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Incentives, goals and task complexity: Studying the effects of non-monetary incentives on team performance

Abstract

This study examines the effects of using non-binding, exogenous team goals on worker effort in a weakest-link team production game. The experimental design varies the team goal (and whether a goal is present) and task complexity level (simple or complex), lending itself to identify a causal effect of complexity on goal effectiveness. Further, the design also varies goal difficulty (easy, moderate and difficult). Preliminary findings suggest that using team goals can alter production, but relationships between goal difficulty and production are not monotonic. While an easier goal reduces individual production, a rather challenging, difficult goal has no impact relative to no goal. At the same time, only a difficult goal seems to improve team production relative to no goal. A non-binding goal also helps minimize wasted performance thereby enhancing within-group coordination. There is evidence that easy goals may discourage individual production but at the same time this is not true for team production, i.e., effects differ when it comes to the weakest-link worker. Interestingly, when complexity increases i.e., higher cognitive costs are placed on individuals, the magnitude by which difficult goals increase team production is relatively smaller as goal difficulty increases. Further, as task complexity increases, while physical effort decreases, cognitive effort increases. Outcomes from the study are expected to highlight the types of goals managers should set based on the amount of cognitive load a task places on individuals in a team, and therefore this research has important managerial implications.

Keywords: complexity; non-binding goals; cognitive effort; team production; weakest-link; non-monetary incentives; real-effort task

3.1 Introduction

In team production settings, problems of performance management and coordination failure among employees often necessitate the use of managerial interventions (Zehnder et al., 2017). Economic theory has traditionally focused on the use of monetary rewards to incentivize employees. However, evidence from behavioral economics (Frey and Jegen, 2001) and managerial economics (Gómez-Miñambres, 2012; Corgnet et al., 2015) suggests that providing non-monetary incentives, such as through a non-binding, wage irrelevant goal (e.g., a production or sales expectation), can also help foster performance. A non-binding goal is an attractive mechanism for managers as goals are presumably costless, and managers may not have direct control over monetary resources to help incentivize effort.

Examples of non-binding goals are evident in workplaces; a sales manager may suggest a recommended sales target or an earlier deadline for completion of other workplace tasks. Such non-binding goals may be thought of as behavioral "nudges". There is a large literature validating the use of behavioral nudges in a variety of contexts, e.g., nutrition and health (Samek, 2019; Vecchio and Cavallo, 2019), tax compliance (Fonseca and Grimshaw, 2017), and workplaces (Bulte et al., 2020; Wu and Paluck, 2021) among others.

An important and related issue is how to motivate team performance when tasks are complex, i.e., are objectively cognitively challenging. Based on an extensive review of the leadership literature in economics, Zehnder et al. (2017) highlight that as tasks become more complex, performance decreases and so does the effectiveness of monetary incentives. While studying task complexity in team settings is novel, predictions from studies focused on individual rather than group incentive mechanisms suggest that an increase in complexity leads to a decrease in the effect of monetary incentives on performance, with the exception of individuals that have high skill and a strong belief that they can accomplish the task (Bonner and Sprinkle, 2002). Laboratory evidence from accounting research supports this prediction and indicates that the probability of monetary incentives affecting an individual's performance positively decreases as task complexity increases (Bonner and Sprinkle, 2002). For this reason, Zehnder et al. (2017) recommend that researchers explore the use of both monetary and non-monetary incentives in complex task settings.

This paper studies task complexity in a strategic team setting and investigates the effects of non-binding goals on team performance. To the best of my knowledege, the only study that analyzes non-binding goals in a team setting is that of Fan and Gómez-Miñambres (2020). Using a laboratory experiment, they find that non-binding goals are effective at not only increasing performance but also in improving team coordination by reducing wasted performance. In their study, Fan and Gómez-Miñambres (2020) allow a subject who acts as a manager in order to assign a non-binding goal. While in theory the goal is allowed to differ in its difficulty level, in practice it turns out that about 50% of the time, managers set unreasonable goals i.e., goals that are too challenging for the weakest-link member. Further, what remains unclear is how task complexity interacts with non-binding goals. The experimental design in the present study, however, explicitly varies the goal which provides a relatively cleaner way of identifying effects of goal difficulty on performance respectively for simple and complex tasks.

The contributions of this study to the literature are as follows. First, I study task complexity in a strategic team production game and empirically explore a causal relationship between complexity and team performance.[1] Second, in a setting with monetary rewards present, I study the effects of introducing and varying a non-binding team goal. The specific behavioral mechanisms by which non-monetary incentives interact with task complexity and team performance are largely unexplored in the economics literature. To that end, a third contribution is to help identify behavioral mechanisms with the aid of a theoretical framework.

[1] It is important to mention the type of complexity that this paper speaks to. Campbell (1999) identifies several sources from which objective complexity may arise. In this paper, I specifically study complexity arising out of uncertainty, high information and cognitive load and unknown consequences of action.

Preliminary findings suggest that using team goals can alter production, but relationships between goal difficulty and production are not monotonic. While an easier goal reduces individual production, a rather challenging, difficult goal has no impact relative to no goal. At the same time, only a difficult goal seems to improve team production relative to no goal. A non-binding goal also helps minimize wasted performance thereby enhancing within-group coordination. There is evidence that easy goals may discourage individual production but at the same time this is not true for team production, i.e., effects differ when it comes to the weakest-link worker. Interestingly, when complexity increases i.e., higher cognitive costs are placed on individuals, the magnitude by which difficult goals increase team production is relatively smaller as goal difficulty increases. Further, as task complexity increases, while physical effort decreases, cognitive effort increases. Data collection is still in progress and these findings should be considered preliminary. Nevertheless, I expect the qualitative findings to persist with an increase in sample size.

3.2 Related Literature

Prior research has extensively studied the effects of group incentives as well as the effects of task complexity on team performance, often in isolation from each other. Some key takeaways from the various strands of literature are as follows. First, as task complexity increases, such that a higher cognitive load is placed on individuals, the probability of success on tasks and task performance itself tends to decrease (Campbell, 1988; Zehnder et al., 2017). While monetary rewards have been explored in order to incentivize performance on complex tasks, studies find that the probability that monetary rewards directly improve performance decreases as tasks become more complex (Bonner and Sprinkle, 2002; Zehnder et al., 2017). Considering this evidence, the literature encourages exploration of monetary as well as non-monetary incentives such as goals, in tandem (Zehnder et al., 2017; Locke and Latham, 2019). The intuition behind this is simple. There is a less than direct relationship between effort and performance in a complex task relative to one that may be cognitively less challenging. Motivated by this guidance, I attempt to explore the interactions between monetary and non-monetary incentives in a complex team production game.

Second, non-binding goals have been shown to improve team performance as well as coordination (Fan and Gómez-Miñambres, 2020). For decades, the literature on goal-setting has largely been concentrated to the study of individuals, however, recent studies have investigated goal setting in teams. Further, studies on goal-setting primarily span the management, leadership and empirical psychology literature; however, recently goals have also explored in the economic literature (Gómez-Miñambres, 2012; Corgnet et al., 2015). The literature does not directly explore the effects of non-binding goals on team performance when tasks are complex. However, research focused on individual decision-making settings finds that while goals are effective at increasing performance, their effectiveness depends on task complexity (Wood et al., 1987). In a team setting, it is natural to expect that an incentive combination of non-binding goals and monetary incentives may be effective in improving performance. Fan and Gómez-Miñambres (2020) study a weak-link team production game and use theory and experiments to explore the effects of non-binding team goals on performance. The present study extends this study in two important ways. First, I use a complex task, and vary the complexity level. Second, Fan and Gómez-Miñambres (2020) assign a manager to each team who sets a goal at the start of each decision round. This potentially clouds identification, and fundamentally changes the game into one where both the manager can influence workers (through the goal choice) and workers can influence the manager (through their behavior). Instead, I exogenously impose goals that are objectively easy, moderately challenging, or difficult for most participants.

Experiments on goal-setting in teams do not vary task complexity and therefore the question of how effective such goals are on performance in complex tasks remains open. One exception to this is the study by Nahrgang et al. (2013). The authors focus on different types of binding goals, specifically, learning and performance goals and analyze their impact on team performance while varying the level of task complexity. Given that their design is focused on testing "binding" goals without varying goal difficulty, the present study differs with respect to theirs in important dimensions. One, the setting I study is a weak-link team production game. The types of goals I study are non-binding and therefore serve as a non-monetary incentive. Also, the present study distinguishes goals with respect to their difficulty level rather than their content as in Nahrgang et al. (2013). Finally, I study a combination of monetary and non-monetary incentives (goals) which may have a differential effect on team performance as complexity level of the task changes.

Studies at the individual-level that explicitly vary goal difficulty find that goals are more effective when they are specific as opposed to vague and difficult as opposed to easy (Locke and Latham, 1990). As goals become more difficult, they become effective motivators, however, there are some exceptions to this finding. As goal difficulty increases, there may be some ambiguous effects on performance depending on task complexity, an individual's self-efficacy (their belief of reaching the goal), and goal commitment (Latham et al., 2002). What is unclear from the literature so far is the effect of goal difficulty in conjunction with task complexity on team performance. This is also where the present study's design can contribute to the literature by identifying effects of goal difficulty on team performance. Further, the idea here is to add a dimension of task complexity thereby contributing to the literature studying task complexity and its interplay with incentives.

The literature studying task complexity has separately explored the impact of monetary incentives and goals on team performance using real-effort tasks (Allison et al., 1993; Fan and Gruenfeld, 1998). Findings suggest that group incentives may be more effective with complex tasks and require team members to coordinate with each other. Overall, the literature is inconclusive about how the effectiveness of incentive schemes is altered by changes in task complexity primarily because either task complexity is not explicitly discussed in the study or not varied in the experimental design (Fan and Gruenfeld, 1998; Allison et al., 1993). Prior experiments only study task type in isolation, some of which are low-powered comparisons as well as do not directly vary the complexity level of the task within the experimental design (van Vijfeijken et al., 2002). Therefore, it is hard to make a clean comparison across studies of how changes in complexity of the task affect the incentive schemes and their effectiveness.

