximizes her monetary payoffs.[6]

We first examine the standard case with no goal-dependent utility. Then, we show effects of including a non-monetary, goal-dependent utility function.

2.2. Coordination Game with only Monetary Payoffs

In the one-stage, asymmetric cost coordination game with only monetary motivation, a worker's payoff function is given by:

$$\pi_i^w(\mathrm{A}, \mathbf{y}, y_i) = A \cdot M(\mathbf{y}) - c(y_i; \theta_i)$$

Worker i's first-order condition is given by:

$$c_y(y_i; \theta_i) = \begin{cases} 0 & \text{if } \; y_i \neq M(\mathbf{y}), \\ A & \text{if } \; y_i = M(\mathbf{y}). \end{cases}$$

[5] In an online appendix, we explore the case when $v(.)$ depends on the difference between team production and the goal. We show that, in this case, the results are equivalent to the case in which only monetary incentives are present.

[6] Note that the manager cannot change monetary team incentives –A- which we assume to be exogenously given. From a methodological point of view, this assumption allows us to focus exclusively on the effect of non-binding goals in teams, our main research goal. Moreover, our framework captures real-world organizations where middle and middle-up managers are not in charge of setting explicit monetary incentives or have a claim on net profits, but they can assign "informal", "non-binding," incentives such as goal setting.

Thus, at the profit-maximizing performance level the marginal cost of producing y_i is equal to the marginal benefit. However, the marginal benefit depends on the team production. When worker i's performance is above the minimum, there is no benefit to choose a higher performance since team production is determined by the minimum performance in the team. This insight helps build the intuition for Proposition 1. All proofs are relegated to the Appendix.

Proposition 1. A vector of effort levels $\boldsymbol{y}^*$ is a pure strategy Nash equilibrium to this game if and only if $y_i^* = y$ for all i, where $y \in [0, \tilde{y}]$, and $\tilde{y}$ is the solution to $c_y(\tilde{y}; \theta_1) = A$.

Proposition 1 indicates that in equilibrium workers' performance is determined by the worker with the lowest ability (or weak-link worker). While $\tilde{y}$ puts an upper bound on best-response choices of y_i^*, any team production level such that $y_i^* \leq \tilde{y}$ can be an equilibrium. [7]

2.3. Coordination Game with a Goal-Dependent Non-Monetary Utility

We now study the effects of non-monetary utility. In particular, we assume that the worker's payoff function is given by the combination of monetary and non-monetary utilities as well as the cost of effort:

$$\pi_i^w(\mathrm{A}, \mathbf{y}, y_i, g) = A \cdot M(\mathbf{y}) + v(y_i - g) - c(y_i; \theta_i)$$

As a reminder, team production $M(\mathbf{y})$ is determined by the lowest performance of all team members so that $M(\mathbf{y}) = \min(y_1, \dots, y_n)$. A worker's payoff maximization problem changes so that the first-order conditions are characterized by:

$$c_y(y_i; \theta_i) = \begin{cases} v'(y_i - g) & \text{if } \; y_i \neq M(\mathbf{y}), \\ A + v'(y_i - g) & \text{if } \; y_i = M(\mathbf{y}). \end{cases}$$

The left-hand side of this equation represents the marginal cost and the right-hand represents the marginal utility of effort, which again depends on team production. Let us define the following variables:

$$\underline{y}(\theta_i, g) = \{y \colon v'(y - g) = c_y(y; \theta_i)\}$$
$$\overline{y}(\theta_i, g) = \{y \colon A + v'(y - g) = c_y(y; \theta_i)\}.$$

Note that $\underline{y}(\theta_i, g)$ and $\overline{y}(\theta_i, g)$ are the effort levels that solve a worker's maximization problem when he is not the weak-link worker and when he is, respectively. In the proposition below we show that,

[7] Our results would not be qualitatively different if we consider a model with uncertainty in production. This is because "moral hazard in teams" (Holmstrom 1982) is not an issue in our environment. The inefficient outcomes of the weak link game that we describe in Proposition 1 are not due to free-riding because a worker's low effort does not affect anyone's payoffs unless he is the weak-link, in which case it affects him just as much as the rest of the team. Therefore, a free rider might cause the whole project to collapse and this motivates everyone to choose the same effort regardless of production uncertainty.

in equilibrium, two groups of workers are formed: *low-ability workers* who choose the same effort level as the weak-link worker and *high-ability workers* whose goal-dependent marginal utility is high enough for them to choose an effort level above the minimum.

Proposition 2. Let us define $L(\theta_1, g) = \left\{i \in N | \underline{y}(\theta_i, g) \leq \bar{y}(\theta_1, g)\right\}$. A vector of effort levels $\boldsymbol{y}^*$ is a pure strategy Nash equilibrium if for all $i \in L(\theta_1, g)$, $y_i^* = y$ and $\underline{y}(\theta_1, g) \leq y \leq \bar{y}(\theta_1, g)$. For all $i \notin L(\theta_1, g)$, $y_i^* = \underline{y}(\theta_i, g)$.

Proposition 2 indicates that, given a goal, there are potentially two groups of workers in equilibrium. The first group consists of low ability workers who choose the same effort level as the weak-link worker, similar to the case with only monetary incentives in Proposition 1. This is because low-ability workers have a marginal cost of effort that is high relative to the marginal non-monetary utility and hence, in equilibrium, their strategies are affected by the team incentives, A. Within this group, the set of best-response effort choices for all workers is determined by the ability of the weak-link worker, just as in the case with only monetary payoffs (Proposition 1). The second group consists of workers with a sufficiently high ability level who choose a level of effort that maximizes non-monetary utility minus the cost of effort and hence is independent of the team incentives. For high-ability workers, the marginal cost of effort relative to the marginal goal-dependent non-monetary utility is low enough for the workers to be motivated simply by the non-monetary incentives derived from goal attainment. In this case, workers' strategies are independent of other workers' decisions and hence different from the case with solely monetary incentives. Therefore, one consequence of our model is that when workers derive a non-monetary utility from their own individual performance, effort levels are actually less coordinated, as high ability workers perform above team production in equilibrium.

To better understand the intuition behind this result let us consider a simple example with $n = 3$. If a worker is producing above the minimum, $i \notin L(\theta_1, g)$, his optimal level of effort would be given by:

$$y_i^* = \underline{y}(\theta_i, g) = \left\{y: v'(y - g) = c_y(y; \theta_i)\right\}$$

On the other hand, the effort of a worker producing at the minimum, $i \in L(\bar{y}, g)$, is given by:

$$y_i^* = \bar{y}(\theta_i, g) = \left\{y: A + v'(y - g) = c_y(y; \theta_i)\right\}$$

It is clear that the lowest ability worker will always be in the low ability group, i.e., $1 \in L(\theta_1, g)$. There may be, however, more workers in this group. Depending on model parameters and y^* we have three cases:

1. If $\underline{y}(\theta_2, g) > \bar{y}(\theta_1, g)$ worker θ_2 would work more than the minimum in equilibrium since his effort without monetary motivation is already above the effort exerted by θ_1. This must also be

true for θ_3 because $\underline{y}(\theta_3, g) > \underline{y}(\theta_2, g)$. Therefore, in equilibrium $L(\theta_1, g) = \{1\}$ and hence $y_1^* < y_2^* < y_3^*$.

2. If $\underline{y}(\theta_2, g) \leq \overline{y}(\theta_1, g) < \underline{y}(\theta_3, g)$ worker θ_2 optimal effort when he is above the minimum would be lower than y_1^*, which means that in equilibrium we must have $y_1^* = y_2^*$. Otherwise worker θ_2 can increase his payoff by decreasing effort. Therefore, in equilibrium $L(\theta_1, g) = \{1,2\}$ and hence $y_1^* = y_2^* < y_3^*$.

3. Finally, if $\underline{y}(\theta_3, g) \leq \overline{y}(\theta_1, g)$ every worker produces the same in equilibrium, $L(\theta_1, g) = \{1,2,3\}$ and hence $y_1^* = y_2^* = y_3^*$. This case is equivalent to the standard case with only monetary motivation.

