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A note on peer effects between teams

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Abstract We run an experiment to test for peer effects between teams. The subjects perform a team-work task in pairs of payoff-independent teams. They receive feedback about the outcome of their own and the paired team. Consistent with peer effects, we find that this feedback induces substantial correlation of effort choices between teams. The correlation translates into the variation of outcomes within and across pairs of teams.

Keywords Peer effects · Organization of work · Public good experiments

JEL Classification C92 · H41 · J2

1 Introduction

Falk and Ichino (2006) report strong effects of exposing workers to peers. The subjects in their experiment perform an individual task and receive payments which are independent of output. The authors compare the output of subjects who work alone with that of subjects who perform the same task at two separately located desks in the same room. Consistent with peer effects, they observe a polarization of output in

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the pair condition. Average output is higher in this condition, and the least productive workers react most strongly to peers.

In this study we run an experiment to test whether peer effects exist when work is organized in teams. Moreover, we aim at contributing to an understanding of the mechanisms that generate such effects. In our design, we randomly subdivide a group of subjects into two independent teams. The subjects perform the same task in each team. To mimic team production, exhibiting effort in this task is costly, but free-riding causes an externality on others within the team. In treatment MUTUAL, the subjects mutually observe the output of the own and the other team. In treatment BASE, they only know the output of the own team. With this design we are able to keep peer effects between the teams apart from repeated game effects within the teams.

The question of whether peer effects exist in teams has significant implications for the organization of work. Individual contributions to team output cannot be frequently enforced, which renders team work susceptible to free-riding. The puzzle is why modern work organizations nevertheless make heavy use of teams.[1] Recent theoretical contributions, which have proposed peer effects as a motive why workers abstain from free riding, associate peer effects with social preferences which induce individuals to conform with the actions of others (e.g., Kandel and Lazear 1992; Barron and Gjerde 1997; Che and Yoo 2001; Huck et al. 2003; Huck and Rey-Biel 2006). This literature illustrates that the benefits of peer effects depend on the nature of preferences that generate these effects as well as the context and institution to which they apply.

The institution used by Falk and Ichino (2006) implemented a fixed payment for performing a task which was independent between subjects. A plausible explanation, consistent with their results, is that the subjects experience a loss in utility if their effort, which is observable to others, deviates from that of peers. This effect could be associated, for instance, with feelings of shame or the fear of appearing incompetent to others.[2] Presumably, more complex mechanisms apply in work processes with effort externalities between workers. Mas and Moretti (2008) analyze the productivity of cashiers in supermarkets to identify peer effects. A feature of the task of cashiers is that, by working slowly, they can cause additional workload for their peers. This feature provides an incentive to free-ride within work-teams. The authors find strong positive peer effects that dominate free-riding. Interestingly, these effects exist only for workers who are in the line-of-vision of their peers. Finally, Bandiera et al. (2005) find a related result, albeit in a situation where individual effort imposes a negative externality on others. They find that workers compress effort under relative incentives. But again, this effect exists only if the workers can be monitored by others.

The subjects in our experiment are anonymous and they receive no feedback on the individual choices of others. By implementing these features into the design we

[1]For example, Osterman (1994) finds that 55 percent from a 1992 survey of American establishments employ teams. According to Lawler (2001), even 72 percent of Fortune 1000 companies make use of work teams.

[2]Houser and Xiao (2006) illustrate the power of shame. In a cooperation game they find that a weak punishment has a large effect if the norm violators can be publicly observed. This effect ceases to exist or even turns into negative if the same punishment is implemented privately.

resemble the core idea of having non-enforceable efforts in teams. On the other hand, we have just illustrated that the possibility to observe individual effort is likely to be an important ingredient to the process of generating peer effects. Hence, the same mechanism that causes free-riding in teams appears to weaken the scope of peer effects to mitigate this behavior.

Our study reveals that the feedback about the performance of the other team induces substantial correlation between the efforts in teams. This correlation leads to greater homogeneity within paired teams and greater heterogeneity across pairs of teams. These findings are consistent with the existence of peer effects. Unlike Falk and Ichino (2006) and Mas and Moretti (2008), we detect no impact of these effects on the aggregate efficiency in our design.