The idea of combining monetary and non-monetary incentives has been supported by prior research. The importance of wage-irrelevant goals has also been shown in principal-agent models (Corgnet et al., 2018). However, research on the interaction of monetary and non-monetary incentives is limited and more so when it comes to complex task environments. van Vijfeijken et al. (2002) propose that a combination of the two performance management methods i.e., incentives and goals may enhance performance depending on the task characteristics.[2] Brandts and Cooper (2007) analyze the effects of financial incentives and communication on coordination in a weakest-link game. While the study does not have an element of task complexity, it is useful to point out that combinations of monetary and non-monetary incentives have been explored when studying team performance. Participants assigned the role of manager choose the bonus rate for their assigned team, and the communication allowed varies across treatments (no communication, one-way communication, and two-way communication). The overarching result is that effective communication between managers and employees about benefits of high effort is a much more effective tool than increasing financial incentives (Brandts and Cooper, 2007).

Finally, an important goal of the present study is to highlight the underlying behavioral mechanisms through which team goals operate. In its simplest sense, a team goal acts as a coordination device. Social psychology, however, has suggested the importance of investigating alternative mechanisms tied to effectiveness of goals. The most popular idea in the goal-setting literature is to think of goals as a reference point (Corgnet et al., 2015; Fan and Gómez-Miñambres, 2020). The goal-setting

[2] The task characteristics specifically refer to the task complexity that determines the cognitive load placed on an individual.

literature suggests that difficult goals increase performance by motivating individuals to put forth more effort through an increase in the intrinsic rewards from goal achievement. On the flip side, expectancy theory and self-efficacy theory from social psychology suggest that difficult goals have two competing effects on performance. On one hand, a difficult goal decreases the likelihood of attaining the goal which reduces motivation thereby decreasing effort. On the other hand, the intrinsic reward from goal attainment increases when a difficult goal is achieved which increases effort (Meyer et al., 1988). As such, only when high intrinsic rewards from a difficult goal outweigh the low probability of attainment, both theories can be reconciled in their predictions. From the task complexity literature, it is not clear how performance responds to a change in the difficulty level of the goal. Therefore, the present study complements prior literature by identifying the relationship between goal difficulty and task complexity. Moreover, by highlighting behavioral motives triggered by non-binding goals, I attempt to integrate the study of leadership in economics with social psychology to understand how intrinsic incentives influence behavior.[3,4]

3.3 Theory

The theoretical framework builds on the seminal model of a coordination game by Van Huyck et al. (1990). The game involves a team of n players. Each player simultaneously exerts effort e_i and is paid an amount A for each unit of team production. Assume that an individual's "production" is a nonlinear function of effort, i.e., $y_i = q(e_i, \epsilon_i)$, where ϵ_i is a random shock to output, uncorrelated with e_i. Team production is determined by a weakest-link production function that imposes extreme strategic complementarity. In particular, let team production be denoted

[3]In this study, leader behavior is captured by the non-binding goal condition but there is no physical leader per se.

[4]Table 3.1 in Appendix C summarizes the experimental literature on exogenous goal-setting and compares the key elements to that of the present study.

by $M(\vec{y}) = min(y_1, y_2, ...y_n)$ such that team production is determined by the lowest individual production among all team members.

Let $C(\cdot)$ denote the cost-of-effort function which depends on the level of effort exerted by an individual, e_i, their ability parameter θ_i and complexity cost of the task, ζ. As ζ increases, cost of complexity increases, i.e., the task becomes more complex, all else equal. The cost function is continuous, twice-differentiable and strictly convex in effort, i.e., $C_e(\cdot) > 0$ and $C_{ee}(\cdot) > 0$. Players are asymmetric depending on their ability level and therefore face asymmetric cost-of-effort functions. For simplicity, I assume that players have complete information about the ability parameter of each team member.

In the absence of a non-binding goal, the worker's maximization problem is:

$$\max_{e_i} \Pi_i^w = A \cdot M(\vec{y}(e_i)) - C(e_i; \theta_i, \zeta) \tag{1}$$

The associated first-order necessary condition is:

$$C_e(e_i; \theta_i, \zeta) \leq A \cdot y_e(\cdot) \tag{2}$$

Note that equation (2) holds with equality for the weak-link worker for any $e_i \in [0, e^*]$, where e^* is the solution to (2). Given the relationship between output, y and effort e, I can obtain $y^* = q(e^*)$. The cost function is also increasing in the level of task complexity and therefore team production (dependent on output of the weak-link worker) will be decreasing in the level of task complexity. Due to the nature of the production function, there are multiple equilibria. Any combination of e_i that leads to equal individual production (y_i) for all workers constitutes a pure-strategy Nash equilibrium.

3.3.1 Non-binding goals and behavioral theories

A non-binding goal is a type of managerial incentive that has been shown to enhance productivity in the workplace. Non-binding goals are particularly attractive because a manager with limited monetary resources is able to provide a costless incentive to motivate his/her employees. In this section, I consider behavioral extensions to the theory based on prior work in management and psychology. The most popular idea in this literature is to think about a goal as a reference point (Heath et al., 1999). Fan and Gómez-Miñambres (2020) extend the basic model by Van Huyck et al. (1990) to include a reference-dependent utility from a non-binding goal.[5] Using their setup, I allow the task to differ in its complexity costs and the team goal to differ in its difficulty level.

Other popular mechanisms highlighted in the psychology literature rely on the self-efficacy and expectancy theory to explain observed effects of goals. Ideas from self-efficacy and expectancy theory together suggest that although goals are helpful motivators, their efficacy depends on the difficulty level of goals. This is based on the evidence that in some cases, goals may either be counterproductive or perhaps may not alter production at all. This theory suggests that there are both costs and benefits arising out of a goal (and its difficulty level) which suggests that the directional effect of goals on production will depend on whether its benefits outweigh the costs or vice versa. Finally, goals may establish a group norm for behavior such that an individual's utility is decreasing in deviations from the group goal. This theory suggests that goals may or may not raise production in comparison to the baseline model (without a goal) depending upon the difficulty level of the goal. Below I discuss these behavioral theories in detail.

[5]Note that the utility is non-monetary because there are no direct monetary gains/losses tied to the goal. If, however, the goal increases production, then of course the monetary gains associated with that production level would be higher.

3.3.2 Reference-dependent utility

In a model with monetary incentives and non-binding goals, a worker's payoff Π_i^w is a sum of his/her monetary gains from team production and non-monetary gains (losses) from reaching (not reaching) the goal less cost of effort:

$$\Pi_i^w(y(e_i), g, \zeta, A) = \begin{cases} A \cdot M(\vec{y}(e_i)) + v(y_i - g) - C(e_i; \theta_i, \zeta), & \text{if } y_i > g. \\ A \cdot M(\vec{y}(e_i)) + \lambda(v(y_i - g)) - C(e_i; \theta_i, \zeta), & \text{if } y_i \leq g. \end{cases} \tag{3}$$

Here, $v(\cdot)$ is the goal-dependent non-monetary utility function such that $v(\cdot) > 0$ for $y > g$, $v(\cdot) < 0$ for $y < g$, and $v(\cdot) = 0$ for $y = g$. $v(\cdot)$ satisfies the properties of prospect theory in non-monetary terms as shown by Heath et al. (1999) and Fan and Gómez-Miñambres (2020). $\lambda > 1$ represents the loss-aversion parameter and g is the non-binding team goal. The goal is quantified in terms of the team production level, and so a higher g corresponds to a more difficult goal.

The necessary first order condition associated with (3), with respect to a worker's effort level for a given complexity level ζ, is the following:

$$\Pi_e^w(.) = \begin{cases} C_e(e_i; \theta_i, \zeta) \leq A \cdot y_e(\cdot) + v'(y_i - g), & \text{if } y_i > g. \\ C_e(e_i; \theta_i, \zeta) \leq A \cdot y_e(\cdot) + \lambda(v'(y_i - g)), & \text{if } y_i \leq g. \end{cases} \tag{4}$$

Assuming there is a non-monetary utility associated with the non-binding team goal, production should be weakly higher than in the case with only monetary incentives (the baseline). If $y_i > g$, utility is higher than in the baseline. If, however, the worker fails to reach a goal i.e., $y_i \leq g$, utility is lower than the baseline. The model suggests that goals (whether they are easy or difficult) help by increasing effort thereby also enhancing production. Consider an example to understand the relationship between goals, effort and performance. Suppose, Betty's usual test-score is 70 on a scale of 100 points. Assume that she derives a non-monetary utility from a goal g set at 80 points. As per goal-setting theory, a goal of 80 would increase her motivation to study harder, i.e., this increases her effort and possibly her performance. If she is able to reach the goal and score 82 points, then besides an increase in her performance, there is also an increase in her total utility (because she derives a positive non-monetary utility from reaching the goal). If she is not able to reach the goal, and falls short by say 4 points then her score is 76 points. There is still an increase in performance but she derives a negative non-monetary utility from not reaching the goal. In both cases, performance responds positively to the goal but utility may or may not. All in all, when I compare the baseline model with the goal-setting model, a goal increases performance.[6]

3.3.3 Self-efficacy and expectancy theory

Self-efficacy is defined as the belief in one's own ability of completing a task (Bandura, 1997). According to this theory, self-efficacy is an important determinant of performance. In part, self-efficacy has to do with the confidence of an individual about how likely they are to complete a certain task. Put differently, self-efficacy is an individual's belief of attaining a certain goal. The relationship between one's own self-efficacy belief and performance is moderated by goal difficulty. So, as goals become more difficult, an individual's self-efficacy decreases. Further, there is evidence that self-efficacy decreases as task complexity increases (Wood et al., 2000). Typically, cost of effort in a simple real-effort task such as a slider task refers to physical effort while in complex real-effort tasks, it may involve both physical and cognitive or mental costs. For complex tasks, cognitive effort (e.g. search for strategies) probably matters more than just physical effort; low self-efficacy may inflict an additional cognitive cost besides the complexity cost on an individual. While this cost may be high or low depending upon many alternative factors, based on the self-efficacy theory, a reasonable specification is that the cost is an increasing function of goal difficulty.

[6]It is possible that some goals may be set too high and may seem unattainable to the individual. In such cases, typically workers reject goals or are not committed to the goals which explains similar behavior in the baseline v. goal-setting model.

A similar idea is proposed by expectancy theory from the psychology literature. According to expectancy theory, introducing a non-binding goal gives rise to two competing effects: (1) expectancy, i.e., subjective probability of goal attainment; and (2) valence, i.e., expected value of goal attainment (Meyer et al., 1988). The first effect is often referred to as task-specific confidence which decreases as goals become difficult. It captures the idea proposed by self-efficacy theory. The second effect refers to the utility gain from goal attainment. The social psychology literature argues that assigned goals could have negative, positive or no effects on performance depending upon which of the two competing effects (expectancy or valence) outweigh each other (Meyer et al., 1983; Meyer et al., 1988). Most empirical studies show that goals in general increase performance so it is likely that the valence effect is stronger; however, there are some cases where a negative or a null effect may be expected such as in cases of unattainable goals, i.e., difficult goals that lead to a decrease in an individual's self-efficacy.