We now look at the manager's problem and analyze how she should set the team goal to maximize team production. In order to do so, we require an equilibrium refinement criterion. This is due to the possible multiplicity of equilibria in the low-ability group. Therefore, we make the assumption that when workers in the low-ability group face multiple equilibria in the weak-link game, they choose an effort level corresponding with the payoff-dominant equilibrium; $y_i^* = \overline{y}(\theta_1, g)$ for all $i \in L(\theta_1, g)$. This effort level corresponds to the highest effort the weak-link worker would willingly exert. The payoff dominance equilibrium refinement implies a unique pure strategy Nash equilibrium, where

$$y_i^* = \begin{cases} \overline{y}(\theta_1, g) & if \quad i \in L(\theta_1, g) \\ \underline{y}(\theta_i, g) & if \quad i \notin L(\theta_1, g) \end{cases}$$

We note that determining whether the payoff dominance equilibrium refinement is a reasonable assumption becomes an empirical question. Classic weak-link coordination experiments with abstract effort rarely observe the payoff-dominant equilibrium (Van Huyck et al. 1990, Knez and Camerer 1994, Brandts et al. 2011). In fact, most of these experiments observe outcomes tending towards the least efficient equilibrium. However, recent coordination experiments (Bortolotti et al. 2009, Vranceanu et al. 2013) using real effort find the opposite; subjects' individual performance and coordination outcomes increase over time and approach the payoff dominant equilibrium when one exists. As we show below, our results corroborate the findings from previous real effort coordination experiments, and we argue that the assumption of payoff dominance is reasonable in our setting. The intuition for Proposition 3 below would be qualitatively similar under other equilibrium refinement assumptions such as the risk-dominance in the low-ability group, where all workers choose $\underline{y}(\theta_1, g)$, which corresponds with the least efficient equilibrium.

In the next proposition we summarize important results on how the manager should set her goal. These results will help us build hypotheses for our experiment.

Proposition 3. For the payoff dominant equilibrium,

(i) $\frac{dy_i^*}{dg} > 0\ (< 0)$ if and only if $y_i^* > g\ (< g)$,

(ii) The optimal goal set by the manager is given by $g^* = \underset{g}{\operatorname{argmax}}\, \overline{y}(\theta_1, g)$, with $g^* < y_1^*$.

Proposition 3.i states that a worker's performance increases with the goal if his performance exceeds the goal (the goal is "attainable") while the opposite is true if worker's performance does not exceed the goal (the goal is "unattainable"). Therefore, increasing a goal that is too easy for a worker will be motivating, while increasing a goal that is too difficult for a worker will have a demotivating effect. Because the manager is only concerned about monetary payoffs from team production, which is unaffected by workers' performance above the minimum, a profit-maximizing manager focuses on maximizing the performance of the weak-link worker and hence will assign the maximum goal that he is willing and able to attain (Proposition 3.ii). Since this goal is met by the weak-link worker it will also be attainable by higher ability workers whose production is at or above $y_1^* = \overline{y}(\theta_1, g^*)$. Thus, in equilibrium, all workers of the team will attain the goal assigned by the manager.

We finish our theory section by discussing another implication of goals as reference points suggested by Heath et al. (1999), namely that difficult but attainable goals lead performance to "pile up" around the goal. Piling-up follows directly from loss aversion (property iii of the value function): loss aversion implies that a worker is substantially more motivated when just short of a goal than further away from meeting the goal. In our environment, piling-up indicates that the weak-link worker is just motivated enough to meet g^* but if the goal would be any higher then weak link's performance will decrease substantially.[8] Note that this also implies that higher and lower goals than g^* would yield a higher variation in performance. Thus, the optimal goal would have the lowest spread of work performance. In the next proposition, we show that wasted performance (performance above the weak-link level) is minimized at the optimal goal

Proposition 4. Let us define $\Delta_i(g) = \underline{y}(\theta_i, g) - \overline{y}(\theta_1, g)$ for $i \notin L(\theta_1, g)$; then $\Delta_i(g^*) < \Delta_i(g)$ for all $g \neq g^*$.

[8] The size of this reduction is positively related to the loss aversion parameter λ. Thus, the more loss averse the worker is, the higher the difference in performance between attainable and unattainable goals will be.

Proposition 4 is a direct implication of piling-up. Goals that are higher than g^* may boost high ability workers' performance but decrease the weak-link worker's performance, generating not only a lower team production but also higher wasted performance. Similarly, goals that are lower than g^* would decrease the performance of all workers in the team, but due to piling-up, the decrease in the weak-link worker's performance will be more pronounced, leading again to lower team production and higher wasted performance.

To sum up, the optimal goal does not only maximize team production (Proposition 3) but also generates the lowest variation in performance among team members, minimizing wasted work performance (Proposition 4).

3. Experimental design

We design our experiment to measure the impact of non-binding goals on team outcomes. In Section 3.1, we discuss the real effort task in the experiment, commonly called the slider task. In Section 3.2, we detail the experimental design and timeline.

3.1. Real effort task-slider task

We employ the slider task introduced by Gill and Prowse (2012). The authors describe the task as consisting "of a single screen displaying a number of sliders [...] When the screen containing the effort task is first displayed to the subject all of the sliders are positioned at 0 [...] By using the mouse, the subject can position each slider at any integer location between 0 and 100 inclusive. Each slider can be adjusted and readjusted an unlimited number of times, and the current position of each slider is displayed to the right of the slider. The subject's "points score" in the task is the number of sliders positioned at 50 at the end of the allotted time" (p. 472). We chose this real effort task for our experiment due to a number of desirable features, which are also noted in Gill and Prowse (2012). The task is easy to understand, requires no previous knowledge to complete, and is tedious to complete. Therefore, performance in the task is highly correlated with effort exerted.

3.2. Experimental procedure

Subjects act as managers or workers on a team to complete the task at hand. Our experiment consist on two basic treatments, referred to as the *baseline* and the *goal* treatment. Treatments last for 13 rounds; in each round, subjects have two minutes to complete as many slider tasks as possible. In all treatments, subjects first attempt the real effort task for three individual rounds to become familiar with the task and establish a standard of ability. In these individual rounds, workers' payoffs are piece rate and determined by their individual performance. We use these initial rounds to compute subjects' ability levels.

In the *baseline* and *goal* treatments, players are randomly assigned to groups of four (one manager and three workers) and participate in the real effort weak-link coordination game. In each team round, workers complete the slider task for 2 minutes, after which the team production, the minimum performance among workers, is revealed to the group. Before the team rounds begin, the performance of each worker in the third individual round is revealed to the team. The manager has the option to complete the task as well, but his or her performance has no impact on team production, and it is never revealed to the workers. We allow managers to complete the task in case they want to remind themselves of how difficult the task may be. This is important because managers need information about the task difficulty in order to assign realistic goals. The payoff of all group members is determined by the minimum performance in each group. Therefore, every round, all subjects' monetary payoffs are identical within each group.

The only difference between the baseline and the goal-setting treatment is that managers can assign a non-binding goal for team production in the *goal* treatment, while no such an option is available in the *baseline*. The groups in the *baseline* treatment still have a manager, though managers do not set goals for the team. Managers are subjects recruited from workers in a previous session where they get experience with the slider task.

We conducted all experimental sessions at between January 2015 and October 2017. We ran 24 sessions of the *baseline* treatment, and 24 sessions of the *goal* treatment, though 2 sessions of the *goal* treatment had to be dropped due to network connectivity issues. Therefore, we have 24 teams in the *baseline* treatment and 22 teams in the *goal* treatment, with a total of 184 subjects in our experiment. Our subject pool consisted of undergraduate students recruited through the automated online recruitment system. The experiment lasted for one hour, and subjects earned on average $14.78 in the *baseline* treatment and $16.41 in the *goal* treatment.

3.3. Theoretical predictions

According to the theoretical analysis presented in Section 2 we have two different predictions for the individual effort depending on whether workers have a non-monetary utility. If workers do not have a non-monetary utility, the outcome of the coordination game would be consistent with Proposition 1, where effort is symmetric across all n workers in equilibrium and the weak-link worker (θ_1) sets the upper bound of equilibrium team production.

Hypothesis 1.A. *If workers only care about monetary payoffs, all workers' performance converge to a level that is a best response for the weak-link worker in both treatments.*

Under the assumption that workers do not have a non-monetary utility to complete the task, workers are only motivated by monetary incentives. Therefore, workers will not have incentives to perform above what is a best-response for the weak-link worker, as shown in Proposition 1. However, if workers derive a non-monetary utility from their individual performance that is independent of the team incentives, the prediction in both treatments could be given by the equilibria characterized in Proposition 2. When assigned goals are not present (in the *baseline*) the reference point is unobserved and idiosyncratic to each worker. Even though, in both treatments, workers may derive a non-monetary utility from their own performance regardless of team incentives, the extensive goal setting literature (see Locke and Latham (2002) for review) indicates that assigned goals foster workers' motivation relative to a situation with no goals. Therefore, we can set the following hypothesis.

Hypothesis 1.B. *If workers derive a non-monetary utility from their own performance,*

- *i.* *Average workers performance should be higher than team production in both treatments.*
- *ii.* *Average workers performance and team production should be higher in the goal treatment than in the baseline*

It also follows from our theory (Proposition 3.i) that the goal that maximizes a worker's performance is the maximum goal that he is willing and able to achieve; consequently, profit-maximizing managers should assigning goals that are challenging but achievable for the weak-link worker, since the weak link's performance determines team production and hence monetary payoffs (Proposition 3.ii).

