Rac(g)e Against the Machine? Social Incentives When Humans Meet Robots

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Incentives, social pressure, social preferences, personnel economics, organizational behavior, automation

JEL codes:
C92, D23, D91, M52

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"*Computers are magnificent tools for the realization of our dreams, but no machine can replace the human spark of spirit, compassion, love, and understanding*."

Louis V. Gerstner, Jr., Former Chairman and CEO, IBM

1. Introduction

Social Incentives at Work

A growing number of studies have recognized the importance of the social context when setting incentives at work thus coining the term 'social incentives' (Bandiera, Barankay and Rasul, 2010; Ashraf and Bandiera, 2018). Incentives become social when the presence of others affects workers' effort levels. Social incentives naturally arise in situations in which workers influence each other's payoffs such as is the case of the widely-used team incentive schemes and gainsharing plans (see Miller and Schuster, 1987; Ledford, Lawler and Mohrman, 1995; Hamilton, Nickerson and Owan, 2003; Lazear and Shaw, 2007; Nyberg et al. 2018). These schemes have been particularly successful despite well-known free-riding issues (see e.g. Holmström, 1982). One common explanation for this success lies on workers' prosocial motives that lead them to exert extra effort in order to boost their coworkers' pay (see Rotemberg, 1994; Dur and Sol, 2010).

Social incentives are likely to be pervasive in the workplace as they can operate even in situations in which workers cannot affect each other's pay. This is the case for example when social comparisons or social pressure mechanisms are prevalent. As is illustrated in Ashraf and Bandiera (2018), workers who care about relative payoff and are, for example, inequality averse (see Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Fehr and Fischbacher, 2002) may exert more effort when their coworkers do so (see Rey-Biel, 2008; Bartling and von Siemens, 2010; Englmaier and Wambach, 2010). Workers may thus be motivated by envy and exert extra effort to avoid falling behind their coworkers in terms of pay (Bartling and von Siemens, 2010). Thus, any pieces of information regarding workers' relative performance might affect their performance level even in the absence of payoff interdependences among workers (e.g. Eriksson, Poulsen and Villeval, 2009; Azmat and Iriberri, 2010, 2016).

It is also the case that, abstracting away from concerns regarding pay, the mere presence of others can positively influence one's performance (e.g. Zajonc, 1965; Kandel and Lazear, 1992). Previous works have shown that workers who are being observed by a peer who cannot affect their pay tend to exert more effort than those who work in isolation (see Herbst and Mas, 2015 for a review) whether the setting involves a mental-effort task in a laboratory context (Beugnot et al.

2013; Rosaz, Slonim and Villeval, 2016), clerical tasks completed in the field (Falk and Ichino, 2006; Mas and Moretti, 2009) or physical effort tasks (Guryan, Kroft and Notowidigdo, 2009). This positive effect of the presence of others has been referred to as social pressure (see e.g. Mas and Moretti, 2009) and has been shown to explain the success of team incentives (Kandel and Lazear, 1992; Corgnet, Hernan-Gonzalez and Rassenti, 2015b). The extent to which social pressure alleviates free riding in teams has also been shown to depend on the strength of group ties and on the existence of a strong group identity (Charness, Rigotti and Rustichini, 2007; Charness, Cobo-Reyes and Jiménez, 2014; Dugar and Shahriar, 2012) which are other relevant dimensions of social incentives.

Social incentives are thus key to induce workers to exert high effort in contexts in which free-riding would otherwise be prevalent. This argument is also central to the literature on relational incentives (e.g. Levin, 2003; Baron and Kreps; 2013) which is especially connected to the works on social incentives when prosocial concerns and social interaction are explicitly introduced (e.g. Dur and Tichem, 2015). The literature in social and relational incentives puts forth that the social component of the workplace is crucial to understand the conditions under which organizations may outperform markets.[2] Any disruption of the social context of the workplace could thus seriously undermine the effectiveness of organizations.

Social Incentives in the Age of Machines

Given the growing automation of the workplace (see Brynjolfsson and McAfee, 2014; Ford, 2015; Boston Consulting Group, 2015), humans spend an increasing amount of time interacting with machines in lieu of other humans thus possibly weakening the magnitude of social incentives at work. Our focus is to study the potentially disruptive effect of automation on the workplace social context extending previous economics research focusing on the effect of automation on the demand for human labor (see e.g. Autor, Katz and Kearney, 2006; Goos, Manning and Salomons, 2014; Autor, 2015; Deming, 2017; Acemoglu and Restrepo, 2018a, 2018b).