Taken together, both theories highlight that there are competing positive and negative effects from goals and their interaction with task complexity. To capture the competing effects from expectancy theory and self-efficacy theory, I also consider a model where goals add to a cognitive cost in addition to a non-monetary benefit. The net effect on performance depends on the two competing channels. This model suggests that besides an increase in utility from reaching a non-binding goal, the goal may also impose an additional cost that increases in the value of the goal. This is distinct from the cost function considered in the previous discussion in that this cost is also sensitive to the value of the goal.

In this model, a worker's payoff Π_i^w is the sum of her monetary gains from team production and non-monetary gains from reaching the goal less total cost (physical and cognitive cost):

$$\Pi_i^w(y(e_i), g, \zeta, A) = A \cdot M(\vec{y}(e_i)) + F(y_i \geq g) \cdot f(g) - C(e_i; \theta_i, \zeta, g) \qquad (5)$$

where $f(\cdot)$ is the utility from the goal and it increases in the value of the goal i.e., $f'(\cdot) > 0$. $F(\cdot)$ is the probability that an individual reaches the goal. The probability increases as individual performance, y_i, increases and it equals 1 when the individual reaches the goal. The idea here is to capture that an individual's non-monetary gain is positive if they reach the goal, 0 otherwise. The cost $C(\cdot)$ is increasing in both the task complexity level and the value of the goal.

The necessary first order condition associated to (5), with respect to a worker's effort level for a given complexity level ζ is the following:

$$\Pi_e^w(.) = \begin{cases} C_e(e_i; \theta_i, \zeta, g) \leq A \cdot y_e(\cdot) + f(g), & \text{if } y_i \geq g. \\ C_e(e_i; \theta_i, \zeta, g) \leq A \cdot y_e(\cdot), & \text{if } y_i < g. \end{cases} \tag{6}$$

The equilibrium output will be weakly higher with a goal than without one, similar to the reference dependence model. But, an important difference here is that a relatively easier goal may increase output by more than what a difficult goal could. With an easy goal, the probability of reaching a goal $F(\cdot)$ is higher than with a difficult goal. So, it is more likely that an individual reaches the easier goal.

The interaction of task complexity and goal difficulty is important to this theory simply because while a difficult goal may add to an individual's cognitive cost, in a simple task, it is more likely to reach the goal by increasing effort than in a more complex task. The cost is such that it depends on an interaction between complexity and goal difficulty i.e., $\frac{dC''(\cdot)}{d\zeta dg} > 0$. This captures that a difficult goal triggers the cognitive cost in a complex task relative to a simpler task. If this is true, a simple goal does not add to the cognitive cost but only generates a non-monetary gain i.e., $f(g)$. Therefore, with a simple goal in any task (simple or complex), equilibrium output is higher with a goal than without and utility is higher if the individual is able to reach the goal.

The effects of a difficult goal in a complex task are slightly complicated. A difficult goal adds to the cost and also provides higher utility $f'(g) > 0$ but, at the same time, the probability of reaching a difficult goal is smaller for an easier goal, i.e., $F(\cdot)$ is decreasing in g. So, in cases where an individual believes she is very unlikely to reach a difficult goal, the goal only adds to her cost (refer to the FOC when $y_i < g$). In this case, the equilibrium output is lower with an easier goal and weakly lower than the no goal case. In the case an individual rejects the goal, the output will be the same as the basic model, i.e., without a non-binding goal.

For a simple task, the model predicts that the dominating mechanism is the utility gain from goal attainment while in a complex task, utility gain may be partly or fully offset by the cognitive cost of a goal. This explains why goals (even difficult ones) have a positive effect on relatively simpler tasks as compared to complex ones. If the non-monetary utility from goal attainment outweighs the cognitive cost that the goal imposes, then the goal should increase effort and performance. The opposite is true if costs outweigh the utility from goal attainment.

3.3.4 Social norms

In a team environment, it is natural for one's actions to be influenced by their peers. When production technology is such that it imposes a strong complementarity between team members' actions, effects of peer influence may be non-trivial. Research in the social psychology literature suggests that individuals tend to conform to peer behavior (Schnuerch and Gibbons, 2014). Akerlof and Kranton (2000) propose an identity model where individuals conform to a norm established by their social category. Further, norm-based interventions have been shown to foster what are considered positive behaviors such as reduced alcohol use or energy consumption (Miller and Prentice, 2016). This suggests existence and influence of social norms.

A non-binding goal may be thought of as an exogenously imposed norm. As such, social norms may arise in team production settings where team members derive a utility in conforming to the norm or a disutility in deviations from the norm. Social norms have been explored in the economics literature, however, their theoretical exploration in the context of non-binding goals is fairly limited. Fischer and Huddart (2008) study the existence of personal and social norms in a contracting model. While they study endogenous social norms, in the present study, it is more appropriate to consider a non-binding goal as an exogenous norm. The central idea is to add a cost function associated with deviations from the norm.

In a model with social norms, a worker's payoff Π_i^w is such that:

$$\Pi_i^w = A \cdot M(\vec{y}(e_i)) - C(e_i; \theta_i, \zeta) - h(y_i - g), \tag{7}$$

where $h(\cdot)$ is the social norm function such that $h'(\cdot)$, $h''(\cdot) > 0$. This indicates that the cost to an individual increases with a larger deviation from the social norm or goal 'g'. The cost is decreasing in the value of the norm such that $h_{yg} < 0$. As the goal value increases, effort increases, i.e., difficult goals increase effort. When comparing across models with and without goals, the social norm model is expected to predict the following. When the optimal performance in a team is such that $y^* < g_E$, where g_E is the easy goal, both easy and difficult goals are expected to increase performance relative to the baseline. However, when $y^* > g_E$, an easy goal will decrease effort and performance whereas a difficult goal will increase performance. This means that the model predicts that there exists a set of goals below which goals have negative effects on performance.

3.3.5 Main Hypotheses

Based on the study design and research question of interest, I am primarily interested in testing the following hypotheses. Because the behavioral theories give rise to differences in the directional effects of goals, expected effects in Hypotheses 3-6 are stated in reference to these theories.

H1: Individual production decreases as complexity increases.

H2: Team production decreases as complexity increases.

H3: Individual production increases when a non-binding goal is present if behavior is explained by the model of reference-dependence utility, ambiguous otherwise.

H4: Team production increases when a non-binding goal is present if behavior is explained by the model of reference-dependence utility, ambiguous otherwise.

H5: Individual production increases as goal difficulty increases if behavior is explained by the model of reference-dependence utility or social norms, ambiguous otherwise.

H6: Team production increases as goal difficulty increases if behavior is explained by the model of reference-dependence utility or social norms, ambiguous otherwise (depends on self-efficacy).

3.4 Experimental Design

The experimental design varies the: (a) presence/absence of a team goal; (b) goal type (easy, moderate and difficult), when a goal is present; and (c) complexity level of the task (low or high).[7] There are four between-subject treatments (no goal, easy goal, moderate goal, and difficult goal). The complexity level is varied within sessions, and whether the low or high level is encountered first will be randomized to help control for order effects. The treatments are summarized by Table 3.1.

3.4.1 Real-effort task: Ball-catching

The task employed is the ball-catching task introduced by Gächter et al. (2016). It requires participants to catch balls that fall from the top of the task box by using a tray at the bottom (see Figure 3.1). Participants can move the tray by clicking their mouse towards the left or right. The unique thing about this real-effort task is that "induced" costs are attached to each mouse "click". This gives the researcher a control

[7] Please note that throughout the rest of the paper, a simple task may also be referred to as a low complexity one while a complex task refers to the high complexity condition.

over costs such that the cost of complexity can be varied as per the experimental design. Balls fall at random in four separate columns as can be seen in Figure 3.1 and therefore add the element of "uncertainty" usually associated with complex tasks. The uncertainty exists throughout and forces participants to update strategies given the random falling pattern.

It is worth noting that this particular task helps separate physical effort from cognitive effort although the latter is still unobservable to an extent. Physical effort is defined as the number of clicks an individual makes in order to catch the balls. Cognitive effort, on the other hand, measures the amount of effort used in planning the scarce clicks. In the results section that follows, I analyze cognitive effort and discuss its measure in detail.

In the low complexity condition, the cost per click is 5 tokens while it is 20 tokens in the high complexity condition. The reward for catching one ball is 30 tokens; however, note that the group earns 30 tokens per catch only for the weakest or lowest scoring member of the group. The cost-to-prize ratio is 1/6 for the low complexity condition while for the high complexity condition it is 4/6, i.e., cost in the complex condition is four times that of the simple condition. When the cost of a mouse click and the cost-to-prize ratio is small (1/6), the number of predicted clicks is large. When the cost-to-prize increases (4/6), it increases cognitive effort as participants are expected to think hard and plan the number of clicks more carefully. Therefore, the high complexity condition depicts a scenario where physical effort and cognitive effort both matter for profit maximization. This is especially true given the weakest-link production technology in the theory and related experiment. Further, the task fits in the definition of a complex task as defined by Campbell (1988).

3.4.2 Pilot experiment and power analysis

To help inform the experimental design, a pilot experiment was conducted using the no goal treatment. Participants were drawn from the same population and experimental procedures followed the final protocols described later.

In addition to the ball-catching task described above, I also considered the verbal rule task, as employed by Oprea (2020). In this task, physical and cognitive costs are entirely unobservable. The task involves showing participants a verbal rule to be implemented on a sequence of letters selected randomly and shown one at a time. The Participants' task is to correctly implement the rule. The benefit of using this task is that it objectively defines complexity and it is easy to alter in order to make the task as simple or complex as needed. Two pilot sessions were conducted to test the verbal-rule task (Oprea, 2020) and the ball-catching task (Gächter et al., 2016). The pilot session for the verbal-rule task revealed lower than usual variation in measures of individual and team production across the low and high complexity conditions, partly due to the scoring rule chosen. Further, there was uncertainty in whether participants were just "guessing" to get at the correct answer. Based on pilot testing, it was deemed appropriate to use the ball-catching task for this study. Data from the ball-catching task pilot is not included in the analysis at this point but given that procedures and parameters were very similar, it may be included in future analyses.