Hypothesis 2. *In the goal-setting treatment we expect that,*

- *i.* *Goals that are challenging but achievable maximize workers' performance.*
- *ii.* *Managers set goals that are challenging but achievable for the weak link worker.*

Finally, Proposition 4 indicates that the optimal goal minimizes wasted performance, the difference between worker's performance and team production.

Hypothesis 3. In the goal-setting treatment, we expect that goals that are challenging but achievable for the weak-link worker minimize wasted performance in the team.

4. Results

We start the results section in §4.1 by looking at team production and individual workers performance in the *baseline* and *goal* treatments. We then proceed to look at goals set by the manager in §4.2 and study the effect of setting reasonably accurate goals for the weak-link worker, who determines team production. In §4.3 we study the selection of team goals by managers in more detail. Finally, in §4.4 we analyze the effect of goal setting on the dispersion of performance among team members and wasted performance.

In the analysis of the results, we use workers' third round performance (last round of the individual production phase) as a measure of ability, which we call "task ability". Average task ability for all workers is 13.97 in the *baseline* and 13.12 in the *goal* treatment; while average task ability is slightly higher in the baseline treatment, this difference is not statistically significant (t = 1.51, p-value = 0.134). We define "weak-link ability" as the lowest ability in each group in round three.[9]

4.1. Goal Setting, Team Production and Worker Performance

We begin by examining worker performance and team production in the *baseline* and *goal* treatments. Table 1 provides a summary of average worker performance and team production in the team rounds for both treatments, as well as the difference between treatments.

Table 1: Average worker performance and team production in team rounds

	Worker Performance	Team Production
Baseline	12.48	10.47
Goal Treatment	14.1	12.55
Difference (Goal – Baseline)	1.62	2.08
Difference %	13.0%	19.8%

Average worker performance is consistently above the weak-link worker's performance in both treatments. The average effort of all workers in each group relative to team production is 112.4% in the *goal* setting treatment and 119.2% in the *baseline*. This suggests that workers may derive intrinsic utility from the act of working, in line with our Hypothesis 1.B.i. Of course, there are alternative explanations for this result. For example, workers might work rather than do nothing due to lack of alternatives, a common problem in lab experiments known as the "active participation hypothesis." Another possibility is that the desire not to be the weak-link worker drives up individual performance. These alternative explanations, however, do not explain why all workers perform better when assigned goals are present, which is a result consistent with our Hypothesis 1.B.ii. When managers set goals for the team, team production is on average 19.8% higher compared to the baseline treatment. This difference is statistically significant under both the Wilcoxon rank-sum (p-value < 0.01, z = -3.56) and Kolmogorov-Smirnov (p-value < 0.01) tests.

[9] Our results are qualitatively similar and statistically significant using several different measures for worker ability. These include round two performance, and average or median of early rounds' performance.

In Figure 1 we report team production and workers' performance over the 10 rounds in both treatments. We see that not only are team production and worker performance above the minimum level of 0, but also that they increase over time in both treatments.

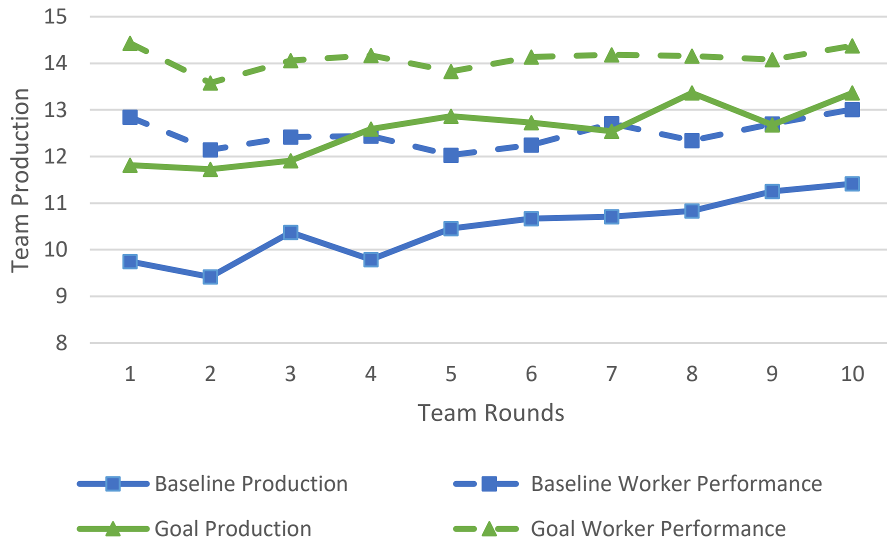

FIGURE 1: Average team production and workers performance in both treatments

We present a paneled OLS regression estimate of the effect of goal setting on team production at the group level in Table 2. We find that team production is significantly higher in the goal treatment at the 0.1% level when controlling for weak-link ability. This implies that the difference in team productions can be attributed to the *goal* treatment and not differences in individual workers between treatments. Based on these results we conclude that goal setting has a significant positive effect on aggregate team production, which is consistent with our Hypothesis 1.B.ii. We also see that the time trend is always statistically significant and positive for team production; team production is increasing over time for both treatments. Though this finding is unlike previous weak-link experiments with abstract effort, our result is in line with other real effort coordination experiments (Bortolotti et al. 2009, Vranceanu et al. 2013). We take a closer look at what goals managers set in the next section.

TABLE 2: Paneled OLS regression on team production at group level, robust SE

	(1)
	Team Production
Round	0.185****
	(0.0453)
Goal Treatment (d)	2.317****
	(0.475)
Weak-link Ability	0.211**
	(0.104)
Constant	6.514****
	(1.268)
Observations	460

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$. Standard errors in parentheses. (d) for dummy variable.

RESULT 1 (WORKERS PERFORMANCE AND TEAM PRODUCTION). Workers performance and team production are significantly greater in the *goal* setting treatment than in the *baseline* in line with Hypothesis 1.B.

4.2. Goal Accuracy for the Weak-Link Worker and Team Production

We now study the effect of goal accuracy in the performance of the weak-link worker, which determines team production and hence monetary payoffs. The weak-link worker is fairly consistent within each group; 76% of the time, it is the same worker that determines team production. From our theory, we predict that setting the maximum goal the weak-link worker would attain in equilibrium maximizes his individual performance and hence team production (Hypothesis 2.i). In Figure 3, we plot the average team production and average goal set by the manager. Upon initial inspection, managers appear to be setting goals that are too challenging for the weak-link worker; the average goal is 16.6, which is 4.1 units higher than the average team production.[10] The average goal is so challenging that there are only 79 rounds out of the possible 220 where the team production meets or exceeds the goal. This result appears to be inconsistent with our theoretical conjectures.

[10] Since there are 48 sliders on the screen, goals above 48 (which are impossible to attain) were set to 48 in our data. The impossible goals were all set by one manager in the last four rounds of a session and they ranged from 200 to 200,000. Our results are consistent if we drop these observations instead.

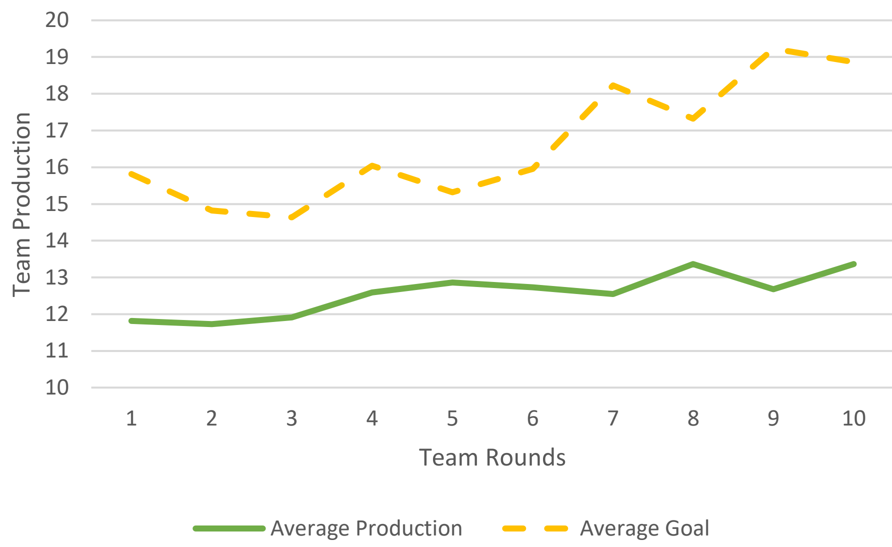

FIGURE 3: Goals vs. Team Production

One possible interpretation of this results is that managers set goals that are, on average, unattainable by weak-link workers because, in contrast to our theoretical framework, they find these goals to be most effective. In order to test the effectiveness of manager's goal setting decisions we need to identify reasonably accurate goals in the sense of being attainable yet challenging for the weak-link worker. Similar to Corgnet et al. (2015), we start by using the weak-link ability, the weak-link worker's output in round three, to establish a basis for what goals are reasonable. However, in our team rounds with strategic complementarity, weak-link ability alone is not a good predictor of team production, and defining a goal as reasonable based on this predictor yields no insight.[11] Therefore, using data from the *baseline* treatment, we estimate task ability in the current round as follows.

$$predicted\ task\ ability_t = \hat{\alpha}_1 \times lagged\ team\ production + \hat{\alpha}_2 \times double\ lagged\ team\ production,$$

where $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are estimated from the *baseline* treatment data with the following feasible generalized least squares linear panel regression with no constant:[12]

$$team\ production_t = \alpha_1 \times lagged\ production + \alpha_2 \times double\ lagged\ production + \epsilon_t.$$

We obtain $\hat{\alpha}_1 = 0.61$ and $\hat{\alpha}_2 = 0.39$, indicating that predicted task ability for a given round, 61% of the weight is placed on last round's team production, and 39% of the weight is placed on team production from two rounds ago.

