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Piece-rates and tournaments: Implications for learning in a cognitively challenging task

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ABSTRACT

We compare the impact of piece-rate and tournament payment schemes on learning in a cognitively challenging task. In each one of multiple rounds, subjects are shown two cue values, Cue A and Cue B, and asked to predict the value of a third variable X, which is a noisy function of the two cue values. The subjects' aim is to predict the value of X as accurately as possible. Our metric of performance is the absolute error, i.e., the absolute distance between the actual and predicted values of X. We implement four treatments which are based on two different payment schemes: (1) piece rates, where subjects are paid linearly on the basis of their own absolute errors and (2) a two-person winner-take-all-tournament, where subjects are paired and the one with a smaller absolute error earns a fixed payoff, while the other earns nothing. We find that it is only in the tournament payment scheme, and particularly in a more complex version of the task, that subjects show significant evidence of learning over time, in that their predictions get closer to the actual value of X. This learning process is driven by the all-or-nothing nature of the payoff structure in tournaments.

1. Introduction

Piece-rates and tournaments are two oft-used mechanisms for paying workers. However, piece-rates, which pay individual workers on the basis of cardinal output, are hard to implement where output cannot be easily observed or measured. In such cases, employers often rely on tournament pay schemes that pay on the basis of relative rather than absolute output or performance. Theoretical analyses of tournaments (e.g., Lazear and Rosen, 1981; Green and Stokey, 1983; Nalebuff and Stiglitz, 1983) show that in many cases tournaments are effective in eliciting effort at a level analogous to piece rates. This insight is borne out by results in a classic laboratory experiment by Bull et al. (1987), where they show that, on average,

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numerical effort choices made in tournaments are statistically no different than those under piece rates, though the variance of effort choices in tournaments is larger.

However, prior studies have not really focused on which type of payment schemes foster better learning, especially in tasks that are complex and cognitively challenging. Part of this is due to the fact that most prior studies implement somewhat mechanistic tasks that do not provide scope for learning over time.[1] In fact, existing evidence suggests that in tasks that require significant learning over time, the reward structure may play a crucial role in enhancing or impeding that learning. Merlo and Schotter (1999) study learning in the stylized two-person tournament introduced in Bull et al. (1987) except in the former, one player is replaced by a computer, which always chooses the same effort number and subjects are informed of the computer's effort choice.[2] This has the effect of transforming the two-person tournament into an individual decision making exercise where subjects are essentially looking to find the maximum of the underlying payoff function. Merlo and Schotter (1999) report that subjects' choices in the final round are much closer to the Nash equilibrium in the *Learn-before-you-earn* (LBYE) treatment (where subjects play for 74 rounds without getting paid and then play a 75th round with substantial money at stake) than those in the *Learn-while-you-earn* (LWYE) treatment (where subjects play for 75 rounds with small payments in each round). This is mostly due to the fact that in the LWYE treatment subjects adopted a much more "myopic" view of the task by focusing on wins or losses in each round. Those in the LBYE treatment, on the other hand, engaged in greater "experimentation" in the non-payment rounds in an attempt to identify the optimum.[3]

Given that many, if not most, tasks in the field and certainly all so-called "white-collar" jobs require cognitive effort, it is of interest to understand which commonly used payment schemes, if any, lead to better facility at the task. Therefore, in this paper, we explore the impact of payment schemes on learning, using a multiple cue probabilistic learning (MCPL) task introduced by Brown (1995, 1998). We provide details of the task below in the section on experimental design. Here, we provide an overview. In each of multiple rounds subjects are shown two cue values (Cue A and Cue B) and asked to predict the value of a variable (X), which is an unknown noisy function of those two cue values. The cue values shown to subjects change from one round to the next but the (deterministic part of the) underlying function does not. The goal for the subjects is to make accurate predictions on the basis of the cue values shown to them in each round, where accuracy is measured by the absolute distance of their predicted value from the actual value of the variable. This absolute prediction error, i.e., |(Actual value of X) − (Predicted value of X)|, is our metric for performance. The smaller the absolute error, the better the productivity. By *learning* we will refer to decreasing absolute errors (increasing productivity) over time, which, in turn, implies increasing prediction accuracy. We implement four different treatments that are based on two different payment schemes: *piece-rate* refers to a linear payment scheme that relies only on the subject's own absolute error; in the *winner-take-all tournament* payment scheme, in each round subjects are paired and the winner earns a fixed amount, while the loser earns nothing. The remaining treatments manipulate the nature of the feedback provided to the subjects, allowing us to isolate the factors that impact learning. We also manipulate task difficulty, by employing two versions of the task described above. In the simpler, single cue version, one of the cues (cue A) is fixed for the duration of the experiment, whereas in the more complex, dual cue version, both cues are changing randomly from one round to the next.

We observe that while there are no differences in learning patterns, in terms of increasing prediction accuracy, across pay schemes for the simpler task, learning in the more complex task is facilitated most by a winner-take-all tournament. Evidence from an additional control treatment suggests that it is the winner-take-all nature of the payment scheme that fosters this effect of tournament incentives on learning, rather than the provision of relative rank information. The effect is particularly pronounced for those who were adept at the task to start with; but even those who were not, perform relatively better over time under a tournament payment scheme as compared to the others. We proceed as follows. In Section 2 we explain our experimental design. In Section 3 we present our results and finally in Section 4 we discuss the results and make some concluding comments.

[1] For instance, Kuhnen and Tymula (2012) and Cadsby et al. (2010) use an arithmetic task, where subjects are asked to add a sequence of five two-digit numbers without recourse to calculators, as in Niederle and Vesterlund (2007), while Charness et al. (2014) use a decoding task. These tasks mainly rely on mechanical effort in order to do well; there is nothing to 'learn' per se. Our task is different, in that, it is cognitively challenging. In order to improve forecasts, subjects need to uncover the underlying relationship between the cue values and the actual value of X, or at least, get as close to it, as possible. Our task relates more closely to those used to specifically study the processes and mechanics of learning. For example, in Merlo and Schotter (1999, 2003) players need to search for the equilibrium best response that maximises payoffs. In multi-player strategic games (Cardella, 2012; Charness and Levin, 2005; Erev and Roth, 1998; Rick and Weber, 2010; Roth and Erev, 1995) the 'way to play' is often prescribed as a dominant strategy (or, at least, one that is not dominated), which players should learn to play over time.

[2] This, in turn, implies that payoff is maximized by simply choosing what the computer is choosing in each round, i.e., 37.

[3] Chaudhuri et al. (2006) extend Merlo and Schotter's (1999) study by adopting an inter-generational framework, where a group of subjects are recruited into the lab and play the same stage game for 10 rounds. Each player can then leave advice for his laboratory descendant, who then plays the game for another 10 rounds as a member of a fresh group of subjects. Chaudhuri et al. find that the presence of advice makes a difference in that the experimental groups who get advice perform better – their decisions are closer to the Nash equilibrium – compared to a control group of subjects that plays the game with no recourse to such advice. Iyengar and Schotter (2008) also rely on the Merlo and Schotter (1999) framework but use two-player teams, where one player is allowed to pass advice to another, who can choose to ignore this advice. In one treatment, ignoring advice is costly while in another, it is costless. Iyengar and Schotter (2008) report that when advice is costly to ignore both advisors and advisees learn to make decisions that are closer to the Nash equilibrium.