2 Experimental design

The subjects participate in a standard linear public good game. This game constitutes a typical team dilemma since every team member profits from the team output regardless of whether he or she bears the cost of individual effort. Subjects are randomly organized into teams. There are 4 people in each team and each subject is endowed with 20 experimental points. The points can either be kept or invested into a joint team project that generates a payoff for everyone in the team. Payoffs are determined according to $\pi_i = 20 - x_i + \alpha \sum_{h=1}^{4} x_h$. Here, π_i is subject i's payoff in points, x_i is i's contribution to the team project, and α is the marginal per-capita return of contributing to the team project. In the experiment, α has a value of 0.4.

The game is repeated over 20 periods with the composition of teams held constant. In every period, at the time a new decision has to be made, the subjects receive feedback about the total sum of contributions of their team as well as their private earnings in the previous period. In addition, we provide information about the average team earnings accumulated over all previous periods (see the journal web page for the instructions).

The design has two treatments. Treatment "BASE" implements the standard version of the public good game. The subjects play the game in isolated teams and receive the above mentioned information about their own team. In treatment "MUTUAL", a group of 8 subjects is randomly subdivided into two teams X and Y, so that for every team X there exists a team Y. The subjects in team Y are paid according to $\pi_j = 20 - y_j + \alpha \sum_{k=1}^{4} y_k$, where π_j and y_j denote payoff and contributions of subject j in team Y. Note that the payoffs in a team X are independent of the contributions in team Y. Hence, subjects still play the game in isolated teams. The only difference between the treatments is the information available to the subjects. In MUTUAL they additionally learn about the performance of the paired team. In particular, in every period the subjects see the last period's overall contributions and the accumulated average earnings in the paired team. This information enables the subjects to evaluate their relative team performance in the previous period as well as in the experiment as a whole. The instructions ensure that this information is common knowledge.

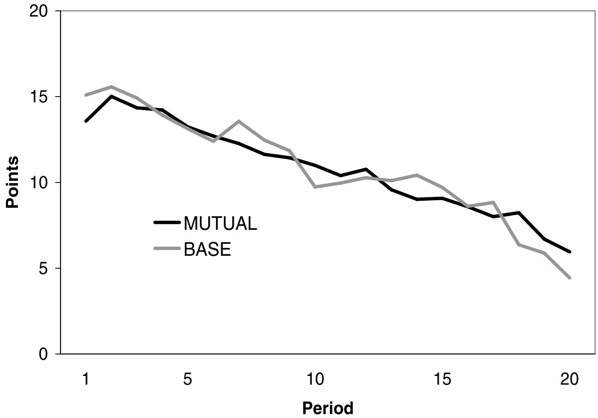


Fig. 1 Time series of average contributions

3 Experimental results

The experiment was run at the University of Innsbruck. A total of 196 undergraduate students from various majors participated. There were 120 subjects in treatment MUTUAL, and 76 in BASE. The average subject earned Euro 8 (US $ 12.50) within approximately 30 minutes. The experiment was programmed and conducted with the software z-Tree (Fischbacher 2007).

Falk and Ichino (2006) and Mas and Moretti (2008) have found strong effort-enhancing effects of exposing workers to the presence of peers. A question of immediate interest is whether the production of a team increases with feedback about another team in our experiment. The answer is no. The mean contribution per subject, averaged across all periods and teams, is 10.8 points in MUTUAL and 10.9 points in BASE ($p = 0.780$ according to a Wilcoxon rank-sum test).[3] Moreover, Fig. 1 shows that there are no treatment effects over time. The figure depicts the pattern of average effort contributions per treatment over the repeated decision periods. In both treatments the contributions on average start out at a level of about 75% of the endowment. From there they almost linearly decay towards approximately 25% of the endowment in the last period.