[11] Our predictive models of ability based purely on the individual performance rounds yield extremely poor estimates of weak-link team production. This is due to the team structure and strategic uncertainty in the team production rounds.

[12] The linear panel feasible generalized least squares model allows us to suppress the constant while estimating the weighted coefficients of lagged dependent variables, unlike GMM dynamic panels. By necessity, task ability in the first team round is based on the weak-link worker's output in the third individual round.

Based on predicted task ability, we define the variable "Reasonable Goal" as a dummy that takes a value of one if the goal lies within a range of two units of predicted task ability, defined above as the weighted average of the team production from two previous rounds. We chose a range of two for our definition based on the standard deviation of team productions, which is 2.56 in the *goal* treatment and 2.68 in the *baseline*. We observe reasonable goals for the weak-link worker in 117 out of the 220 rounds, which is 53.2% of the rounds. Figure 4 shows the distribution of all goals minus predicted task ability; the red bars represent reasonable goals.

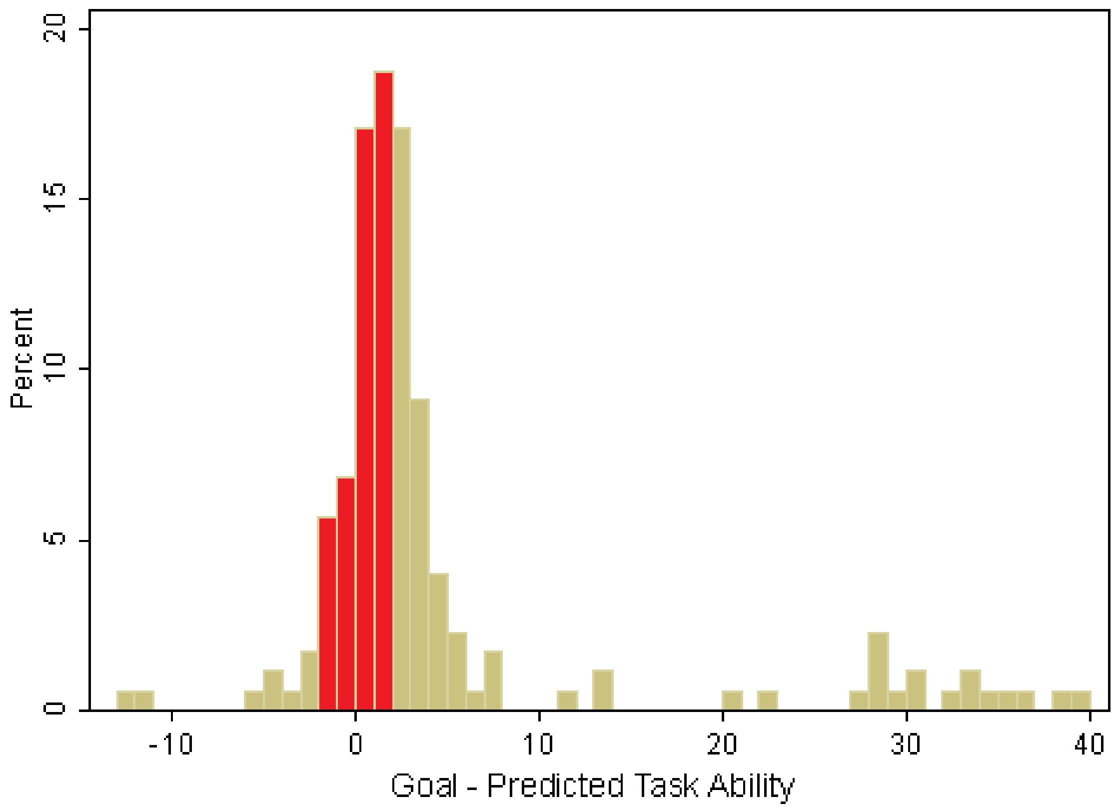

FIGURE 4: Distribution of Goals – Predicted Task Ability; Reasonable Goals in Red

Next, we separate workers into two groups, weak-link workers and other (higher ability) workers. As we indicated above, team production (i.e., performance of the weak-link) is higher when goals are reasonable. In particular, weak-link workers on average complete 12.08 units when the goal is not reasonable, and 13.0 units when the goal is reasonable for them. This difference is statistically significant as the session level under the Wilcoxon rank-sum test (p-value = 0.01). Conversely, the two other workers in the group complete 17.7 units when the goal is not reasonable for the weak-link worker and 17.9 units when the goal is reasonable for the weak-link worker. This difference is not statistically significant (p-value = 0.24). In Figure 5 we report the aggregate effect of reasonable goals on team production. As noted in Section 4.1, team production is 2.08 units higher in the goal treatment compared to the baseline, which is an increase of 19%. When we look at reasonable goals compared to unreasonable goals, we see an even clearer picture: aggregate team production under reasonable goals is 13.0, an increase of 24% compared to the *baseline*. On the contrary, team production under unreasonable goals for the weak-link worker is 12.08, which is only a 15% increase between the *baseline* and *goal* treatment. Therefore, we find empirical evidence that setting a reasonable goal for the weak-link worker is important to team success. Managers who set reasonable goals for the weak-link worker increase monetary payoffs for their teams by almost 25%, while managers who set unreasonable goals observe much smaller gains to team production.

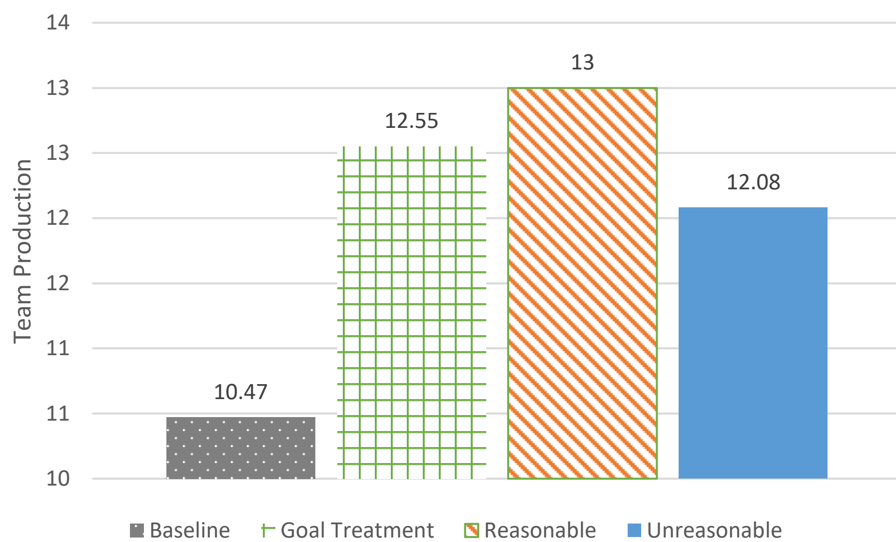

FIGURE 5: Reasonable vs. Unreasonable Goals for the Weak-Link Worker & Team Production

While setting reasonable goals for the weak-link worker theoretically (Hypothesis 2.ii) and empirically increases team production, we still find that almost half of the managers in our sample seem to assign goals according to different criteria, which prevents them from fully capitalizing on the monetary gains of goal setting policies. We study manager's goal selection in more detail in the next section where we propose a possible interpretation of these results.

RESULT 2 (GOAL ACCURACY AND TEAM PRODUCTION). Managers set reasonable goals for the weak-link worker in 53.2% of the rounds, so empirical support for Hypothesis 2.ii is ambiguous. Reasonable goals improve aggregate team production by 24% compared to the *baseline*. Unreasonable goals have a smaller effect. This is clear empirical support for Hypothesis 2.i.