To study the effect of the presence of robots on social incentives, we develop a model in which workers complete an effortful sequential task in company of other humans or robots. In our setup, workers exhibit social motives such as altruism and envy, which are only activated when interacting

[2] One could thus see this literature as offering a modern Behavioral Theory of the firm (see Cyert and March, 1992 for the classical Behavioral Theory of the firm).

with other humans. Robots are thus unable to induce social concerns from human coworkers (see Autor, 2015). Because the magnitude of social incentives crucially hinges on whether workers can affect each other's pay or not (Ashraf and Bandiera, 2018), we study a pay scheme in which it is the case (team pay) and one in which it is not (piece rate). We derive three main conjectures. Because humans are assumed not to care about the robot's welfare, we show that, under team pay, altruistic workers are less likely to exert effort when working with robots than when working only with humans. Under piece rate, altruistic workers cannot increase their coworkers' pay by exerting extra effort so that human effort should not be affected by whether coworkers are humans or robots. At the same time, envious workers should exert extra effort under piece rate to ensure that they earn at least as much as their human coworkers. This positive effect of envy on work performance should, however, not be observed when human workers interact with robots under the assumption that humans do not feel envy toward robots. In line with previous empirical works (Mas and Moretti, 2009; Corgnet, Hernan-Gonzalez and Rassenti, 2015b), we also conjecture that social pressure will be prevalent when humans work with other humans whereas it will not operate in the presence of robots. More specifically, we model social pressure as resulting from workers not willing to be seen as hurting the pay of their human coworkers. In that context, we show that social pressure leads workers to exert more effort when their performance is directly observed by another human rather than a robot and when workers are rewarded according to team pay. Under piece rate, workers do not affect the pay of the coworker observing their performance so that social pressure, if it exists, cannot rely on workers not willing to be seen as hurting others' payoffs. We thus predict social pressure to be less effective under piece rate than under team pay.

To test our conjectures, we develop a real-effort assembly line task experiment involving three workers. This controlled environment allows us to assess the causal effect of the presence of robots on workers' performance on the task. We consider environments in which either all workers were human (*human* treatments) or one automated robot –calibrated to perform the same as an average human worker–replaced one of the human workers (*robot* treatments). For both robot and human setups, we conducted two different treatments in which the rewards of human workers were either based on individual performance (*piece rate* treatments) or team performance (*team pay* treatments). In team pay treatments, participants were rewarded one third of total output, which was measured as the sum of all workers' production (including the robot's production when one was present in the line). This 2×2 factorial design allowed us to study the interaction between monetary incentives (team pay or piece rate) and social incentives (high in human treatments or low in robot treatments). The choice of the experimental method allows us to control for several aspects of the workplace environment which could confound our findings such as the presence of implicit incentives (Becker and Stigler, 1974; Klein and Leffler, 1981; Shapiro and Stiglitz, 1984; MacLeod and Malcomson, 1989), the existence of a corporate culture (Hermalin, 2013), the use of hierarchies (Williamson, 1967; Radner, 1992; Qian, 1994), employee's monitoring (Alchian and Demsetz, 1972) and the delegation of authority (Aghion and Tirole, 1997; Van den Steen 2009). Evidently, these elements are crucial to understand the functioning of organizations and our aim is not to downplay their importance but instead to proceed step by step highlighting first how robots can affect the magnitude of social incentives in a stylized work environment. Beyond control, another crucial advantage of our empirical methodology is that we could elicit workers' social motives by using standard social preferences tests (Bartling et al. 2009). Assessing workers' social preferences is key to the testing of our conjectures.

Our experimental data largely support our conjectures emphasizing the key role of the social context, which we manipulated by populating the workplace with either humans or robots, in assessing workers' performance. By quantifying the negative causal effect of automation on social incentives using a controlled laboratory setting, our work contributes to shed light on these neglected costs. Our results suggest that firms' calculations regarding the efficiency of cost-reducing automated workplaces should factor in the negative impact of robotization on the strength of social incentives. Our work also provides guidance to practitioners regarding which incentive schemes to choose in a highly-automated workplace. Payment schemes based on group production will be less effective in the presence of robots because social pressure and altruistic motives, which are crucial to avoid free-riding in teams, will be attenuated.

2. Model

2.1. Social incentives

We rely on previous social preferences and social pressure models to study the effect of social incentives on effort provision (see Kandel and Lazear, 1992; Rotemberg 1994; Fehr and Schmidt, 1999; Rey-Biel, 2008; Bartling and von Siemens, 2010; Dur and Sol, 2010; Englmaier and Wambach, 2010). We derive our hypotheses using the moral-hazard in teams' model introduced by Holmström (1982). We consider n workers producing a total output $\mathrm{f} \coloneqq \mathrm{f}(\mathrm{e}_1, \mathrm{e}_2, \dots, \mathrm{e}_\mathrm{n})$ which depends on each worker's effort $e_i \geq 0$ where $i \in \{1, \dots, n\} \coloneqq N$. In the rest of the paper, including the experimental design, we will consider a sequential task so that *i* will stand for the position of the worker in the task. The cost of effort is represented by $C(e_i)$ where $C^{'}(e_i) \geq 0$ and $C^{''}(e_i) \leq 0$ and the utility function of worker *i* is:

$$v_i \coloneqq s_i f - C(e_i) \qquad [1]$$

where s_i stands for the share of total output assigned to worker *i*.