Based on the estimated individual-level variances from the pilot (no goal treatment), the sample sizes required for tests to be sufficiently powered are N=80 (NG, EG), N=65 (MG) and N=50 (DG). The analysis assumes 10 decision rounds for each of the two complexity levels (low or high) and allows for correlation across rounds. Using the suitable econometric methods and the planned sample sizes, power calculations suggest the following.

In the simple condition, the minimum detectable effect (MDE) size is 1.5 units when comparing between NG and EG treatments. A comparison between NG and MG gives an MDE of 2 units while it is 2.5 units between NG and DG. In the complex condition, the minimum detectable effect size for the several between-subject comparisons is - 1.8 units (NG and EG), 2 units (NG and MG) and 2.3 units (NG and DG). Goal-setting studies find that the impact of goals on production ranges from 10-30% (Fan and Gómez-Miñambres, 2020). This means the smallest treatment effect in a low complexity task would be 2.3 units while that in a high complexity task will be 1.9 units. Overall, the total sample size of 275 participants should be sufficient to identify said differences.

Power calculations are of course only approximations as the true underlying outcome distributions are unknown. I expect lower variation in individual and group production for the goal treatment, and to the extent this is true, the calculations above are under-estimates of the minimum detectable effect sizes. Moreover, controlling for other factors, such as participant characteristics, in the econometric models is expected to increase power as these factors should explain variation in outcomes but be uncorrelated with treatment assignment.

3.4.3 Non-binding Goals

For a weakest-link team production game, there are important considerations about whether to set the team goal based on individual performance or that of the team. A team goal with this production technology basically targets the weakest-link worker within a team. Note that the manager's objective is to maximize monetary payoffs from team production, and a team goal consistent with profit maximization should be based on the weakest-link worker's performance. If goals are set with this notion in mind, the team should ideally respond to reasonable goals; if not, unreasonable goals may not have any effect on team production (Fan and Gómez-Miñambres, 2020).

In order to determine where to set the goals, I rely on the distribution of team production outcomes from the no goal treatments (N=30 including data from the pilot). For the simple task, the goals are 16 (easy), 20 (moderate) and 24 (difficult) and as for the complex task, they are 11 (easy), 15 (moderate) and 19 (difficult).

These goals reflect the 20^{th} (easy), 50^{th} (moderate), and 90^{th} (difficult) percentiles of the respective team production outcome distributions from the pilot.

3.4.4 Experimental Procedures

A typical experimental session proceeds as follows. Participants are assigned an ID number tied to their order of entry into the online experiment via Zoom. The experiment instructions are displayed using Zoom's screenshare feature, and the same moderator reads instructions aloud while participants follow along. In addition, the moderator follows several lab protocols mentioned in the consent form before getting the experiment started. Participants are informed that instructions contain only true information, and their decisions will be kept anonymous. All decisions are made on the participants' personal computers. The moderator encourages questions, which are asked through online chat, and exchanges are private to the inquiring participant and the moderator. The experiment is programmed and facilitated using the software z-Tree (Fischbacher, 2007) as well as z-Tree unleashed (Duch et al., 2020).

In all treatments, participants are randomly placed in three-person groups at the start of each round and therefore members of every group randomly change throughout the experiment.[8] The design is such that there is an exogenous manager/leader that depicts the two broad types of incentive conditions i.e., a monetary incentive with no team goal versus a monetary incentive with a team goal recommendation.

The participants first go through a paid risk elicitation task using the design by Holt and Laury (2002) in order to elicit risk preferences. Following this, during the second stage, the participants go through a loss aversion task. The goal here is to gauge whether participants' preferences are consistent with loss aversion therefore the task only varies the loss amount in each lottery while keeping the gain amount fixed.

[8]This particular design choice is made to ensure that any endogenous goal formation from repeated interactions with the same people overtime do not act as a confound in identifying effects of exogenously set goals.

It is implemented in accordance with procedures described by Bibby and Ferguson (2011) and Gächter et al. (2022).

In the third stage, participants engage in the team production experiment. In each round, every group member is assigned the ball-catching task to complete within a minute (60 seconds). After the task has been completed, the group members see a result screen with the individual and group outcomes (individual score, group score, total individual cost and individual earnings) i.e., the design incorporates individual and group feedback. Particularly for the goal treatments, participants are also shown whether their team met the goal in a round. Following similar procedures, each group plays the game for 10 rounds with the low complexity level, and then another 10 rounds with the high complexity level.[9]

The monetary payoff of a player is:

$$\Pi_i = A \cdot \text{group score} - \text{cost} \cdot \#\text{ of clicks} \tag{8}$$

Participants earn $A = 30$ tokens for every ball caught by the team, i.e., by the lowest performing member. The payoff is determined by subtracting the participant's total cost of clicking (determined by their individual # of clicks and cost per click) from the reward. At the end of the experiment, participants are paid their earnings from two separate rounds selected at random (one from the low complexity condition and the other from the high complexity condition).

Note that the group reward is determined by the parameter $A = 30$ while the cost tied to clicks is specific to task-type - low complexity ($cost = 5$) or high complexity ($cost = 20$). While the cost of clicks is observable given the unique real-effort task, cognitive costs are still unobservable and therefore total cost may still be weakly higher in the high complexity condition.

[9] Note that, the order of simple or complex tasks will be varied in the experiment overall, but, given the preliminary data, all sessions use the order of simple task followed by complex. The reason is simply to avoid order effects from confounding potential treatment effects in a small sample.

3.4.5 Participants

Four experiment sessions were conducted in July 2022. In total, I have data from 60 participants (not including the pilot). All sessions were conducted online and facilitated via Zoom. Undergraduate students enrolled at the University of Tennessee were recruited from a large existing database that had previously registered to receive invitations for economics experiments. People were not allowed to attend more than one session of the experiment. Earnings in the ball-catching task were dominated in "tokens" and exchanged for U.S. dollars at an announced exchange rate. The experiment lasted approximately 75 minutes and on average participants earned $19 for the session.

Table 3.4 describes the experiment data. Overall, 68% of participants are female, and 84% had participated in a prior economics experiment. Forty-one percent can be characterized as risk averse based on the incentivized risk elicitation task while 76% may be characterized as loss averse. Responses from the post-experiment questionnaire suggest that a majority (69%) felt they were sufficiently compensated. In response to a Likert-scale question that ranged from "1" ("poorly understood") to "5" ("well understood"), the vast majority (84%) selected a 4 or 5, indicating a strong self-assessment of how well instructions were understood.

3.5 Results

3.5.1 Individual and team production

I begin the analysis with linear regression models of production (i.e., number of catches) at the individual and group level, where the latter is as defined as the production of the group member with the lowest individual production. In regressions with individual-level observations, I cluster standard errors by participant and by decision round (for participants within the same session). This allows for within-person serial correlation as well as contemporaneous correlation across participants within the same session. For regressions with group-level observations, errors are clustered to allow contemporaneous correlations across groups within the same session. I define Round from 0 through 9 for both complexity conditions (low and high) such that the variable resets to 0 when the task changes in complexity.

Table 3.4 presents a basic regression analysis of the effects of task complexity on individual production. Model (1) pools data from all treatments while models (2) through (5) are specific to the goal condition (i.e., no goal, easy, moderate and difficult goals, respectively). In all models, I reject the null hypothesis that individual-level production is equal between the low and high complexity conditions. Based on Model (1), production at the individual-level is approximately 3.8 points lower in the high complexity condition, but the point estimates vary slightly across goal conditions with the highest difference being when a difficult goal is assigned (approximately 5.6 points). This result is not surprising as the complex condition increases both physical as well as cognitive costs for participants and therefore output is expected to decrease. Table 3.5 adds controls to all specifications from Table 3.4. While the magnitudes decrease due to presence of strong time trends, the directional results are robust to inclusion of controls for all models.

Table 3.6 presents the team production analog to Table 3.4. Based on the coefficients, I can reject the null hypothesis that team production is statistically equal between the low and high complexity conditions across Models (1), (2), (4) and (5). Altogether, there is support for Hypothesis 1 and 2.

Table 3.7 presents regression specifications that can be used to test Hypotheses 3-6. Specification (1) pools data from all goal treatments, and the variable "Goal" is an indicator variable that equals 1 if a goal (easy, moderate or difficult) is assigned to the team. The interaction of task type with the "Goal" indicator helps identify effects of having a goal in the low or high complexity conditions relative to the no goal setting. This model reveals that a goal has no effect on individual production, on average, in either of the two settings. A popular result from the in the experimental psychology literature is that non-binding goals help improve an individual's performance (Locke and Latham, 2002). This result has been established with respect to tasks that do not necessarily place a cognitive load on individuals, however, note that prior studies do not exogenously vary the goal. Instead, a subject acts as a manager and assigns goals to teams. As mentioned earlier, Fan and Gómez-Miñambres (2020) find that about 50% of the time, managers set goals that are too challenging or "unrealistic" such that team production does not respond to goals. This is evidence that managers may not always set goals that maximize team production. Turning to effects of goals on team production, Table 3.8 is the team analog to 3.7 and it depicts how goals influence the weakest-link worker's production. Results suggest that in a pooled model, goals have no effect on team production in either a low or high complexity condition.

To identify effects of goal difficulty on production, specification (2) in Table 3.7 and 3.8 allows the effects of easy, moderate and difficult goals on individual and team production to differ by task type. Specification (3) adds controls to (2). Results suggest that easier goals tend to lower individual production in the low complexity condition (by 1.5 points approximately); however, moderate or difficult goals have no impact relative to the no goal treatment. Adding controls does not change the quantitative effects of goals but depicts presence of a strong time trend. Based on specification (3) in 3.7 and 3.8, easy goals decrease individual production relative to no goals, however, there production is not altered when goals are either moderately challenging or difficult. With respect to team production, while easy goals have no significant impact on production, difficult goals appear to increase production. A difficult goal has a relatively large effect (almost double) on production compared when task complexity is low. Goal effectiveness is defined as the magnitude (in %) by which a non-binding goal increases production relative to a no goal setting. Based on the results so far, difficult goals seem to be more effective when task complexity is low compared to the high complexity condition.