4.3. Managers' Goal Selection

We saw in the previous section that some managers in our experiment are not setting the goals that maximize team production. Out of the 103 observations of unreasonable goals, 87 of these are goals that are above actual team production; 23 of these goals are at least 10 units above actual team production. These managers may believe that setting increasingly difficult and unattainable goals will motivate the weak-link worker to improve performance, contrary to our theory and empirical evidence; or they may be setting goals for reasons different from profit maximization. In Table 3, we present two linear dynamic panel-data models on goals at the group level when they are unreasonable and when they are reasonable.[13] In particular, reasonable goals are correlated with team production in the previous round, while unreasonable goals are not. The result suggests that managers who set reasonable goals for the weak-link update goals based on feedback from previous team production. However, managers assigning unreasonable goals do not seem to consider team production at all. In other words, only managers who set reasonable goals seem to focus on the weak-link's previous performance, which our theory and empirical evidence suggest is the optimal way of assigning goals.

TABLE 3: GMM linear dynamic panel-data model on goals at session level

	(1) Unreasonable Goal	(2) Reasonable Goal
Lagged Goal	0.224	0.0185
	(0.222)	(0.0663)
Lagged Production	-0.116	0.319***
	(0.349)	(0.0921)
Weak-link Ability	-1.103	0.273
	(2.080)	(0.450)
High Task Ability	1.776*	0.0637
	(0.859)	(0.223)
Manager Ability	1.495	0.186
	(0.923)	(0.120)
Round	1.738*	-0.0826
	(0.784)	(0.0979)
Observations	81	117

* *$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$. Standard errors in parentheses.*

We also see that the time trend is marginally statistically significant and positive for unreasonable goals, indicating that these managers are setting increasingly difficult goals over time, even though most team productions are far below these goals. If all managers were learning to set more motivating goals over time, we would see the difference between goals and team productions to be shrinking over time. Instead, unreasonable goals become increasingly difficult and unrealistic compared to team production.

[13] We use the Arellano-Bover/Blundell-Bond Generalized method of moments system estimator to avoid endogeneity bias that may arise in paneled OLS estimations with lagged dependent and independent variables.

Lastly, we look at the correlation between goals and the ability of the most productive worker, which we call *High Task Ability*. This variable measure the third round performance of the most productive worker on the team, similar to weak-link ability. For goals that are unreasonable, the most productive worker's ability is marginally correlated with the goal, while team production is not. This evidence suggests that some managers are setting goals that are appropriate for the best workers of the team, but these goals are too difficult for the weak-link. This failure to adapt goal-setting strategy in a team production environment lowers profits for all team members.

Our results are in line with other economic, psychology, and management science studies, which find that some managers are reluctant to adapt their strategies to feedback on workers' characteristics and feedback. For example, using data from a company that provide online job testing services, Hoffman et al. (2018) studies the effects of job testing on managerial hiring decisions and performance. The authors found that HR managers who frequently use their discretion to override the results of a proprietary skills test hired workers who performed worse than workers hired by other managers. Similarly, in a laboratory experiment, Corgnet and Hernán González (2013) report evidence that consulting workers was beneficial to managers as long as they follow the workers' advice; nevertheless, most managers were reluctant to change their mind and adopt the workers' proposal. Thus, most managers ignore proposals in favor of their original plan despite the monetary costs. This "rigidity of mind" may arise because people focus too much on their own beliefs instead of adapting their strategies to somebody else feedback. In other words, managers may suffer from the well-documented self-serving bias (Lowenstein et al. 1993; Babcock et al. 1996; Babcock and Lowenstein 1997). In line with this idea, some managers in our experiment may believe that all workers should achieve the performance dictated by the highest ability workers without paying proper attention to the negative motivational effects of setting too challenging goals for the weak link. When these workers fail to reach the goal, some managers ignore this feedback and do not adjust their strategy even when it is in their material interest to do so. The observation that some managers misunderstand or ignore feedback is common in the operations and management literature as well. For example, Sterman (1989) found that human subjects experience several "misperceptions of feedback" in a multi-tier inventory distribution system with time delay, commonly known as the beer game. The "misperceptions of feedback" results in the bullwhip effect, and Chen et al. (2000) demonstrates that the behavioral phenomenon does not disappear even with centralized demand information.[14]

[14] For a recent review of behavioral responses to feedback, see Bendoly et al. (2006).

RESULT 3 (MANAGERIAL GOAL SELECTION). While 53.2% of the time managers set reasonable goals, some managers persistently set unreasonable goals that increase in difficulty over time. This finding is contrary to our Hypothesis 2.ii and suggests that some managers have alternative strategies on how to set goals; strategies that are suboptimal from the point of view of profit maximization.

4.4. Dispersion of Workers Performance and Wasted Performance

Finally, we look at the dispersion of workers' performance within each treatment. Table 4 summarizes the mean and standard deviation of all workers performance, as well as the mean and standard deviation of weak-link workers' performance vs. other workers, and the test of equality of standard deviations statistics between the *baseline* and *goal* treatment, both at the session level.[15] We see that there is greater dispersion of performance when goals are present. This empirically suggests that on average, goals set by managers' act as a motivation device rather than a coordination device. Thus, goals increase all workers performance but they also disperse individual worker performance.

TABLE 4: Test of equality of standard deviations for workers' performance at session level

		N	Mean	Std. Dev.	F test
All	Baseline	122	13.27	3.05	P-value = 0.02
Workers	Goal Treatment	114	15.02	3.72	Reject
Weak-Link Workers	Baseline	54	11.06	2.00	P-value = 0.11
(Team Outcome)	Goal Treatment	52	12.57	2.39	Fail to reject
Other	Baseline	68	15.55	2.57	P-value = 0.01
Workers	Goal Treatment	62	17.74	3.39	Reject

In order to understand why goals increase the standard deviation of workers performance we introduce the variable "wasted performance", which we define as a worker's performance above the weak link's level. As we explained in Section 4.1., we chose the label "wasted" because performance levels above the minimum do not result in monetary earnings. Our theory suggest that because of piling up, wasted performance is minimized when goals are challenging but attainable for the weak link. Table 5 presents results from a Z-test of equality of means, clustered by session, for wasted performance from the other two higher ability workers, as by definition the weak-link worker wasted performance is zero. We note that there is no statistical difference in wasted performance between the *baseline* and *goal* treatment. However, when we analyze wasted performance in the *goal* treatment and separate observations by when there is an unreasonable vs. reasonable goal, we find that wasted performance is significantly higher at the session level when workers face an unreasonable goal. This finding is consistent with our Hypothesis 3:

[15] Results are qualitatively unchanged using Levene's or Brown and Forsythe's robust test statistics for equality of variance under non-normality.

reasonable goals that are challenging but attainable for the weak-link worker minimize wasted performance and hence decrease the standard deviation of performance.

TABLE 5: Z-test of equality of means for wasted performance at session level

	N	Clusters	Mean	T-test
Baseline	456	24	5.19	P-value = 0.57
Goal Treatment	416	22	5.26	Fail to reject
Unreasonable Goal	198	22	5.46	P-value = 0.03
Reasonable Goal	218	21	5.09	Reject

RESULT 4 (WASTED PERFORMANCE). The standard deviation of workers' performance is higher when goals are present. We show that this is because unreasonable goals significantly increase wasted performance. However, reasonable goals significantly decrease wasted performance and hence the spread of performance among workers in the team. These results are consistent with Hypothesis 3.

5. Discussion

In this study, we test the efficacy of non-binding goals in teams where production depends on the weak-link worker. To do so, we model team production as a real effort weak-link coordination game among workers, where managers can set a goal for the team. We find that non-binding goals are effective motivators for teams in our experiment. In particular, aggregate team production increases by 19.8% when goals are present and this positive effect is more pronounced when the goal is reasonable for the weak-link worker. The positive effect of goals on teams' production holds even when controlling for measures of workers' individual ability within groups. We also find that, in the absence of goals, team production does not fall to the worst possible outcome of zero. This finding differs from the large body of literature on abstract effort minimum coordination games, where convergence to the least efficient equilibrium is the norm, but is consistent with other real effort experiments.

Our paper shows that workers in teams respond to non-monetary incentives such as goal setting. Using non-binding managerial goals in organizations is particularly appealing, as these goals are easy and costless to implement. Furthermore, these goals can significantly increase team production while also avoiding conflicts of interest between management and workers. When a goal is binding, the firm or manager must pay the monetary incentive when the goal is met; this can lead the firm or manager to set goals that do not maximize team production. Non-binding goals can align the incentives of both parties.