We extend the utility function of worker *i* in [1] to account for social incentives. First, we assume worker *i* has altruistic concerns toward worker *j* (e.g. see Rotemberg, 1994; Dur and Sol, 2010), captured by parameter $\xi_{i,j} \geq 0$, and is subject to social pressure from worker *j* which is captured by $\chi_{i,j} \geq 0$ (see equation [2] below). An altruistic person ($\xi_{i,j} > 0$) values other workers' pay positively, even in the absence of social pressure ($\chi_{i,j} = 0$). In our model, we consider that social preferences as well as social pressure are driven by individuals' considerations regarding their coworkers' payoffs. Altruistic workers ($\xi_{i,j} > 0$) value others' payoffs positively whereas social pressure ($\chi_{i,j} > 0$) may lead non-altruistic workers ($\xi_{i,j} = 0$) to value others' payoffs. We thus model social pressure as workers' willingness not to hurt the payoffs of observers. We consider that workers will only be subject to social pressure from the worker who follow them in the sequential task so that $\chi_{i,j} = 0$ for any $j < i$.

We could have modeled social pressure more broadly considering that workers do not want to be seen as hurting the utility of observers. This would allow us to consider the case in which social pressure may derive from fairness considerations as in Andreoni and Bernheim (2009). However, this specification would require a more convoluted model in which we need to take into account workers' beliefs regarding their coworkers' social motives. Instead, we consider the simplest possible model in which social preferences and social pressure can affect workers' effort decisions so that we can derive clear-cut testable predictions.[3] Our modeling of social pressure is also consistent with the empirical findings of Mas and Moretti (2009) and Corgnet, Hernan-Gonzalez and Rassenti (2015b) because in both studies workers could increase the welfare of their coworkers by exerting more effort. In our case, workers are thus subjected to social pressure whenever a person follows them in the sequential task and when the payment scheme, such as for example team pay, creates positive interdependences across workers' monetary payoffs.

[3] Our aim is thus not to compare the predictive power of different models.

In addition to altruistic concerns, research on social preferences and incentive theory (see Barling and von Siemens, 2010; Englmaier and Wambach, 2010) has put forth the importance of inequality aversion à la Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) in understanding compensation practices. These works stress that inequality aversion may lead to weaker incentives so as to avoid wage inequalities. Principals may voluntarily compress wages to reduce the inequality premium workers would demand as a compensation for working in an environment in which wage inequalities are large. Empirical evidence of the effect of wage inequality has recently accumulated showing that workers may indeed react negatively to wage inequality (see e.g. Charness and Kuhn, 2007; Clark, Masclet and Villeval, 2010; Card et al. 2012; Cohn et al. 2014; Breza, Kaur and Shamdasani, 2018).

We account for inequality aversion by augmenting the utility function specified in [1] to allow for workers' envy, which is captured by parameter $\alpha_{i,j}$, and workers' shame (or pity), which is captured by parameter $\beta_{i,j}$:

$$U_i \coloneqq s_i f - C(e_i) + \sum_{j \neq i}^{n} \left(\xi_{i,j} + \chi_{i,j}\right) s_j f$$

$$- \frac{1}{n-1} \textstyle\sum_{j \neq i}^{n} \alpha_{i,j} \max\left[s_j f - s_i f, 0\right] - \frac{1}{n-1} \sum_{j \neq i}^{n} \beta_{i,j} \max[s_i f - s_j f, 0] \qquad [2]$$

Envy (shame) captures one's discomfort with disadvantageous (advantageous) inequality (see Fehr and Schmidt, 1999). Although evidence of negative envy ($\alpha_{i,j} < 0$) is scarce, negative shame ($\beta_{i,j} < 0$), which represents the motives of someone seeking to surpass others in terms of payoffs, is not negligible (see Dhami, 2016 for a review). Similarly to altruism and social pressure, our model considers that inequality aversion is derived from payoffs rather than utility comparisons. We thus do not contemplate the possibility that workers are driven by inequity rather than inequality considerations in which case individuals' costs of effort and ability levels would play a crucial role in assessing whether a payoff allocation is perceived to be equitable (see Konow, 2000; Konow, Saijo and Akai, 2016). We put aside inequity concerns because our aim is to derive conjectures which do not depend on workers' exact cost of effort functions and ability levels. In addition, equality considerations have been seen as more prominent than equity considerations in a context in which all participants have a stake in the outcome (see Konow, Saijo and Akai, 2016) as is the case of our model.