It is also worthwhile to compare how production at the individual and team level differs across the three goal types while holding complexity fixed. Specification (3) in 3.7 and 3.8 can be used to compare the coefficients on the interaction of task with goal type. In the low complexity condition, this comparison reveals that individual production is statistically higher when a a moderate or a difficult goal is assigned relative to an easy goal ($p < 0.10$; $p < 0.01$). For the high complexity condition, individual production is statistically higher when a moderate or a difficult goal is assigned relative to an easy goal ($p < 0.05$; $p < 0.01$). Differences do not arise between moderate and difficult goals. With respect to team production, differences arise between difficult v. easy and difficult v. moderate goals in the low complexity condition ($p < 0.01$; $p < 0.05$). For the high complexity condition, differences arise between easy v. difficult ($p < 0.01$) and moderate v. difficult ($p < 0.05$). There are no differences across easy and moderate goals.

Effects of the control variables are as follows. Individual and team production decreases as the experiment progresses. This is expected in general because the weakest-link production technology induces coordination in production outcomes, i.e., higher-performing individuals are likely to learn that they are wasting effort early in the game, leading to lower effort as the experiment progresses. Prior experience in economics experiments, a higher average GPA, being risk averse and loss averse also lower individual production. The results are summarized below.

Result 1. Individual and team production reduces as complexity costs increase.

Result 2. Individual production is statistically lower between the baseline (no goal) treatment and treatments with a non-binding goal. This result holds for easy goals.

Result 3. Team production is statistically higher between the baseline (no goal) treatment and treatments with a non-binding goal. This result holds for difficult goals.

Result 4. Easier goals tend to lower *individual* production by a slightly larger magnitude for the low complexity condition, relative to the high complexity condition.

Result 5. The magnitude of goal effectiveness on *team* production is lower for the low complexity condition, relative to the high complexity condition. This holds true for difficult goals.

3.5.2 Physical and cognitive effort

In this section, I analyze individual and team effort, precisely the number of clicks.[10] Table 3.9 presents the results from the exact empirical specifications as before. When a task is complex, it reduces effort (i.e., the number of clicks) by approximately 6.5 units.[11] This is evidence that high complexity costs may demotivate individuals and discourage effort relative to tasks with a lower cost. This further solidifies Result 1. Moreover, effort decreases when an easy goal is assigned in a high complexity condition. There are no significant effects of moderate or difficult goals on effort. Accounting for task-specific time trends, it seems that effort is relatively higher with moderate goals relative to easy or difficult goals.

Analysis of team effort (Table 3.10) indicates that effort is lower when complexity is high (by about 5 units). Further, it depicts that difficult goals increases effort but the magnitude of goal effectiveness is much higher in the low complexity condition. Typically a complex task would discourage physical effort given that there is a relatively lower control over the output. This is what results indicate in general. But, when analyzing the effects of goals in conjunction with task complexity, differences arise only for a few comparisons. A case could be made about higher effort as complexity increases if say an individual has higher than average ability. A similar ambiguity holds for cognitive effort, but typically higher amount of cognitive effort is required in high complexity relative to low complexity conditions.

As the self-efficacy theory suggests that goals in conjunction with complex tasks could impose higher cognitive costs, it may be worthwhile to analyze cognitive effort for several goal conditions. While cognitive effort remains unobservable for the most

[10] Gächter et al. (2016) derive theoretical predictions for effort under different cost-to-prize ratios. By using a similar approach as theirs I show that the estimates of the ball-catching production function in the present study, $q(\cdot)$, is not very different from theirs. Please see section C.2 in Appendix C for details.

[11] Note that as the cost of complexity, measured by cost per click, increases, physical effort becomes a rather incomplete measure of the overall effort exerted. With clicking becoming more expensive, individuals need to exert more cognitive effort as well in order to utilize the scarce clicks. For this reason, I also analyze a measure of cognitive effort later on in the analysis.

part, this particular task does provide a crude way of measuring it. Insights from data analysis and the questionnaire specific to cognitive effort are discussed below.

Cognitive effort may be defined as "catches per click" as when individuals spend time carefully planning their clicks so as to catch more balls per click. If complex tasks do place a high cognitive cost on individuals relative to simple tasks then, the cognitive effort is expected to increase under such conditions. Table 3.11 reports the results for individual production while Table 3.12 depicts results for team production.

Specification (1) shows that cognitive effort is statistically higher in the high complexity condition relative to the low complexity condition by approximately 2 points. Put simply, for every click that an individual makes, they catch 2 more balls in the high complexity condition relative to the low complexity condition. The post-experimental questionnaire asked individuals to state whether they had to think more carefully and plan every click when the cost was higher (i.e., the high complexity condition) and 93% stated "Yes". Finally, with respect to the effect of goals on cognitive effort, there are no significant differences except marginal evidence that a difficult goal reduces cognitive effort in both task types. This is somewhat suggestive of a cognitive cost placed by a challenging, difficult goal as suggested by self-efficacy theory since the magnitude is higher for complex tasks (see interactions of task type with difficult goals in Tables 3.11 and 3.12).

Result 6. Task complexity appears to decrease physical effort but increase cognitive effort.

3.5.3 Within-group coordination and wasted performance

In this subsection, I analyze the effects of goals on individuals' attempts at coordination in production outcomes. I start by analyzing wasted production which is defined as the difference between an individual's production (number of catches) and the team production (the lowest performing member's number of catches) per round. This measure captures wasted performance on a team. By definition, this value is zero for the weakest-link member.

Table 3.13 presents specification to help identify the effects of goals on wasted performance or production.[12] Specification (1) depicts the pooled model and shows that a non-binding goal reduces wasted production regardless of its difficulty level. However, this is only true, on average, for the low complexity task. Therefore, coordination may not depend directly on goal difficulty for the low complexity task. Goals, on average, do not alter wasted production when task complexity is high.

Specification (2) and (3) show that easier goals reduce wasted production for both the low and high complexity levels while difficult goals do so only when complexity is low. While goal difficulty may have some opposing directional effects on production as highlighted in the prior analysis, overall it seems that a goal reduces the variance of production thereby reducing wasted performance relative to a no goal treatment. Easier goals reduce wasted production with a relatively higher magnitude when it comes to a high complexity task. However, difficult goals tend to reduce production only when complexity is low. Fan and Gómez-Miñambres (2020) find in a team setting that goals minimize wasted performance thereby enhancing coordination in production outcomes among team members, which is indicative of the results in the present study as well. Across all three specifications, there are no differences between wasted production between the low and high complexity levels.

Result 7. A non-binding goal helps reduce wasted performance thereby enhancing coordination.

3.5.4 Behavioral mechanisms underlying non-binding goals

The questionnaire includes several items to help evaluate the behavioral effects of non-binding goals. More specifically, it includes rating questions that help compute

[12] I chose to rely on linear regression models, although another alternative empirical specification could be a poisson regression.

an individual's own-assessment of their self-efficacy. These questions ask individuals to rate how confident they are when solving difficult problems, accomplishing goals set by a superior or their own personal goals. Further, there are a few Likert-scale rating questions that provide evidence of whether individuals have a tendency to follow a group's social norm.

Based on the preliminary data, the average self-efficacy score on a scale of 0 to 600 is 478 and 90% of the present sample state high self-efficacy. Further, it appears that individuals are more confident or possess a high self-efficacy belief in the no goal (NG) treatments relative to the easy goal (EG) treatment which suggest that both effort and production is expected to be lower with an easy goal relative to the no goal case. This is in fact what results reveal. There are no statistical differences in the overall self-efficacy belief score for the two other pairwise comparisons (NG and MG; NG and DG). The Likert-rating on the more direct social norm questions do not appear to provide any evidence with respect to social norms. There is evidence to show that participants are more likely to follow group behavior when no goal is present. This could be a potential reason why some of the differences between the no goal treatment and goal treatments appear relatively small. Regardless, the fact that easy goals reduce both production and effort seem to point toward the directional effects expected under the social norm model. If individuals anchor to the goal assuming that the team collectively aims for goal attainment, then an easier goal may not motivate individuals to try harder once the goal is attained.

The questionnaire also included an item designed to identify and control for any personal goals that individuals may have set for themselves. This is done to validate that individual's effort and production respond to exogenous team goals rather than unobservable personal goals. Seventy-seven percent of the participants state that they did not set any personal goal and therefore it is highly unlikely to be a confounding factor. Further, the relatively small proportion of participants who do set personal goals is balanced between the three goal treatments.

The loss-aversion task conducted in the second stage of the experiment reveals interesting findings. In a low complexity task, being loss averse tends to decrease individual production in treatments with no goal and an easy goal while it increases individual production when the goal is difficult. As task complexity increases, being loss averse only tends to lower individual production in treatments with no goal while increases it when goals are either moderately challenging or difficult. This would appear to further increase the treatment effect for the comparison between difficult goal v. no goal case while lowering the treatment effect between easy goal v. no goal. However, based on the results for individual production, it seems quite the opposite is happening. Despite the shrinkage effect that loss aversion may have on the treatment effect (easy v. no goal), easier goals still appear to lower individual production. Based on the evidence so far, it seems that a theory of self-efficacy is more likely to explain the results. A higher self-efficacy score in the no goal case may be responsible for higher production levels relative to the treatment with easy goals. The directional effects do seem in line with a theory of social norms, but at the moment there isn't overwhelming evidence supporting it based on the questionnaire data.

3.6 Conclusion

The goal of this study is to test the effectiveness of non-monetary incentives in a weakest-link team production game where individuals are paid based on team production and tasks are of a complex nature. I do so by conducting an online experiment where teams are engaged in tasks that differ in their complexity, and the level of a non-binding team production goal (and whether there is a goal) is varied across teams. Further, by studying complexity in a strategic team environment, this study helps identify how task complexity affects the relationship between incentives and performance.

Prior literature provides suggestive evidence that the effectiveness of monetary incentives decreases as tasks become more complex. Therefore, the management literature highlights the importance of non-monetary incentives and transformational leadership behaviors (Zehnder et al., 2017). The effects of goals on performance may be ambiguous and may very well depend on conditions such as task complexity, goal difficulty, and their interactions. The present study provides a direct test of non-binding goals under these conditions.