The absence of treatment effects on the level of aggregate contributions does not yet rule out the existence of peer effects. In our design, if subjects mutually respond to the feedback about another team's performance this would transfer into correlated contributions between teams. Such feedback effects should then lead to greater homogeneity within paired teams and an increased heterogeneity across pairs of teams. We will now test this intuition empirically. We start by running the following regression to test for correlated behavior within paired teams:

$$x_{it} = \beta_0 + \beta_1 x_{i(t-1)} + \beta_2 \overline{x}_{-i(t-1)} + \beta_3 \overline{y}_{j(t-1)} + t + \epsilon_{it},$$

where x_{it} is the subject's current contribution to the project in team X, $x_{i(t-1)}$ is the subject's past contribution, $\overline{x}_{-i(t-1)}$ is the average contribution of the other team-X

[3]The test employs 19 isolated teams in BASE and 15 paired teams in MUTUAL as units of independent observations.

Table 1 OLS regression: MUTUAL and BASE

Independent variable	Dependent variable: x_{it}	
	Coefficient (robust std. error)	
	MUTUAL	BASE
t	−0.084**	−0.157***
	(0.035)	(0.034)
$x_{i(t-1)}$	0.608***	0.548***
	(0.054)	(0.089)
$\overline{x}_{-i(t-1)}$	0.181***	0.266**
	(0.056)	(0.101)
$\overline{y}_{j(t-1)}$	0.099***	−0.022
	(0.023)	(0.051)
Constant	1.777*	3.145**
	(0.863)	(1.217)
	$N = 1140$	$N = 684$
	$F(5, 14) = 1139.0$***	$F(5, 8) = 502.3$***
	$R^2 = 0.83$	$R^2 = 0.79$

*** = significance at 1%,
** = significance at 5%,
* = significance at 10%

members in the past period, $\overline{y}_{j(t-1)}$ is the average past contribution in the paired team Y, t is a time trend, and ϵ_{it} denotes the error term. To account for the simultaneity between choices within a pair of X- and Y-teams, we exclusively use the contributions of the members in the X-team as the dependent variable. We employ the same procedures for treatment BASE. In particular, in this treatment we also group the teams into pairs consisting of an X- and Y-team each.[4] By these means we obtain the past contribution of a paired team Y as independent variable also for treatment BASE.

In the regression we include variable $x_{i(t-1)}$ to avoid serial correlation in the error term.[5] Previous research has taken a positively significant β_2 as evidence for social preferences in the guise of conditional cooperation, as it indicates that a change in other team members' contributions impacts on the own contribution in the same direction (see, e.g., Croson 1998; Keser and van Winden 2000; Fischbacher et al. 2001; Falk et al. 2003). A positively significant estimate of β_3 would be consistent with the existence of peer effects between teams. Finally, the above cited studies have found a significantly negative time trend, even after controlling for conditional cooperation.

We first ran this regression separately for treatments MUTUAL and BASE. Then we estimated a single equation allowing for clustering pairs of teams and employed a Chow test to see if the coefficients are different between the treatments. Table 1 shows

[4]In BASE, two teams were paired if they were in the same experimental session. In one session we had 16 subjects participating in treatment MUTUAL and only 4 subjects in BASE. These 4 subjects are not included in the regression. Hence, the analysis includes 72 subjects (=9 "virtual" pairs of teams) in BASE.

[5]Standard tests of autocorrelation strongly suggest including this variable. Dropping it, however, does not qualitatively change the results.

the results obtained from OLS.[6] The numbers in parentheses show robust standard errors adjusted for clustering of independent groups (i.e., groups of 8 subjects who are subdivided into 2 teams). Our main question is whether subjects respond systematically to the feedback about another team's performance. If the answer is positive, we shall observe a significant influence of the paired team in MUTUAL, but not in BASE.

Table 1 shows that in MUTUAL the estimated coefficient of variable $\overline{y}_{j(t-1)}$ is significantly different from zero and has a value of 0.099. The same variable $\overline{y}_{j(t-1)}$ is insignificant in treatment BASE. The Chow test reveals that the estimated coefficient β_3 is significantly different across MUTUAL and BASE ($p = 0.036$). The correlation between teams is not small. The literature on social preferences suggests that subjects have strategic incentives to react towards others in the own team. With payoffs being independent, such strategic incentives are largely absent between paired teams in our design. Nevertheless, in treatment MUTUAL β_3 is more than half the value of β_2. At sample means, a 1% increase in the average contribution of the paired team is associated with a 0.1% increase of the own contribution. In comparison to that, the elasticity of the own contribution with respect to other's contributions within the own team is 0.18.