An important feature of the strength of social incentives in our setup is to consider whether one's coworkers are humans or robots. Let us denote by $N_R \subset N$ the set of workers who are robots. We assume that social incentives, whether they arise from workers' altruism, inequality aversion or social pressure are absent when interacting with robots. In other words, humans do not feel altruistic ($\xi_{i,j} = 0$ for $j \in N_R$), envious or shameful ($\alpha_{i,j} = \beta_{i,j} = 0$ for $j \in N_R$) toward robots nor do they feel social pressure from them ($\chi_{i,j} = 0$ for $j \in N_R$). It follows that in our setup, unlike Fehr and Schmidt (1999), the extent of social preferences critically depends on the identity of one's coworkers in line with, for example, Levine's (1998) model.

2.2. Payment schemes

We consider two types of payment schemes which differ regarding the way in which workers' shares are calculated. Under team pay, all workers share total output equally so that $s_i = \frac{1}{n}$. Under piece rate, workers are rewarded according to their actual contribution to the total output. For simplicity, we assume that $f(\cdot)$ is linear and separable in workers' efforts $f \coloneqq \sum_{i=1}^{n} a_i e_i$, where $a_i > 0$ is the marginal product of effort of worker i, so that $s_i = \frac{a_i e_i}{\sum_{l=1}^{n} a_l e_l}$ in the case of piece rate. By assuming separability in workers' effort, our production function allows us to identify each worker's individual contribution thus permitting a direct comparison between piece rate and team pay schemes. It follows that considering a sequential task is not motivated by the willingness to study complex production functions in which a worker's level of effort can affect the productivity of other workers (e.g. Kremer, 1993; Winter, 2006; Goette and Senn, 2016). Instead, our aim is to study social pressure in a natural work environment in which one's effort can be observed by subsequent workers in the line.[4] We leave the study of the interaction effect between social incentives and task interdependencies in the presence of robots for future research.[5]

[4] Doing so, we deviate from Kandel and Lazear (1992) who assume non-separability in effort so as to justify the existence of partnerships and eliminate the possibility of self-employment. In this paper, we do not aim at justifying the existence of partnerships and simply assume separability of the utility function to study social incentives. Our work also deviates from Winter (2006) who focuses on incentive setting when sequential tasks are characterized by interdependencies across workers' levels of effort.

[5] In the case of task interdependencies, we would expect the effect of social incentives to be magnified because social motives related to altruism as well as social pressure would apply not only under team pay but also in the case of piece rate.

For illustrative purposes, we consider two types of ability levels: $a_L(a_H)$ that respectively characterize low- (high-) ability workers where $a_L < a_H$. We denote by $N_L(N_H)$ the set of low- (high-) ability human workers where $N_L \subset N$ ($N_H \subset N$), and $n_L(n_H)$ is the corresponding number of such workers.

2.3. Conjectures

We derive a series of conjectures regarding the impact of the presence of robots on the positive effect of altruism (Conjecture 2), envy and shame (Conjecture 3) and social pressure (Conjecture 4) on the effort provision of human workers. Because incentive contracts are exogenous, our conjectures directly follow from workers' utility maximization. In our setup, we thus focus on the incentive compatibility constraint assuming workers' participation. A selfish worker who is not affected by social pressure ($\xi_{i,j} = \chi_{i,j} = \alpha_{i,j} = \beta_{i,j} = 0$) will choose effort so that the marginal cost of effort equals its marginal revenue so that according to equation[1]: $\frac{\partial s_i f}{\partial e_i} = C^{'}(e_i)\ , \forall\ i \in N$. In the case of workers responding to social incentives, the first order conditions derived from maximizing the utility function in [2] can be written as follows:[6]

$$\begin{cases} \frac{\partial s_i f}{\partial e_i} + \sum_{j<i, j \not\subset N_R}^{n} \xi_{i,j} \frac{\partial s_j f}{\partial e_i} + \sum_{j>i, j \not\subset N_R}^{n} (\xi_{i,j} + \chi_{i,j}) \frac{\partial s_j f}{\partial e_i} - \beta_{i,j} \frac{n_L}{n-1} \left(\frac{\partial s_i f}{\partial e_i} - \frac{\partial s_j f}{\partial e_i}\right) = C^{'}(e_i)\ , \forall\ i \in N_H \\ \frac{\partial s_i f}{\partial e_i} + \sum_{j<i, j \not\subset N_R}^{n} \xi_{i,j} \frac{\partial s_j f}{\partial e_i} + \sum_{j>i, j \not\subset N_R}^{n} (\xi_{i,j} + \chi_{i,j}) \frac{\partial s_j f}{\partial e_i} + \alpha_{i,j} \frac{n_H}{n-1} \left(\frac{\partial s_i f}{\partial e_i} - \frac{\partial s_j f}{\partial e_i}\right) = C^{'}(e_i)\ , \forall\ i \in N_L \end{cases} \quad [3]$$