Our results also indicate that not all goals are equally effective. In particular, we find that setting unrealistic team goals (goals that are too difficult for the weak link) is much less effective than setting reasonable goals. Unfortunately, almost half of the time our managers set goals that are too difficult, and this effect is persistent. We argue that this important result is consistent with similar findings in the literature on self-serving biases. Our results suggest that it would be beneficial to train managers to overcome their "rigidity of mind" when setting goals for others. Through training, organizations can teach managers to overcome personal idiosyncrasies and assign better goals for their teams. When managers are able to empathize with their weak link workers and use available information to set challenging yet achievable goals for them, teams as well as managers benefit. Moreover, our finding that suboptimal goals also increase wasted performance suggest that improving goal-setting strategies is especially important in production settings where over-performance is costly for the firm (scrap, energy use, inventory costs, lower prices due to oversupply, etc.).

Our findings suggest several interesting lines for future research. First, the result that some managers are unsuccessful at setting optimal goals even when the necessary information is at their disposal motivates the question of how to minimize the impact of managerial mistakes or biases in setting team goals. Firms may adopt policies to improve managers' goal setting behavior, such as increasing feedback about goals that are challenging but attainable for the weak-link. Moreover, it would be interesting to delve more into the role that managerial leadership has on goal effectiveness in teams. In our experiment, we focus on a vertical leadership environment in which managers are always in charge of goal-setting; however, one might imagine that workers might be more committed to attain a team goal when they participate in setting them (horizontal leadership) or when the manager simply asks for the workers' opinion before assigning the goal (consultative leadership). Different leadership structures may moderate the impact of non-binding goals and intrinsic motivation on worker performance and team production. From a theoretical standpoint, our model could be generalized to consider randomness in workers' production, which would lead to a more complex probability distribution over outcomes and hence additional coordination problems. Finally, it is worth exploring the impact of binding goals on teams with diverse production technologies. Binding goals such as sales quotas and project deadlines directly affect a worker's monetary incentives, and these goals are commonplace as well. Whether managers set optimal binding goals for teams and what impact these goals have on team production remain important open questions.

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Appendix

Proof of Proposition 1

First, we show that $y_i = y_{-i}$ with $0 \le y_i \le \tilde{y}$ is a Nash equilibrium. Suppose $y_i = y^*$ for all i and $0 \le y \le \tilde{y}$. Now suppose worker i chooses $y_i > y$. Worker i's payoff is given by $\pi_i^W(y_i, y_{-i}) = A \cdot M(\mathbf{y}) - c(y_i; \theta_i) < A \cdot M(\mathbf{y}) - c(y; \theta_i) = \pi_i^W(y^*)$. This is because $c(\cdot)$ is increasing in y for all workers. Therefore worker i has no incentive to increase effort above y^*.

Now consider any $y_i < y$. In other words, worker i unilaterally sets the minimum. By assumption, $0 \le y \le \tilde{y}$, and in this range, $\pi^W(y_i, y_{-i}) < \pi^W(y, y_{-i})$. That is to say, in this range, the monetary payoff from a higher team production level outweighs the increased cost of effort for all workers. Therefore, a worker has no incentive to decrease effort.

Now we show that any Nash equilibrium to this game satisfies $y_i = y_{-i}$ with $0 \le y_i \le \tilde{y}$. Suppose $\boldsymbol{y}^*$ is a pure strategy Nash equilibrium. First assume $\boldsymbol{y}^*$ is not a constant vector. Then there exists $y_i > M(\boldsymbol{y})$ for some i, so worker i can increase profits by setting $y_i = M(\boldsymbol{y})$. Doing so will decrease his cost of effort without decreasing his monetary payoffs. Now assume $\boldsymbol{y}^* > \tilde{y}$. For any worker with ability parameter θ_1, his profit function is decreasing in this range. He can increase profits by choosing $y_i < \boldsymbol{y}^*$.

■

Proof of Proposition 2

Following Wu et al (2008) we consider a special case of optimization referred to as "myopic optimization." We require this assumption because solutions of the optimization problem with a prospect theory value function are not necessarily unique.

Assumption 1 (Myopic optimization): The worker stops performing when the marginal cost of obtaining an additional unit first exceed the marginal benefit of obtaining that unit. Thus, the optimal performance is given by $y^* = \min\{y_1, \dots, y_n\}$, where $y_1, \dots, y_n$ are solutions to $v'(y - g) = c_y(y; \theta)$.

Essentially, Assumption 1 guarantees that the solution will be the minimum performance of all possible equilibria. Thus, without this assumption, the optimal work performance that we compute below could be higher but none of our qualitative results, in particular the relationship between work performance and goal setting, would change.

In order to prove Proposition 2 we stablished the following Lemma.

Lemma 1: Let Assumption 1 hold. Then, $v''(y^* - g) < c_{yy}(y^*; \theta)$

Proof of Lemma 1: Since y^* is the profit maximizing performance given goal g, $v'(y^* - g) = c_y(y^*; \theta)$. Since $v(\cdot)$ is concave for gains and $c(\cdot)$ is convex, Assumption 1 implies $v'(y^* - g - \varepsilon) > c_y(y^* - \varepsilon; \theta)$. Therefore, $v''(y^* - g) < c_{yy}(y^*; \theta)$.

Note that Lemma 1 assures that second order condition for the performance that maximizes worker's overall utility, $\pi^W(\cdot) = A \cdot M(\mathbf{y}) + v(y_i - g) - c(y_i; \theta_i)$, holds.

Let us consider $\theta \in [\theta_1, \theta_n]$. A worker with ability θ producing above the minimum is not affected by monetary incentives and his best-response effort choice is characterized by:

$$\underline{y}(\theta, g) = \{y: v'(y - g) = c_y(y; \theta)\}. \qquad \text{[A1]}$$

On the other hand, a worker producing at the minimum must be affected by monetary incentives and his best-response effort choice is given by:

$$\overline{y}(\theta, g) = \{y: A + v'(y - g) = c_y(y; \theta)\}. \qquad \text{[A2]}$$

Note that for $A > 0$, $\underline{y}(\theta, g) < \overline{y}(\theta, g)$ for all workers. We first prove that both $\overline{y}(\cdot)$ and $\underline{y}(\cdot)$ increase in θ for a given g. Note that by differentiating $\overline{y}(\theta, g)$ or $\underline{y}(\theta, g)$ with respect to θ and using the implicit function theorem we get:

$$v''(y - g)\frac{dy}{d\theta} = c_{yy}(y; \theta)\frac{dy}{d\theta} + c_{y\theta}(y; \theta)$$

where y stands for either $\overline{y}(\cdot)$ or $\underline{y}(\cdot)$.

By rearranging terms we get:

$$\frac{dy}{d\theta} = \frac{c_{y\theta}(y; \theta)}{v''(y - g) - c_{yy}(y; \theta)}$$

The denominator of this expression is negative because of Lemma 1, while the numerator is negative by the properties of $c(\cdot)$. Hence, $\frac{dy}{d\theta} > 0$, and both $\overline{y}(\cdot)$ and $\underline{y}(\cdot)$ increase in θ for a given g.

Now, for a given $g \geq 0$, let us define the threshold ability level $\tilde{\theta}(\theta_1)$ as $\underline{y}(\tilde{\theta}(\theta_1), g) = \overline{y}(\theta_1, g)$. Note that since both $\underline{y}(\cdot)$ and $\overline{y}(\cdot)$ increase in θ, $\theta \geq \tilde{\theta}(\theta_1)$ if and only if $\overline{y}(\theta_1, g) \leq \underline{y}(\theta, g)$. Therefore, we can define the "low ability" workers group as $L(\theta_1, g) = \{i \in N | \underline{y}(\theta_i, g) \leq \overline{y}(\theta_1, g)\}$, which has cardinality of at least 1; thus, θ_1 will always be in this group. If $|L(\theta_1, g)| = 1$, worker θ_1 is the only low ability worker, and his best response effort level is the solution to $A + v'(y - g) = c_y(y; \theta_1)$. This is a unique pure strategy Nash equilibrium.

If $|L(\theta_1, g)| \geq 2$ then, applying the logic of Proposition 1, we see that for all $i \in L(\theta_1, g)$, $y_i = y^*$ where $\underline{y}(\theta_1, g) \leq y^* \leq \overline{y}(\theta_1, g)$. Finally, for all $i \notin L(\theta_1, g)$ it holds that $\underline{y}(\theta_i, g) > \overline{y}(\theta_1, g)$. Hence, in equilibrium, these workers' best response effort level are not affected by monetary team-incentives, and $y_i = \overline{y}(\theta_i, g) = \{y: v'(y-g) = c_y(y;\theta_i)\}$ is a pure strategy Nash equilibrium.

■

Proof of Proposition 3

To prove Proposition 3, we assume a widely accepted equilibrium refinement criterion that states when workers in the low ability group face multiple equilibria in the coordination game; they choose an effort level corresponding with the payoff-dominant equilibrium.