Considering the other variables in the regression, our data corroborates the results from previous experiments regarding the existence of conditional cooperation as measured by β_2, and a negative time trend. The time trend and the coefficients β_0, β_1, and β_2 are at the margin of being jointly significant across the treatments ($p = 0.094$). This suggests that the influence of the other team has some effect on the behavior within the own team. Such an effect is plausible, for example, if the subjects use the feedback to update their beliefs. On the other hand, none of the latter estimates differ across treatments based on individual parameter tests; i.e., we cannot trace back this effect to a particular variable.

The analysis so far has revealed results consistent with peer effects between teams. These effects should consequently translate into the variation of outcomes. First, with peer effects we should observe greater homogeneity between two paired teams in MUTUAL than between two isolated teams in BASE. Figure 2 shows the absolute distance between the average team contributions of two paired teams X and Y, $|\overline{x}_i - \overline{y}_j|$, averaged over all pairs of teams per period. In MUTUAL, one point in this figure represents the distance between two teams X and Y, averaged over 15 pairs of teams. In BASE, a point shows the distance between two teams X and Y, averaged over 9 "virtual" pairs of teams.[7] Aggregated over all periods the distance of average team contributions within a pair is 4.2 points in MUTUAL and 4.5 points in BASE. Although these numbers are not statistically different based on absolute levels ($p = 0.976$), the figure indicates a trend towards greater homogeneity in treatment MUTUAL as compared to BASE.[8] We have estimated a single regression with

[6]We have also estimated a double-censored Tobit regression to account for the fact that contributions are censored from below by 0 and from above by 20. This regression reveals the same results.

[7]See footnote 4 for an explanation how we have constructed these "virtual" pairs of teams in BASE.

[8]The reader might notice that the distance between team contributions within the pairs increases in both treatments in early periods. The reason for this observation is that the teams differ in their ability to sustain

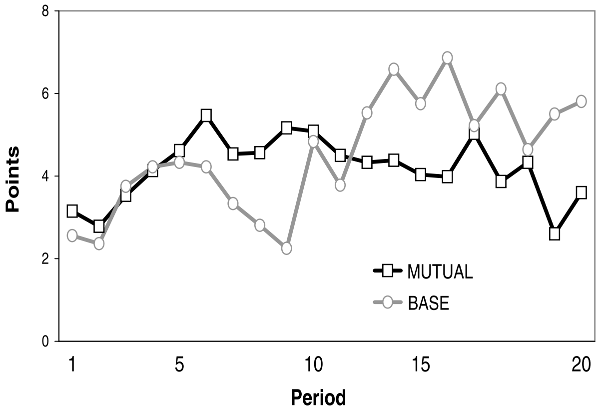


Fig. 2 Average distance between team outputs within paired teams

the pooled data including a constant and a time trend that allows the trend to differ between the treatments. The estimated time trend is -0.002 in MUTUAL and 0.174 in BASE. These estimates differ significantly across the treatments ($p = 0.001$). This result establishes that the effort distributions of two teams stay closer over the periods when the teams are able to observe each others' performance.[9]

Second, if peer effects exist between teams we shall observe more heterogeneous outputs across the pairs of teams in MUTUAL than in BASE. Figure 3 shows the standard deviation of total contributions of paired teams, $Std\{\sum_i x_i + \sum_j y_j\}$, per period and treatment. The black line shows the standard deviation across the total output of 15 pairs of teams in MUTUAL and the grey line that of 9 "virtual" pairs in BASE. Consistent with peer effects, the figure shows an increase in heterogeneity between paired teams, which is stronger in MUTUAL than BASE. The estimated trend is 0.318 for BASE and 1.066 for MUTUAL. These estimates are significantly different across the treatments ($p = 0.013$).