It follows that both altruism ($\xi_{i,j}$) and social pressure ($\chi_{i,j}$) increase the marginal benefit of effort which, in turn, will increase workers' optimal level of effort. Regarding inequality aversion, we also expect a positive overall effect on effort as long as we consider the common assumption that envy is much more prominent than shame (see Fehr and Schmidt, 1999). In that case, the positive effect of envy on the marginal benefit of effort of low-ability workers will more than offset the negative effect of shame on the marginal benefit of effort of high-ability workers.

Importantly, the larger the proportion of robots involved in the sequential task the less prominent social incentives will be and the lower the optimal level of effort will be. As long as a proportion of human workers respond to social incentives, we can state the following general conjecture.

[6] We make use of the fact that the pay of low-ability workers cannot be higher than the pay of high-ability workers given the two payment schemes we consider.

Conjecture 1 (Rage against the machine)

Human workers will exert higher effort in a work environment in which they only interact with other humans compared to an environment in which some humans are replaced with robots.

More specifically, the negative effect of the presence of robots on work production is explained by the lack of altruism and envy as well as by the absence of social pressure toward robots. In the next three conjectures, we detail each of these effects separately.

Our model implies that the higher the level of altruism of workers, the more negatively they will be impacted by the presence of robots. It is important to note that $\frac{\partial s_j f}{\partial e_i} > 0, \forall\, i \neq j$ under team pay whereas $\frac{\partial s_j f}{\partial e_i} = 0$ for piece rate. This implies from [3] that the positive effect of altruistic concerns should only be observed under team pay. In the following conjecture, we summarize the effect of altruism on effort provision when robots are present in the work environment.

Conjecture 2 (Altruism and robots)

i) Under team pay, altruistic workers will exert higher effort than non-altruistic workers in an environment in which they interact with humans.

ii) Under team pay, altruistic workers will exert higher effort in a work environment in which they only interact with humans compared to an environment in which some humans are replaced with robots.

iii) Under piece rate, altruistic workers will exert the same level of effort whether interacting with humans or with robots.

Our model also implies that, under piece rate, envy ($\alpha_{i,j} > 0$) or ahead-seeking motives ($\beta_{i,j} < 0$) have a positive effect on effort provision whereas shame ($\beta_{i,j} > 0$) has a negative effect because $\frac{\partial s_i f}{\partial e_i} > 0$ and $\frac{\partial s_j f}{\partial e_i} = 0, \forall\, i \neq j$ (see [3]). Under team pay, we have that $\frac{\partial s_i f}{\partial e_i} = \frac{\partial s_j f}{\partial e_i}$ so that neither envy nor shame have any impact on workers' production. In the following conjecture, we summarize the effect of envy and shame on the provision of effort of human workers.

Conjecture 3 (Envious, shameful and ahead-seeking workers)

i) Under piece rate, envious or ahead-seeking (shameful) workers will exert higher (lower) effort than non-envious or non-ahead-seeking (non-shameful) workers in an environment in which they interact with humans.

ii) Under piece rate, envious or ahead-seeking (shameful) workers will exert higher (lower) effort in a work environment in which they only interact with humans compared to an environment in which some humans are replaced with robots.
iii) Under team pay, envious, ahead-seeking or shameful workers will exert the same level of effort whether interacting with humans or with robots.

In addition to the positive effect of altruism and envy, we also identify social pressure as playing a key role in understanding the strength of social incentives in the work environment. In particular, our model implies that, under team pay, human workers who are followed by a robot in the line will be less productive than those who are followed by a human. This follows directly from the assumption that robots cannot exert social pressure ($\chi_{i,j} = 0$ for $j \in N_R$). Importantly, in our setup the positive social pressure effect on effort provision is only observed under team pay because $\frac{\partial s_j f}{\partial e_i} > 0$ whereas it is not observed under piece rate in which case a worker's effort does not affect coworkers' pay (i.e. $\frac{\partial s_j f}{\partial e_i}$ =0).[7]

Conjecture 4 (Social pressure and robots)
i) Under team pay, human workers will exert higher effort when they are followed by a human compared to the case in which they are followed by a robot.
ii) Under piece rate, human workers will exert the same level of effort regardless of whether they are followed by a human or a robot.