Assumption 2 (Payoff dominance): Low ability workers with ability parameters $\theta_1, \ldots, \theta_m$ choose the symmetric best response effort level that yields the payoff-dominant equilibrium in the coordination game. In our context, the effort level is the solution to $A + v'(y-g) = c_y(y;\theta_1)$. This effort level is the maximum effort the weak-link worker would willingly exert.

Given Assumption 2, there is a unique pure strategy Nash equilibrium in this game, where low ability workers exert effort $y_i = \overline{y}(\theta_1, g) = \{y: A + v'(y-g) = c_y(y;\theta_1)\}$ and high ability workers exert effort $y_i = \underline{y}(\theta_i, g) = \{y: v'(y-g) = c_y(y;\theta_i)\}$.

The proof of Proposition 3(i) is based on Wu et al. (2008) analysis of a goal-dependent prospect theory value function with exogenously given goals. This result is similar to Proposition 1 in Wu et al. (2008).

Given Proposition 2 and Assumption 2, the optimal production is given by:

$$y_i^* = \begin{cases} \overline{y}(\theta_1, g) & if \quad i \in L(\overline{y}, g) \\ \underline{y}(\theta_i, g) & if \quad i \notin L(\overline{y}, g) \end{cases}$$

Let us start showing how goals affect effort of workers in the high ability group $\left(i \notin L(\theta_1, g)\right)$. Given a goal, the optimal performance for high ability workers is characterized by equation [A1]:

$$v'\left(\underline{y}(\theta, g) - g\right) = c_y\left(\underline{y}(\theta, g); \theta\right)$$

Using the implicit function theorem and differentiating both sides of this expression with respect to g we get:

$$v''\left(\underline{y}(\theta,g)-g\right)\left(\frac{d\underline{y}(\theta,g)}{dg}-1\right)=c_{yy}\left(\underline{y}(\theta,g);\theta\right)\frac{d\underline{y}(\theta,g)}{dg}$$

Thus,

$$\frac{d\underline{y}(\theta,g)}{dg}=\frac{v''\left(\underline{y}(\theta,g)-g\right)}{v''\left(\underline{y}(\theta,g)-g\right)-c_{yy}\left(\underline{y}(\theta,g);\theta\right)}$$

The denominator of this expression must be negative at the optimal performance level because it is the second order condition for an effort level that maximizes a worker's overall utility. Therefore, $\frac{d\underline{y}(\theta,g)}{dg}$ and $v''\left(\underline{y}(\theta,g)-g\right)$ must have opposite signs. Moreover, note that by properties (iv) and (v) of $v(y-g)$, we know that $v''\left(\underline{y}(\theta,g)-g\right)>0(<0)$ if and only if $\underline{y}(\theta,g)<g\ (>g)$. This means that higher goals improve performance of a high ability workers, if his performance exceeds the goals (the goal is "attainable" for him) but decreases performance if his performance does not exceed the goal (the goal is not "attainable" for him). Thus, $\frac{d\underline{y}(\theta,g)}{dg}>0\ (<0)$ if and only if $\underline{y}(\theta,g)>g\ (<g)$.

Similarly, given a goal, the optimal performance for workers in the low ability group $\left(i\in L(\theta_1,g)\right)$ is given by equation [A2]:

$$A+v'(\overline{y}(\theta_1,g)-g)-c_y(\overline{y}(\theta_1,g);\theta_1)$$

By deriving both sides of this expression with respect to g we get:

$$v''(\overline{y}(\theta_1,g)-g)\left(\frac{d\overline{y}(\theta_1,g)}{dg}-1\right)=c_{yy}(\overline{y}(\theta_1,g);\theta)\frac{d\overline{y}(\theta_1,g)}{dg}$$

Thus,

$$\frac{d\overline{y}(\theta_1,g)}{dg}=\frac{v''(\overline{y}(\theta_1,g)-g)}{v''(\overline{y}(\theta_1,g)-g)-c_{yy}(\overline{y}(\theta_1,g);\theta_1)}$$

Using the same argument we used before, $\frac{d\overline{y}(\theta_1,g)}{dg}>0\ (<0)$ if and only if $\overline{y}(\theta_1,g)>g\ (<g)$.

We now proceed to prove the Proposition 3(ii). Note that a profit-maximizing manager should focus on maximizing the performance of the weak-link worker, the only one determining the team's production. In Proposition 3(i) we showed that this goal corresponds to the maximum goal that the weak-link worker is willing and able to attain, i.e., $g^* = \underset{g}{\operatorname{argmax}}\, \overline{y}(\theta_1, g)$.

In order to compute g^*, we start by defining $\hat{g}$ as the minimum goal that the weak-link worker would fail to attain and by $\hat{y}$ its corresponding performance (see Figure A1 below).

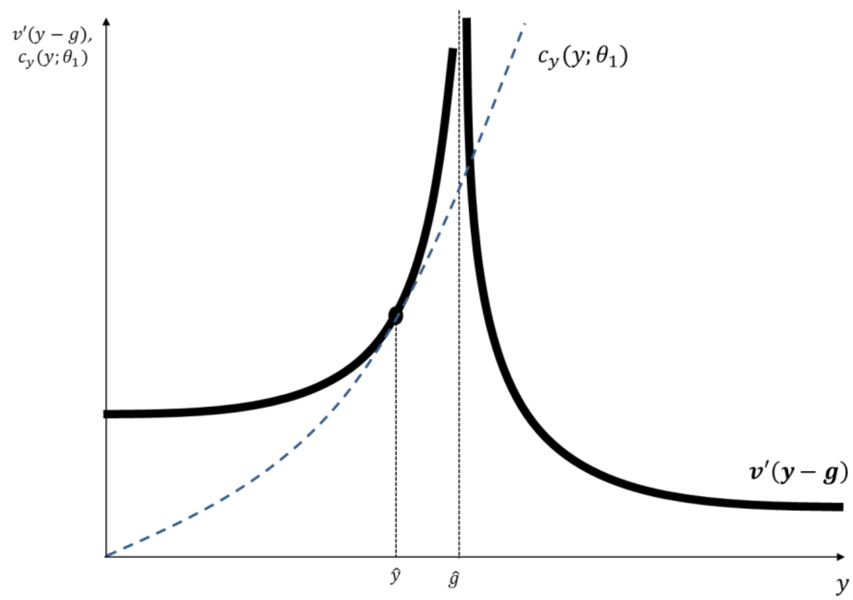

FIGURE A1 – Plot of $\hat{g}$ and $\hat{y}$

From equation A2 we know that:

$$A + v'(\hat{y} - \hat{g}) = c_y(\hat{y};\theta_1)$$

By deriving both sides of this equation with respect to $\hat{y}$ we get:

$$v''(\hat{y} - \hat{g}) = c_{yy}(\hat{y};\theta_1)$$

We can compute $\hat{g}$ and $\hat{y}$ solving the system of equations:

$$v''(\hat{y} - \hat{g}) = c_{yy}(\hat{y};\theta_1)$$

$$v'(\hat{y} - \hat{g}) = c_y(\hat{y};\theta_1)$$

Finally, note that since $\hat{g}$ is the minimum goal that the weak-link worker would fail to attain, the maximum goal that he could attain is slightly lower. Thus,$g^* = \hat{g} - \varepsilon$ with $\varepsilon \to 0$.

We illustrate this result in Figure A.2.

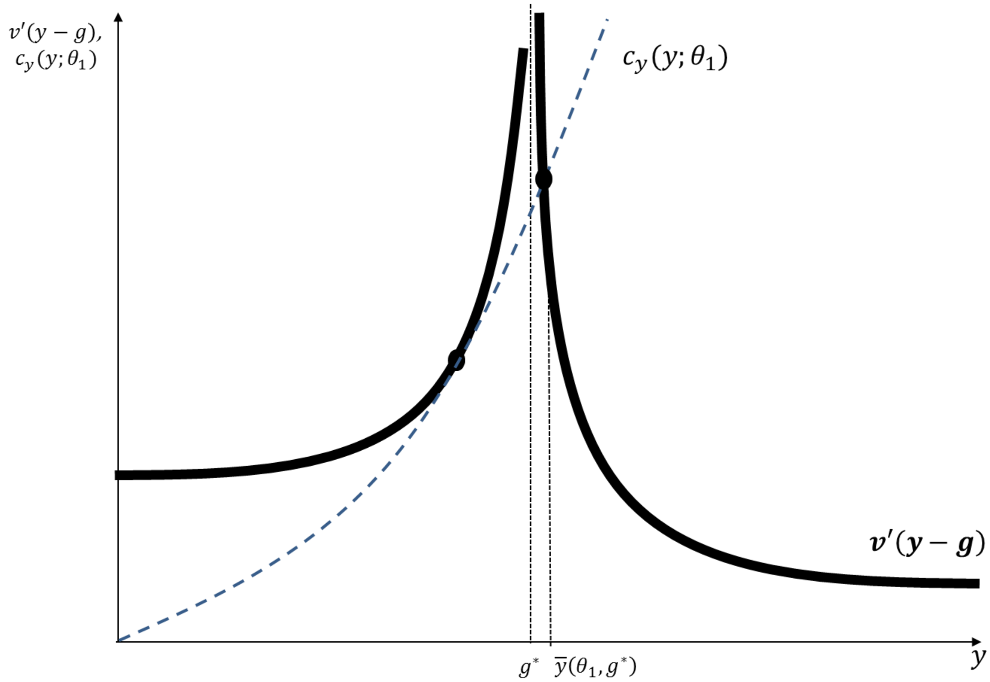

FIGURE A2- Plot of g^* and $\overline{y}(\theta_1, g^*)$.