Preliminary results appear to support some conjectures while refute others. First, I find that production and effort levels decrease as complexity increases. Second, while an easier goal reduces individual production, a rather challenging, difficult goal has no impact relative to no goal. At the same time, only a difficult goal seems to improve team production relative to no goal. Third, a non-binding goal decreases wasted performance thereby enhancing within-group coordination. There is evidence that easy goals may discourage individual production but at the same time this is not true for team production suggesting that the effects of goals differ when it comes to the weakest-link worker. This is somewhat surprising given that individual-level studies find that goals in general improve performance (Corgnet et al., 2015). Finally, when complexity increases, i.e., higher cognitive costs are placed on individuals, the magnitude by which difficult goals increase team production is relatively smaller as goal difficulty increases. Further, as task complexity increases, while physical effort decreases, cognitive effort increases.

This is the first study that exogenously varies the goal to identify effects of goal difficulty. The results provide some insight on the underlying behavioral motivations of people when a non-binding goal is present. As production is not monotonically increasing in goal difficulty, this suggests that a theory of reference-dependent utility inadequately explains behavior in the experiment. Instead, results seem to be more consistent with a theory of self-efficacy and expectancy. Data from the questionnaire provides an indication that self-efficacy beliefs do differ across the goal and no goal treatments. Presently, self-efficacy is higher in the no goal case relative to other treatments and therefore production is expected to be similar or even higher in the no goal treatment than the goal treatments. Despite that, difficult goals appear to improve team production which suggests that difficult goals motivate the weakest-link worker to work harder. Given the opposite directional effects of easier goals, I also suspect that a theory of social norms may be a potential explanation for when goals are too easy. At present, the evidence on behavioral mechanisms is mixed. However, as I collect more data the present study will be sufficiently powered to identify how exogenous goals affect production. It will help understand how goal difficulty affects production depending on task type. Moreover, the study will be able to provide insight into the psychological make up of employees by identifying behavioral mechanisms underlying a non-binding goal.

Overall, this study provides important insights for managers. First, it explores the importance of non-monetary incentives that may be used in organizations. More specifically, by investigating a relationship between goal difficulty and task complexity, the study helps to identify effective goal-incentive combinations.[13] Present findings indicate that setting goals that are difficult may be better if the manager's goal is to improve team production because easier goals may end up in the team coordinating on lower production levels.

The broader goal of the study is to contribute to a more comprehensive view and understanding of incentives in workplaces. This type of a team production game not only captures environments in organizations but also collaboration between researchers and so the results are applicable to a wide variety of economic settings. A comparison that has been of interest but remains unexplored is how teams perform when multiple goals exist at the same time. Although experimentally it is easy to add a condition with more than one goal, it may be challenging to address it in the theory setup considered here. Nevertheless, it remains an open question for future research. The expected results as well as the experimental design further serve as

[13]While varying both the group incentive and goals would have been ideal, it leads to a very large design that may not be feasible. Another reason I consider variance is goals rather than monetary incentives is that the task complexity literature highlights that changes in monetary incentives are not closely related to performance and therefore, I expect that this comparison would not lead to interesting effects.

a building block to incorporate and more formally investigate the impacts of non-monetary leadership tools such as transformational and charismatic leadership styles on team performance. A potential area for future research would be to induce a competitive context such as a Tullock contest (Eisenkopf, 2014; Eisenkopf, 2020).

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Appendix

Appendix C

Appendix

C.1 Tables

Table 3.1: Summary of exogenous goal-setting experiments

Study	Goal-difficulty	Complexity	Goal Type	Setup	Design	Behavioral Theories
Earley et al. (1989)	Yes	Yes	Not mentioned	Individuals	Classroom	–
Nahrgang et al. (2013)	–	Yes	Binding	Teams	Lab	–
Chen and Latham (2014)	–	Yes	No incentives	Individuals	Lab	Automaticity
Smithers (2015)	Yes	–	Non-binding	Individuals	Lab	–
Corgnet et al. (2015)	Yes*	–	Non-binding	Individuals	Lab	Reference-dependence
Fan and Gómez-Miñambres (2020)	Yes*	–	Non-binding	Teams	Lab	Reference-dependence
This paper	Yes	Yes	Non-binding	Teams	Online/lab	Reference-dependence; Self-efficacy; Social Norms

Notes: * This study assigns a manager who sets non-binding goals that may or may not differ every period and it is not necessarily the case that goals increase in difficulty monotonically. Such a design means low variation in goals and that goals vary within a session. Goal-difficulty refers to whether the study varies the difficulty level of the goal explicitly. Complexity refers to whether the study varies the complexity level of the task. The last column titled "Behavioral theories" identifies whether the study highlights underlying mechanisms for goal-effectiveness.

Table 3.2: Summary of treatments

	Complexity	
Incentives	Low ($c = 5$)	High ($c = 20$)
Monetary (without goal)	NG	NG
Monetary (with easy goal)	EG	EG
Monetary (with medium goal)	MG	MG
Monetary (with difficult goal)	DG	DG

Table 3.3: Description of data

Variable Name	Description	Mean	S.D.
Treatment variables			
Low	= 1 when the task has a low complexity cost (cost=5); 0 otherwise	0.50	0.50
High	= 1 when the task has a high complexity cost (cost=20); 0 otherwise	0.50	0.50
Goal	= 1 when a goal (easy, moderate or difficult) is assigned; 0 otherwise	0.75	0.43
EG (Easy)	= 1 when an easy goal is assigned; 0 otherwise	0.25	0.43
MG (Moderate)	= 1 when a moderate goal is assigned; 0 otherwise	0.25	0.43
DG (Difficult)	= 1 when a difficult goal is assigned; 0 otherwise	0.25	0.43
Control variables			
Risk Averse	= 1 if participant selected safe option at least six times in Risk Elicitation task; 0 otherwise	0.41	0.49
Experience	= 1 if the participant had partaken in a prior economics experiment; 0 otherwise	0.84	0.36
Female	= 1 if participant is female; 0 otherwise	0.68	0.46
Employed	= 1 if participant is partly or fully employed, 0 otherwise	0.71	0.45
Loss Averse	= 1 if participant's loss aversion parameter $\lambda > 1$	0.76	0.42
Age	Recorded age of the participant	21.70	2.73
GPA	Participant GPA, recorded as midpoint of chosen interval	3.48	0.36
Earnings	Participants earnings from the experiment in $	18.76	3.25
Comprehension	Rating of instruction comprehension, scale 1 to 5	4.31	0.96
Round	Decision round in the experiment, 0 to 9 for each task (low and high complexity)	4.50	2.87

Table 3.4: Analysis of individual production

	Dep. Var.: Individual-level production				
	(1) Pooled	(2) No goal	(3) Easy	(4) Moderate	(5) Difficult
Constant	23.82***	24.21***	21.69***	23.40***	25.97***
	(0.349)	(0.713)	(0.637)	(0.705)	(0.622)
High	−3.82***	−3.21***	−2.59***	−3.82***	−5.66***
	(0.445)	(0.903)	(0.923)	(0.902)	(0.811)
Low × Round	−0.13**	−0.16	0.08	−0.01	−0.42***
	(0.061)	(0.127)	(0.116)	(0.126)	(0.105)
High × Round	−0.21***	−0.33**	−0.26**	−0.09	−0.150
	(0.070)	(0.152)	(0.131)	(0.147)	(0.131)
R-squared	0.179	0.154	0.207	0.166	0.252
Observations	1200	300	300	300	300

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. No controls. Task-specific trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: Analysis of individual production (with controls)

	Dep. Var.: Individual-level production				
	(1) Pooled	(2) No goal	(3) Easy	(4) Moderate	(5) Difficult
Constant	30.20***	40.16***	30.66***	30.16***	38.01***
	(1.624)	(2.913)	(2.439)	(3.513)	(3.345)
High	−3.76***	−3.21***	−2.85***	−3.24***	−5.66***
	(0.452)	(0.911)	(0.991)	(0.903)	(0.818)
Low × Round	−0.13**	−0.16	0.08	0.01	−0.42***
	(0.061)	(0.123)	(0.120)	(0.109)	(0.109)
High × Round	−0.21***	−0.32**	−0.23*	−0.11	−0.15
	(0.069)	(0.137)	(0.121)	(0.137)	(0.117)
Experience	−1.83***	−0.14	−2.92***	−1.99***	−0.32
	(0.356)	(0.874)	(0.763)	(0.762)	(0.881)
Female	−0.51	2.60***	−1.62***	−1.87**	1.38*
	(0.321)	(0.623)	(0.485)	(0.772)	(0.765)
Risk Averse	−0.66**	3.38***	0.73	−4.73***	0.23
	(0.313)	(0.839)	(0.682)	(0.587)	(0.619)
GPA	−1.04**	−4.60***	−0.73	−0.99	−3.90***
	(0.449)	(0.801)	(0.722)	(1.035)	(1.002)
Loss Averse	−0.74**	−4.22***	−3.59***	1.19	1.20**
	(0.332)	(0.814)	(0.591)	(0.739)	(0.573)
R-squared	0.215	0.264	0.339	0.375	0.346
Observations	1160	300	280	280	300

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. Task-specific trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6: Analysis of team production

	Dep. Var.: Team production				
	(1) Pooled	(2) No goal	(3) Easy	(4) Moderate	(5) Difficult
Constant	19.92***	19.80***	17.99***	19.21***	22.67***
	(0.622)	(1.058)	(1.002)	(0.311)	(0.774)
High	−3.94***	−4.11**	−1.91	−3.92***	−5.82***
	(0.645)	(1.411)	(1.326)	(0.331)	(0.894)
Low × Round	−0.02	−0.05	0.21	0.13*	−0.35**
	(0.097)	(0.152)	(0.176)	(0.069)	(0.114)
High × Round	−0.22***	−0.17	−0.35***	−0.12	−0.26***
	(0.056)	(0.126)	(0.102)	(0.099)	(0.045)
R-squared	0.362	0.282	0.392	0.389	0.503
Observations	400	100	100	100	100

Notes: Cluster-robust standard errors in parentheses; clustered by round. Task-specific trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.7: Analysis of individual-level production: goal effects

	Dep. Var.: Individual Production		
	(1)	(2)	(3)
Constant	23.49***	23.49***	30.57***
	(0.364)	(0.364)	(1.570)
High	−3.95***	−3.95***	−3.60***
	(0.579)	(0.580)	(0.621)
High × Easy Goal		−1.60***	−1.70***
		(0.584)	(0.594)
High × Moderate Goal		−0.38	−0.41
		(0.622)	(0.636)
High × Difficult Goal		0.11	−0.28
		(0.589)	(0.592)
Low × Easy Goal		−1.45***	−1.40***
		(0.480)	(0.489)
Low × Moderate Goal		−0.13	−0.57
		(0.500)	(0.497)
Low × Difficult Goal		0.59	0.20
		(0.478)	(0.491)
Low × Round			−0.13**
			(0.060)
High × Round			−0.21***
			(0.069)
Experience			−1.79***
			(0.361)
Female			−0.43
			(0.332)
Risk Averse			−0.81***
			(0.311)
GPA			−1.07**
			(0.442)
Loss Averse			−0.592*
			(0.341)
Low × Goal	−0.331		
	(0.410)		
High × Goal	−0.622		
	(0.505)		
R-squared	0.172	0.190	0.230
Observations	1200	1200	1160