In the absence of social incentives ($\xi_{i,j} = \chi_{i,j} = \alpha_{i,j} = \beta_{i,j} = 0$), it follows from [3] that workers' effort would be higher under piece rate than under team pay (see Holmström, 1982). It follows that selfish workers ($\xi_{i,j} = 0$) who are neither envious nor shameful ($\alpha_{i,j} = \beta_{i,j} = 0$) and who are never observed by workers because they are last in line ($\chi_{i,j} = 0$) will be more productive

[7] For social incentives to affect effort provision under piece rate, we would have to consider one of two possible situations. First, a worker's effort could affect other workers' effort if there exist interdependencies in the production function. In that case, both altruism and social pressure may operate under piece rate. Second, social pressure may operate even when workers do not affect others' payoff. This could be the case, for example, if workers value being seen as a high performer even though one's performance does not affect the observer's payoff. This type of effects have been observed in the social facilitation literature in psychology (e.g. Allport 1924; Zajonc, 1965). The results obtained by Falk and Ichino (2006) can also be seen as evidence of the facilitation effects encountered in the earlier psychology literature. We discard these effects capturing social pressure as uniquely deriving from workers' willingness not to hurt the pay of the coworkers who observe their performance on the task.

under piece rate than under team pay. More generally, because of the prevalence of social incentives, we expect only small differences in workers' production between piece rate and team pay. That is, social incentives will alleviate the moral-hazard in teams' problem. This argument is in line with the theoretical works of Kandel and Lazear (1992) and Barron and Gjerde (1997). We thus make the following conjecture.

Conjecture 5 (Piece rate versus team pay)

i) Because we expect social incentives to be prevalent, workers will exert a similarly high level of effort under team pay than under piece rate.

ii) Workers who exhibit no social preferences ($\xi_{i,j} = \alpha_{i,j} = \beta_{i,j} = 0$) *and who work last in the sequential task* ($\chi_{i,j} = 0$) *will exert higher effort under piece rate than under team pay.*

3. Design

We develop a real-effort sequential task to study whether interacting with robots instead of humans can alter the strength of social incentives.

3.1. The work task

At the beginning of each of five periods, three workers were randomly matched to a group among the twelve participants in a given session.[8] In addition, each worker in a group was randomly assigned one position in the sequential task at the beginning of each period: first, second or third. Regardless of their position in the task, workers had exactly 12 seconds to reproduce as accurately as possible a colored pattern displayed in a 7×7 grid on the right of their screen (see Figure 1). After 12 seconds, a worker's completed grid was automatically transmitted to the next worker in the sequential task. If a worker was assigned the first position, he or she would act first in the sequential task thus reproducing the blue-color pattern (see left panel in Figure 1). Workers who were in the first position would receive a new and empty grid every 12 seconds. To make sure the other two workers in the sequence could work on the last grid produced by the first worker, the latter did not receive any new empty grid in the last 24 seconds of each period.[9]

[8] In robot treatments sessions, a participant could be a robot.

[9] This implies that workers were presented with a total of 23 grids in a given 5-minute period.

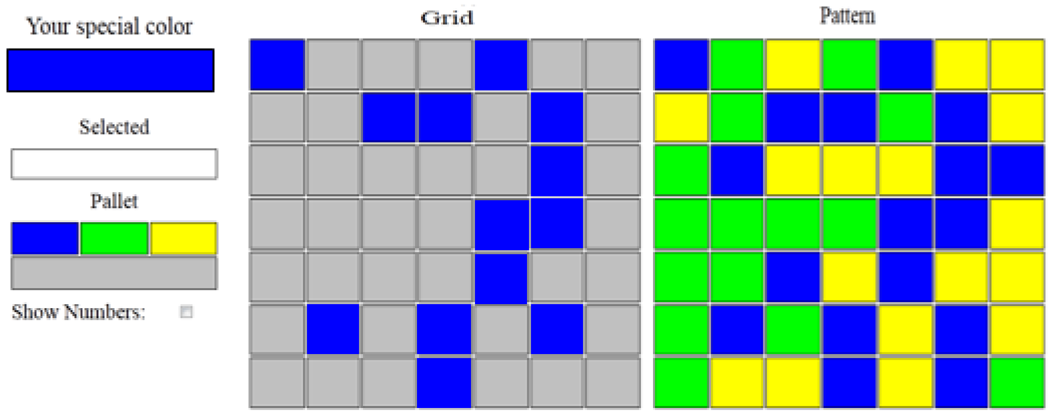

FIGURE 1. First post in the sequential task.
The sequential task as completed by the first worker in the sequence[10]

The worker who was assigned the second position acted second in the sequential task reproducing the yellow-color pattern after receiving the grid previously completed by the first worker (see Figure 2). The last worker in the sequential task inherited the grid completed by the previous two workers and had to finalize the pattern by reproducing the green-color pattern.