As we can see in Figure A2, in equilibrium, the goal is attained by the weak link worker given that $g^* < \overline{y}(\theta_1, g^*)$.

■

Proof of Proposition 4

This proof is based on the proof of Proposition 5 in Wu et al. (2008). First, we formalize the notion of piling-up. Let us call $G(\delta;\theta,\lambda)$ the set of goals in which performance exceeds a particular goal by δ or less. Thus, if $g \in G(\delta;\theta,\lambda)$ then $0 \leq y_i - g \leq \delta$. In order to check how piling-up is related to loss aversion in our environment we proof the following lemma:

Lemma A1 (Piling-up): There exists a sufficiently high level of loss aversion, $\lambda > 1$, such that if $g \in G(\delta;\theta_i,1)$, then $g \in G(\delta;\theta_1,\lambda)$ where $i \notin L(\theta_1, g)$.

<u>Proof of Lemma A1</u>

If $g \in G(\delta; \theta_1, 1)$, Lemma A1 clearly holds. Thus, we must consider the case in which $g \in G(\delta; \theta_i, 1)$ and $g \notin G(\delta; \theta_1, 1)$. The latter implies that the goal g that is attained by worker i is not attained by the weak-link. Thus, for some $y_1 < g$, $A - v'(g - y_1) = c_y(y_1; \theta_1)$. Hence, since $v'(g - y_1) < 0$, for $\lambda > 1$, $A - \lambda v'(g - y_1) > c_y(y_1; \theta_1)$. Therefore, when $\lambda > 1$ the production of the weak-link, y_1, is higher than when $\lambda = 1$; and for a sufficiently high λ it must be the case that $y_1 > g$ so that $A + v'(y_1 - g) = c_y(y_1; \theta_1)$.

Lemma A1 indicates that a loss averse weak-link worker is willing to just attain a goal that a higher ability worker without loss aversion also attains, as long as loss aversion is sufficiently high.

Proposition 4 is a direct consequence of this result (piling-up). When workers are below their goals, they receive high benefits from removing a ''loss;'' and these incentives increase with the level of loss aversion. However, once they reach their goal and enter the domain of gains, the marginal benefits of additional performance will be substantially smaller. The optimal goal that we described in Proposition 3.ii, g^*, is the maximum goal that the weak-link worker is willing and able to attain; given this goal the weak-link worker exceeds the goal by a small margin (see Figure A2). However, if the goal is any higher, $\hat{g} = g^* + \varepsilon$ for an arbitrarily small ε, his performance would be substantially lower (see Figure A1); increasing the difference in performance between high ability workers and the weak-link (wasted performance), $\Delta_i(g)$.

To illustrate, consider an example where $n = 3$ and $L(\theta_1, g) = \{1\}$. Thus, there are three workers: the weak-link and two higher ability workers that produce above the weak-link's level in equilibrium. Figure A3 below shows the case in which the goal is higher than the optimal goal, $g_H > g^*$. In this case

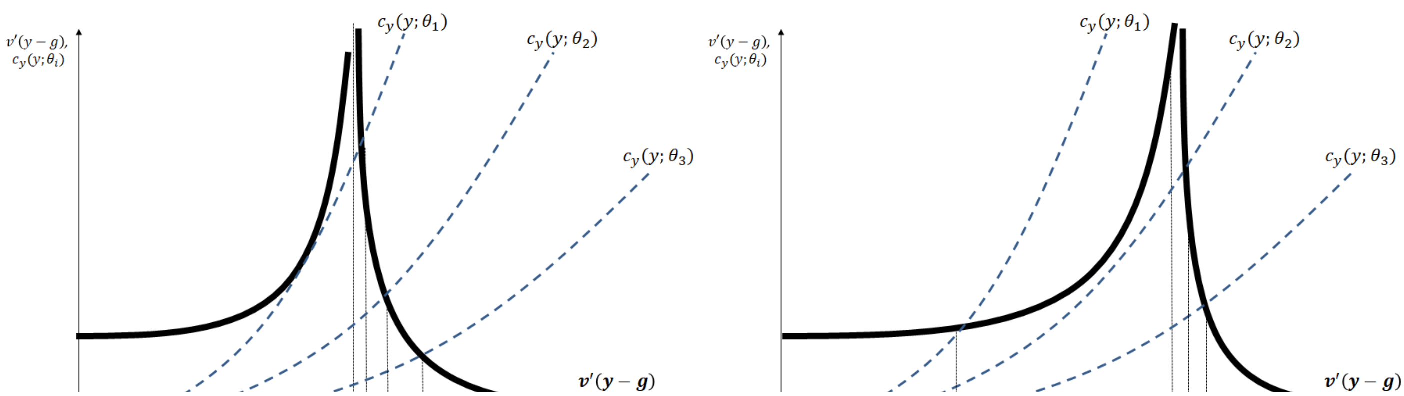

FIGURE A3- Wasted performance of the highest ability worker under the optimal goal (left-hand side) and a higher goal (right-hand side).

the weak-link worker does not meet the goal, g_H, and the wasted performance of the highest ability worker is higher than with the optimal goal, $\Delta_3(g_H) > \Delta_3(g^*)$.

Similarly, when the goal is less than the optimal $g_L < g^*$ all workers exceed the goal by a generous margin but, just as in the high goals case, wasted performance is higher than under optimal goals.

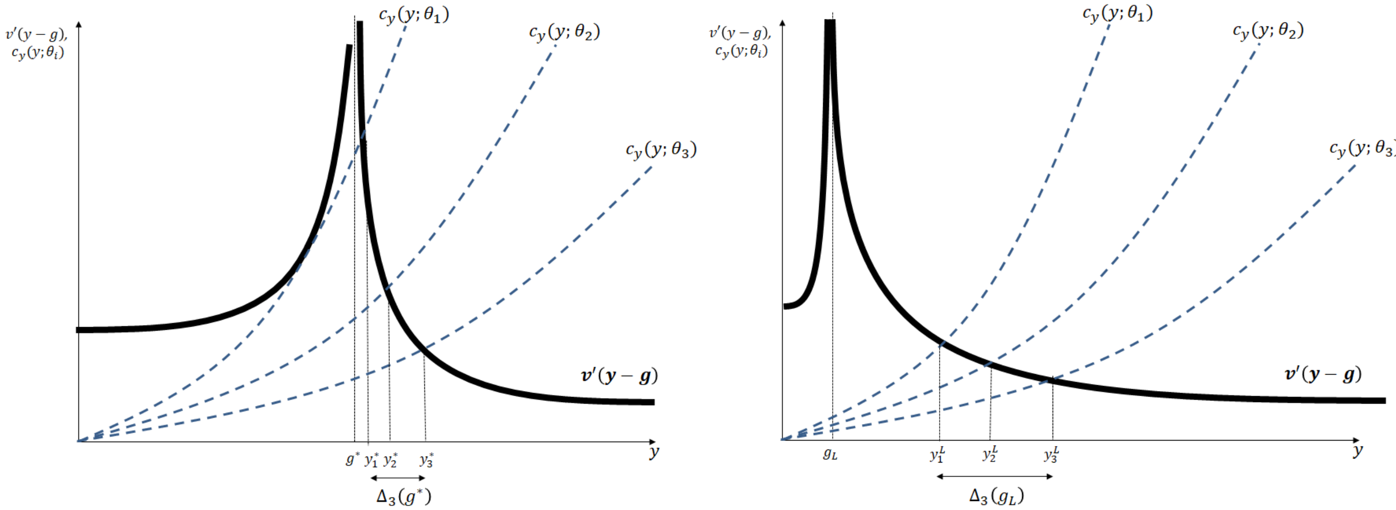

FIGURE A4- Wasted performance of the highest ability worker under the optimal goal (left-hand side) and a lower goal (right-hand side).

Therefore, low and high goals yield the highest wasted performance of high ability workers whereas the optimal goal induces the lowest dispersion.

■