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. Task-specific trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.8: Analysis of team production: goal effects

	Dep. Var.: Team Production		
	(1)	(2)	(3)
Constant	19.60***	19.60***	19.66***
	(0.510)	(0.513)	(0.697)
High	−4.66***	−4.66***	−3.73***
	(0.595)	(0.598)	(0.884)
High × Easy Goal		−0.42	−0.42
		(0.540)	(0.429)
High × Moderate Goal		−0.18	−0.18
		(0.423)	(0.397)
High × Difficult Goal		0.74*	0.74**
		(0.435)	(0.336)
Low × Easy Goal		−0.68	−0.68
		(0.696)	(0.705)
Low × Moderate Goal		0.18	0.18
		(0.596)	(0.603)
Low × Difficult Goal		1.50**	1.50**
		(0.679)	(0.677)
Low × Round			−0.02
			(0.081)
High × Round			−0.22***
			(0.051)
Low × Goal	0.333		
	(0.587)		
High × Goal	0.0467		
	(0.379)		
R-squared	0.351	0.374	0.381
Observations	400	400	400

Notes: Cluster-robust standard errors in parentheses; clustered by round. Task-specific trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.9: Analysis of individual effort

	Dep. Var.: # of clicks		
	(1)	(2)	(3)
Constant	13.67***	13.67***	15.20***
	(0.577)	(0.578)	(0.820)
High	-6.57***	-6.57***	-6.99***
	(0.759)	(0.76)	(0.748)
High × Easy Goal		-1.35**	-1.35**
		(0.624)	(0.617)
High × Moderate Goal		-0.08	-0.08
		(0.680)	(0.675)
High × Difficult Goal		0.89	0.89
		(0.747)	(0.743)
Low × Easy Goal		0.28	0.28
		(0.928)	(0.923)
Low × Moderate Goal		0.25	0.25
		(0.844)	(0.838)
Low × Difficult Goal		2.37***	2.37***
		(0.851)	(0.847)
Low × Round			-0.34***
			(0.119)
High × Round			-0.25***
			(0.080)
Low × Goal	0.96		
	(0.692)		
High × Goal	-0.18		
	(0.566)		
R-squared	0.224	0.235	0.246
Observations	1200	1200	1200

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. Task-specific time trend is included.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.10: Analysis of team effort

	Dep. Var.: (# of clicks)		
	(1)	(2)	(3)
Constant	7.760***	7.760***	8.23***
	(0.436)	(0.438)	(0.482)
High	-5.040***	-5.040***	-4.61***
	(0.566)	(0.569)	(0.499)
High × Easy Goal		-0.50	-0.50
		(0.450)	(0.367)
High × Moderate Goal		0.20	0.20
		(0.501)	(0.418)
High × Difficult Goal		0.58	0.58*
		(0.409)	(0.345)
Low × Easy Goal		-0.44	−0.44
		(0.514)	(0.528)
Low × Moderate Goal		-0.06	−0.06
		(0.565)	(0.584)
Low × Difficult Goal		2.54***	2.54***
		(0.644)	(0.609)
Low × Round			-0.10
			(0.069)
High × Round			-0.20***
			(0.028)
Low × Goal	0.68		
	(0.544)		
High × Goal	0.09		
	(0.402)		
R-squared	0.432	0.473	0.485
Observations	400	400	400

Notes: Cluster-robust standard errors in parentheses; clustered by round. Task-specific time trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.11: Analysis of individual-level cognitive effort

	Dep. Var.: catches/clicks		
	(1)	(2)	(3)
Constant	2.22***	2.22***	2.07***
	(0.117)	(0.117)	(0.146)
High	2.35***	2.35***	1.60***
	(0.331)	(0.332)	(0.350)
High × Easy Goal		-0.13	-0.11
		(0.416)	(0.411)
High × Moderate Goal		-0.43	-0.42***
		(0.430)	(0.423)
High × Difficult Goal		-0.72*	-0.71*
		(0.398)	(0.396)
Low × Easy Goal		0.16	0.16
		(0.208)	(0.208)
Low × Moderate Goal		-0.13	-0.13
		(0.144)	(0.143)
Low × Difficult Goal		-0.42***	-0.42***
		(0.133)	(0.133)
Low × Round			0.03
			(0.020)
High × Round			0.20***
			(0.053)
Low × Goal	-0.13		
	(0.135)		
High × Goal	-0.43		
	(0.348)		
R-squared	0.149	0.155	0.175
Observations	1162	1162	1162

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. Task-specific time trend included.
*** p<0.01, ** p<0.05, * p<0.1.

Table 3.12: Analysis of team-level cognitive effort

	Dep. Var.: catches/clicks		
	(1)	(2)	(3)
Constant	3.21***	3.21***	2.98***
	(0.365)	(0.367)	(0.402)
High	3.94***	3.94***	2.21***
	(0.812)	(0.816)	(0.690)
High x Easy Goal		-0.60	-0.40
		(0.932)	(0.798)
High × Moderate Goal		-0.39	-0.39
		(1.087)	(0.804)
High × Difficult Goal		-1.59*	-1.52**
		(0.803)	(0.749)
Low × Easy Goal		0.48	0.48
		(0.511)	(0.510)
Low × Moderate Goal		-0.36	-0.35
		(0.394)	(0.392)
Low × Difficult Goal		-0.92**	-0.92**
		(0.379)	(0.375)
Low × Round			0.05
			(0.047)
High × Round			0.43***
			(0.084)
Low × Goal	-0.27		
	(0.403)		
High × Goal	-0.89		
	(0.805)		
R-squared	0.242	0.261	0.314
Observations	363	363	363

Notes: Cluster-robust standard errors in parentheses; clustered by round. Task-specific time trend is included. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.13: Analysis of wasted performance: individual-level

	Dep. Var.: Wasted Production		
	(1)	(2)	(3)
Constant	3.88***	3.88***	4.40***
	(0.342)	(0.342)	(0.436)
High	0.71	0.71	0.13
	(0.520)	(0.521)	(0.652)
High × Easy Goal		-1.18**	-1.18**
		(0.540)	(0.540)
High × Moderate Goal		-0.20	-0.20
		(0.590)	(0.590)
High × Difficult Goal		-0.63	-0.63
		(0.581)	(0.581)
Low × Easy Goal		-0.77*	-0.77*
		(0.450)	(0.450)
Low × Moderate Goal		-0.31	-0.31
		(0.481)	(0.481)
Low × Difficult Goal		-0.91**	-0.91**
		(0.447)	(0.447)
Low × Goal	-0.66*		
	(0.385)		
High × Goal	-0.66		
	(0.480)		
R-squared	0.015	0.015	0.018
Observations	1200	1200	1200

Notes: Cluster-robust standard errors in parentheses; clustered by round and subject. *** p<0.01, ** p<0.05, * p<0.1.

C.2 Predictions for effort: Ball-catching task

In this section, I present the theoretical predictions of individual effort arising from the ball-catching task. Gächter et al. (2016) derive the predicted number of clicks, however, their parameters are slightly different from the one used in this study. For this reason, I use the data in this study to estimate the individual production function i.e., relationship between catches and clicks and then use this estimate to predict number of clicks for the low and high complexity conditions respectively. In order to estimate the production function, I rely on the empirical strategy from Gächter et al. (2016). The functional form specification that fits the data is presented below and estimated using a random coefficients panel regression.

$$Catches_{it} = \beta_0 + \beta_1 Clicks_{it}^{0.5} + \beta_2 Clicks_{it}^{2} + (\delta_t + \omega_i + \mu_{it}) Clicks_{it}^{0.5} \tag{8}$$

where $Catches_{it}$ and $Clicks_{it}$ denote the number of catches (output, y) and the number of clicks (effort, e) by subject i in period t. δ_t is the period dummy, $\omega_i \sim (0, \sigma_\omega^2)$ denotes the subject-specific random effect and $\mu_{it} \sim (0, \sigma_\mu^2)$ is the randomly distributed error term.

In order to estimate equation (8), it is transformed by dividing throughout with $Clicks_{it}^{0.5}$ and then estimated using a standard random effects approach.[1] Coefficient estimates from the panel data regressions are reported in Table C.1. Column (1) reports estimates from the full sample (i.e., pooling low and high complexity conditions) while (2) and (3) provide estimates computed separately for both conditions. The estimates are fairly stable across the three models except for the squared clicks term in (3). This could be due to a relatively smaller sample but point predictions do not significantly change if we were to ignore the squared clicks term in (3). Models (2) and (3) are used predict the number of catches and clicks depending on task type.

[1]Please refer to Section 3.3 in Gächter et al. (2016) for details.

Table C.2 compares the predicted number of clicks with the observed averages for several conditions.[2] Results suggest that the observed number of catches and clicks are slightly different from what is predicted. In most cases, magnitudes are small, however, the predicted number of clicks in the low complexity condition is about 9 points higher than the actual number of clicks. One reason why this is the case may be that the weakest-link production setting greatly reduces variation between the weakest-link member and other team members in an effort to minimize own costs. This would reduce average clicks for all individuals and not just for the weakest-link member. The other plausible explanation is that predictions include goal treatments as well which may have counteracting effects on the number of clicks depending on goal type. If we were to remove the goal treatments, or restrict the specification to the data from teams, estimates may not be very stable given the present sample size.

Comparing estimates from regressions in Table C.2 to that of Gächter et al. (2016) shows some promise as coefficients are similar in magnitude. Finally, note that these predictions only account for the material cost of complexity i.e., the cost induced through clicks, however, it does not capture the cognitive costs so these predictions are more likely to be upper bounds of production and effort.

[2] Note that given the weakest link team-production function, I derive the point predictions for the weakest member and this provides a lower bound for other individuals whose catches may be weakly greater than that of the weakest-member.