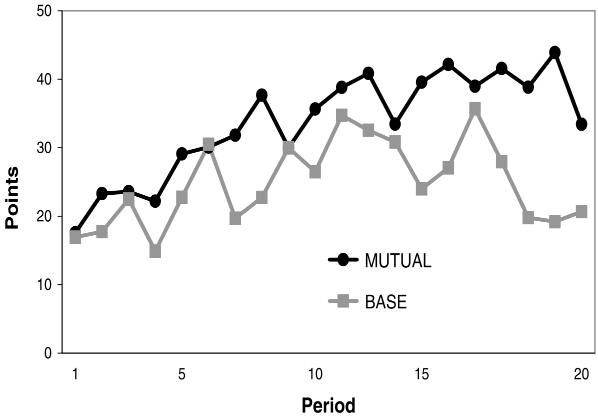
4 Discussion and conclusion

In this study we have tested whether peer effects exist between teams performing a teamwork task. In particular, we tested whether the opportunity of teams to compare each others' performance gives rise to correlated behavior between teams. Testing

cooperation. At the start of the experiment many teams exhibit rather high levels of contributions before cooperation starts to brake down. Typically, the time when this happens differs between the two teams within a pair. Consequently, the distance between the team contributions of a randomly sampled pair of teams first increases, and then decreases again after cooperation rates start to fall also in the second team within the pair.

[9] This result does not necessarily imply an effect on the shape of the effort distribution within the teams. If we assume, for example, that the influence of the other team is the same for everyone in the own team, this would just shift the distribution without affecting its variance or skewness. The within-team standard deviation of contributions aggregated over all periods is 6.2 points in BASE and 6.0 points in MUTUAL. These numbers are not different statistically ($p = 0.618$). However, there is a trend towards higher variation of effort within the teams in BASE as compared to MUTUAL; the estimated trend is 0.071 in BASE and 0.000 in MUTUAL ($p = 0.023$).

Fig. 3 Standard deviation of team output across pairs of teams



for peer effects is difficult in the field because it is hardly possible to find a setting in which the effects of both, endogenous and exogenous characteristics of a team can be controlled for simultaneously (see, Manski 1993).[10] To avoid this identification problem we propose an experiment in which team members contribute effort to independent team projects. Our main finding is that contributions correlate between teams. This correlation leads to greater homogeneity within and greater heterogeneity across pairs of teams. These effects are consistent with peer effects in our design.

Previous studies by Falk and Ichino (2006) and Mas and Moretti (2008) have found strong effort-enhancing peer effects between subjects performing an individual task. While our study corroborates that peer effects exist also between work-teams, these effects do not enhance overall productivity in our design. This observation indicates that the benefits of peer effects depend on the specific situation to which they are applied. In this respect, previous studies have found it important whether individual behavior is observable to others. This possibility is inherently limited in work-teams when subjects have an incentive to free ride.

Our findings can nevertheless have potentially important implications for the organization of work. In particular, regarding the correlation of effort between teams our results suggest that providing teams with mutual information about their performance contributes to a reduction of the variation of output. Depending on the setting (e.g., product assembly, R&D), this feature can be desirable or not. Second, our finding might have implications for the compensation of work. Assume that a firm provides pay based on the relative performance of work teams; peer effects of the sort we have observed in our experiment might then interact with the cost of providing these direct incentives.

Our design aimed at disentangling peer effects from alternative accounts by comparing effort choices between two treatments with and without feedback about another team. Yet, our design is not capable to differentiate between various channels

[10]For example, workers who share certain characteristics may self-select into teams (see, Hamilton et al. 2003). Another case would apply, for instance, if teams improve the opportunities to monitor and sanction free riders for purely organizational reasons (Knez and Simester 2001).

that can generate peer effects. Peer effects can be motivated by self-interest. This motive would apply, for instance, if people try to imitate others in an effort to achieve better outcomes (e.g., Huck et al. 1999). Peer effects might also be due to social preferences. For example, people might use others' behavior as a guide to what is socially appropriate (e.g., Bardsley and Sausgruber 2005).

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