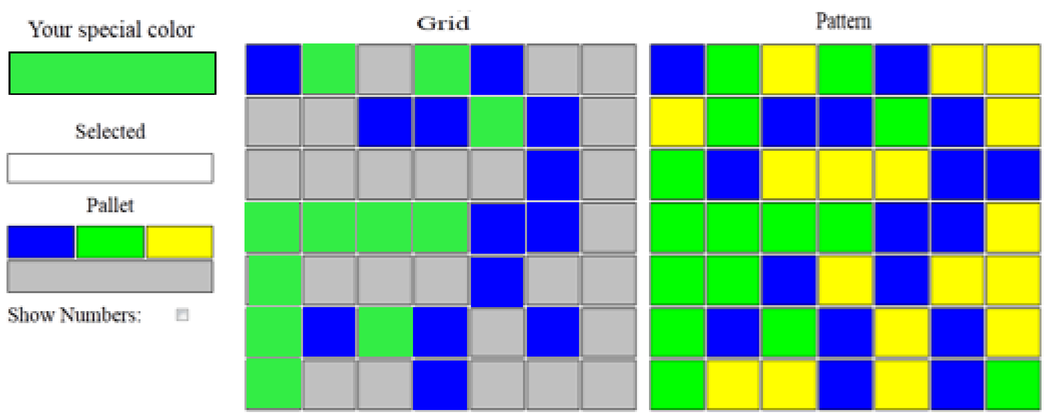

FIGURE 2. Second post in the sequential task.
The sequential task as completed by both the first (blue pattern) and second (green pattern) workers in the sequential task.

We chose the pattern colors (blue, green and yellow) purposefully so as to limit color blindness issues which would preclude some participants to complete the task adequately.[11] In addition, we provided a 'Show Numbers' option on the screen (see Figures 1 and 2) which allowed participants to see their corresponding color pattern represented by white cells filled with numbers instead of a

[10] A video of the sequential task is provided here: https://tinyurl.com/y6u2huyl.
[11] We avoided the most common color blindness which prevents people (mostly males) not to distinguish between green and red colors.

color.[12] In total, workers had to complete a total of 115 (23 × 5 periods) turns each with a different grid. These grids were generated randomly before the first sessions. The same 115 grids were used for all experiments. Depending on the grid, the number of cells filled in a given color was either equal to 15, 16 or 17.

Because each worker's position in the line was assigned a color pattern (see 'Your special color' on the top left corner of Figures 1 and 2), workers' effort did not typically affect other workers' productivity. We do not fully eliminate effort interdependencies in the sequential task because workers who made numerous mistakes could prevent subsequent workers to proficiently complete their part of the task. However, this type of effort interdependencies were kept to a minimum level as error rates, measured as the proportion of cells filled with the wrong color, were very low (1.5%) in our task.[13]

In line with our model specification, we thus implemented a sequential task in which a worker's individual contribution could be readily identified. Our task allows us to study social pressure in the context of a group of workers each undertaking a specific part of a team task. Even though our design of the sequential task aims at minimizing effort interdependencies across workers, it still represents a team task because each worker is endowed with a specific function that needs to be executed for the task to be completed (Hackman and Wageman, 2015).

At the end of each period, all participants received information regarding their period earnings as well as the total group earnings. Participants had to click on a pop-up window before moving to the next period. This implied a short break (about 20 seconds) between periods.

Following Corgnet, Hernan-Gonzalez and Schniter (2015), we allowed participants to browse the internet at any moment in time. This option was, however, not used very often by participants in our experiments. The only two participants who browsed the web in a given period decided to do so for the entire period duration. This may not seem surprising as the task was short and time pressure induced by the 12-second turns made it very costly to browse the web and come back to the task. In addition, we put forward in Conjecture 5 that our sequential task, because of the social incentives it generates, keeps shirking at a minimum level.

[12] In our debriefing questionnaire which took place while participants were waiting for payments, we asked participants feedback about the task. No participants mentioned color blindness as an issue.
[13] We did not observe differences in error rates across treatments.

3.2. Incentive schemes

Each of the 115 grids completed by workers generated monetary value. Each of the 49 cells in the grid generated a value equal to +1¢ whenever the cell was filled with the same color as in the pattern displayed on the right of the screen. When the cell was filled with a different color from the one in the pattern, the value of the cell was negative -1¢. A cell which was left empty generated no value. We can thus calculate the value generated by all three workers in a given period as well as each worker's individual contribution to the total value generated. The individual production of a worker on a given grid is equal to the difference between the value of the grid at the beginning of the worker's 12-second turn and the value of the grid at the end of his or her turn.

To test our conjectures, we considered two types of incentive schemes: piece rate and team pay. Under piece rate, workers are paid according to their individual production whereas under team pay the value generated by all three workers in a given period is equally divided among them.