Table C.1: Empirical production function: Panel data regressions

	Dep. Var.: Number of Catches		
	(1) Full sample	(2) Low ($c = 5$)	(3) High ($c = 20$)
Intercept	10.34***	10.23***	10.93***
	(0.304)	(0.499)	(0.460)
$\text{Clicks}^{0.5}$	3.63***	3.83***	3.36***
	(0.231)	(0.247)	(0.327)
Clicks^2	-0.003***	-0.005***	0.003
	(0.001)	(0.001)	(0.002)
σ_ω	0.118***	0.233***	0.111
	(0.054)	(0.058)	(0.124)
σ_μ	1.256***	0.877***	1.533***
	(0.026)	(0.025)	(0.046)
Observations	1162	599	563

Notes: All period dummies are included and are insignificant except period 6 in (1); period 2 and 6 in (2). *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Comparisons between predictions and observed team averages

	Low Complexity		High Complexity	
	Catches	Clicks	Catches	Clicks
Prediction	25.97	23.12	19.39	6.34
Observed (individual)	23.23	14.39	19.06	6.96
Difference (t-test)	-2.73***	-8.72***	-0.32	0.62***

Notes: *** p<0.01, ** p<0.05, * p<0.1.

C.3 Figures

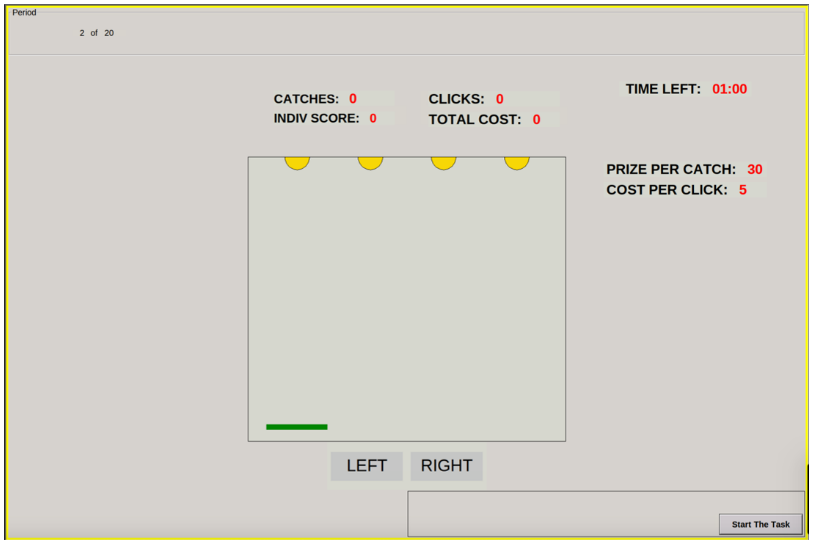

Figure 3.1: Decision Screen, No Goal Treatment

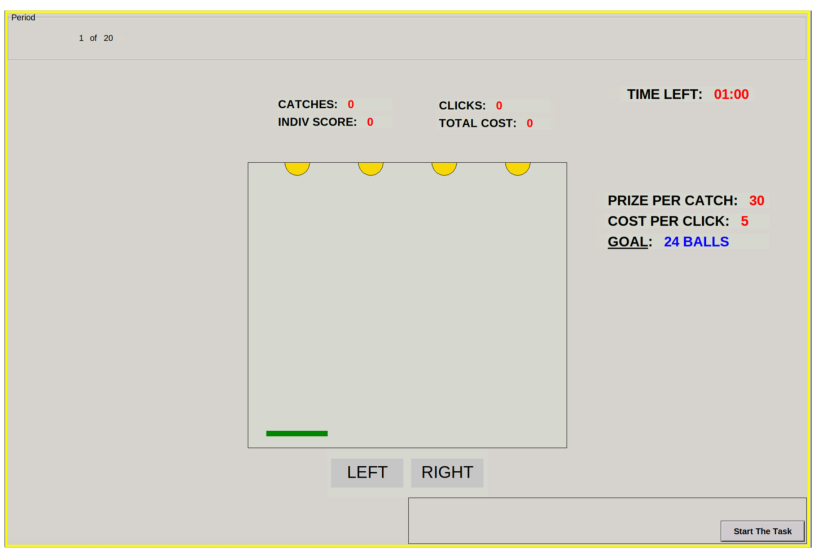

Figure 3.2: Decision Screen, Goal Treatment

C.4 Experiment Instructions

Thank you for participating in today's study.

You will make decisions using a computer, and your decisions will be associated with a randomly assigned ID number. You will never be asked to reveal your identity to anyone. Your name will never be associated with any of your decisions. In order to keep your decisions private, please do not reveal your choices or otherwise communicate with any other participant. Importantly, please refrain from verbally reacting to events that occur.

Today's session has four parts: Experiment 1, Experiment 2, Experiment 3, and a short questionnaire. You will have the opportunity to earn money in all experiments based on your decisions. In addition, you will receive a show-up fee of $7 for completing today's session. You will be paid your earnings privately, and via an amazon gift card, at the end of the experiment session. We will proceed through the written materials together. Please do not enter any decisions on the computer until instructed to do so.

Instructions for Experiment 1

In this experiment, all money amounts are denominated in US dollars. Please refer to your experiment screen while we read the instructions.

We would like you to make a decision for each of 10 scenarios. Each scenario involves a choice between playing a lottery that pays either $4 or $0 according to specified chances (Choice A) or receiving $2 for sure (Choice B).

You will notice that the only differences across scenarios are the chances of receiving the high or low prize for the lottery. At the end of the today's session, ONE of the 10 scenarios will be selected at random and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Before making decisions, are there any questions?

Please proceed to entering decisions on your computer. Once you are ready to submit your decisions, please click the "Submit" button.

Instructions for Experiment 2

In this experiment, all money amounts are denominated in US dollars. Please refer to your experiment screen while we read the instructions.

We would like you to make a decision for each of the 6 scenarios. Each scenario involves a choice between playing a lottery or not. In each scenario, if you choose to play the lottery (Choice A), there is a 50% chance you will you win $3 and a 50% chance you will lose a specified amount. If you do not play the lottery, (Choice B), you earn $0.

You will notice that the only difference across scenarios is the amount at stake to lose by playing the lottery. At the end of the today's session, ONE of the 6 scenarios will be selected at random, and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Note that, in contrast to the previous experiment, if you choose to play the lottery there is a 50% chance of losing money. If this happens, the amount of the loss will be subtracted from your overall earnings in the experiment (i.e., show-up fee, earnings from Experiments 1 and 3).

Before making decisions, are there any questions?

Please proceed to entering decisions on your computer. Once you are ready to submit your decisions, please click the "Submit" button.

Instructions for Experiment 3

In this experiment, all money amounts will be denominated in tokens. At the end of each experiment tokens will be converted to US dollars at a rate of 100 tokens = $1. This experiment has a total of 20 decision rounds. At the start of each round, you will be randomly placed into a group of three players. The members of your group will vary from one round to the next. In each round, you and the other members of your group will be asked to work on a computerized ball-catching task.

Ball-catching task

In each round, there will be a task box in the middle of the task screen like the one shown below:

<insert Figure 3.1 (Figure 3.2) here for no goal (goal) treatment>

Each round lasts one minute. Once you click on the "Start the Task" button, the timer will start, and balls will fall randomly from the top of the task box. You can move the tray at the bottom of the task box to catch the balls by using the mouse to click on the "LEFT" or "RIGHT" buttons.

To catch a ball, your tray must be below the ball before it touches the tray. When the ball touches the tray, your CATCHES increase by one.

Your individual score is calculated as the number of balls you catch multiplied by 30 tokens.

For each mouse click YOU make, you will incur a cost. YOUR individual cost will be 5 tokens per click for the first 10 rounds. In the last 10 rounds, you will incur a cost of 20 tokens per click. Your total cost is equal to the total number of clicks multiplied by 5 or 20 tokens depending on the round.

In each round, the number of balls YOU have caught so far (displayed as CATCHES) and the number of clicks you have made so far (CLICKS) will be shown right above the task box. Also shown above the task box will be your individual score (displayed as INDIV SCORE), which is CATCHES multiplied by the prize per catch and TOTAL COST, which is CLICKS multiplied by the cost per click.

<u>Your Earnings</u>

When you and the other members of your group have finished the task, the computer will calculate your earnings, which will depend on the group score. The group score is equal to the lowest individual score among your group members (including yours).

Your earnings for a decision round will be calculated as follows:

Round Earnings = group score (in tokens) – YOUR total cost (in tokens)

Example. Suppose YOU catch 10 balls by making 5 clicks, then your individual score is 30 tokens $\times$ 10 balls = 300 tokens. Your total cost is 20 tokens $\times$ 5 clicks = 100 tokens.

Suppose further that your group members each catch 20 balls by making 10 clicks i.e., their individual score is 30 tokens $\times$ 20 balls = 600 tokens each. In this case, the group score is 300 tokens because YOU were the lowest scoring member in your group.

Your earnings in this example would then be 300 (group score) – 100 (your total cost) = 200 tokens.

Group performance goal ***(only included in the goal treatments)***

Your group will be assigned a performance goal – a recommended number of balls you and your group members should catch within a round. The goal will be displayed to the right on your decision screen.

Please know that whether you meet the goal will not impact your earnings. Your earnings will depend on the group score (lowest individual score in your group) as well as your total cost of clicking, as described in the instructions.

At the end of each decision round, the computer will display whether your group met the goal, your individual score, your total cost, the group score and your earnings. Any questions?

Proceeding through the experiment

You will now go through a total of 20 decision rounds. At the start of each round, you will be randomly placed into a group of three players. This means that the members of your group will vary from one round to the next.

The number of catches, total cost, your score, and the group performance goal will be displayed on your screen in every round. Your decision screen will look like the example provided in the instructions.

To determine the amount of money you earn from this experiment, the computer will randomly select two of the 20 rounds (one for the first 10 rounds and the other from the last 10 rounds). Your earnings from the two selected rounds will be converted into dollars and added to your earnings total for the experiment.

Each decision round is separate from the other rounds, in the sense that the decisions you make in one round will not affect the outcome or earnings of any other round.

Since you do not know which rounds will be selected, you should make choices in each round carefully.

Before we continue, do you have any questions?

Before continuing, we would like you to answer a few questions to make sure you understand the procedures. Here is the good news: for each question you answer correctly, you will earn 25 cents. You will have a total of 150 seconds (2.5 minutes) to answer all questions. You may use a calculator if you wish.