3.3. Robots

To assess the effect of humans interacting with robots, we consider for each incentive scheme (piece rate and team pay) one treatment in which each group is composed of three human participants (human treatments) and one treatment in which one of the three workers is a robot (robot treatments). We are thus left with a 2×2 between-participant design in which the treatment variables are the incentive schemes (piece rate or team pay treatments) and the presence or absence of a robot (robot or human treatments). We included two humans and one robot in the robot treatments so as to be able to assess how human participants react to being followed in the line by either a robot or a human. This will allow us to test Conjecture 4 on social pressure.

We designed the algorithm for robots so that their average performance on the sequential task closely mimics the average performance of human participants in the human treatments so that we could directly compare human and robot treatments.[14] To that end, we calibrated the robot so that for a given cell the probability of either completing it correctly, filling it erroneously or leaving the cell empty were the same as the average frequencies observed in human treatments. Thus, the contribution of a robot to the value of a grid was calibrated to be the same as the average individual production of human participants in human treatments. Our robots, unlike humans, all had the same

[14] An interesting avenue of future research would be to assess the interaction between humans and highly productive robots.

level of ability. An alternative calibration strategy would have been to induce heterogeneity in robots' productivity levels replicating the distribution of human productivity levels on the task. However, we opted for homogenous robots as it seemed to be a more faithful representation of actual robots. Importantly, our model conjectures are not qualitatively affected by the distribution of robots' productivity levels.

Humans in robot treatments knew they were interacting with a robot. They were told in the instructions that "*the robot you are interacting with, like humans, can make mistakes when filling the grid. The robot can also fail to complete parts of the grid. The accuracy of the robot is specified by a computer algorithm*." (see Appendix A). Importantly, humans knew the position of the robot each period so they knew whether a human or a robot was following them in the line. This information was displayed above the pattern on the top right of the screen (see Appendix A).

3.4. Procedure

This experiment was conducted using the Virtual Workplace developed by Corgnet, Hernan-Gonzalez and Rassenti (2015a,b). The experiment was conducted at a major US University. We ran a total of 20 sessions of 12 participants. We had a total of 4 (6) sessions for each of the four treatments as is shown in Table 1.[15]

TABLE 1. Treatments.

Incentives \ Participants	Human	Robot
Piece rate	*Piece rate human* Three humans paid individual contribution (n = 48)	*Piece rate robot* Two humans and one robot paid individual contribution (n = 48)
Team pay	*Team pay human* Three humans paid one third of team output (n = 48)	*Team pay robot* Two humans and one robot paid one third of team output (n = 48)

Human participants had 20 minutes to read the instructions (see Appendix A) after which they were given a printed summary. Before starting the sequential task for pay, participants completed

[15] We needed two more sessions in the robot treatments because we kept the number of workers (12) per session constant across treatments although we needed to collect the same number of human participants observations across treatments.

a 3-minute practice period. After the five periods of the sequential task were over, participants had to complete a 10-minute survey including demographics, a cognitive skills test (Cognitive Reflection Test, CRT henceforth, Frederick, 2005) and a social preferences test (Bartling et al. 2009) (see Appendix A). We assessed self-reported affective reaction to the sequential task collecting data on arousal, satisfaction and dominance using the self-assessment manikin (SAM) developed by Bradley and Lang (1994) (see Appendix A). These three affective dimensions have been identified in the emotion literature dating back to Wundt (1896) as key to capture people's internal feelings (see also Oatley, Keltner and Jenkins, 2006). This 30-second 3-item questionnaire was completed right after the practice period, once more after the second period and one last time at the end of the last period of the experiment. Participants earned on average $25.5 (including a $7 show-up fee) for an experiment lasting one hour and fifteen minutes.

4. Results

4.1. Rage against the machine? (Conjecture 1)

We first compare the performance of human participants in human and robot treatments. We measure performance by the individual production (measured in cents of a dollar) of human participants on the sequential task. In Figure 3, we observe that humans produced less in robot treatments compared to human treatments (p-value = 0.012, Mann-Whitney-Wilcoxon Test, MWW henceforth).[16]

In Table 2, we report linear panel regressions using individual production as dependent variable. We define as regressors the 'Robot Treatment Dummy' which takes value one if a human participant was assigned to a robot treatment, and the 'Team pay Treatment Dummy' which takes value one if a human participant was assigned to a team pay treatment. We also include cognitive skills (CRT score) obtained in the post-experiment survey as a regressor. CRT scores are an accurate measure of general fluid intelligence which is itself a good predictor of performance on motor tasks that require quick reaction times like the real-effort sequential task used in the current experiment (see Mackintosh, 2011). In addition, a pilot study conducted with 48 human participants using the same real-effort sequential task and paid according to a piece rate scheme showed a positive and significant correlation between participants' individual performance and their CRT

[16] This test does not take into account the time dependence in the data. However, we obtain similar results using panel regressions (see Table 2).

score (ϱ=0.412, p-value = 0.0037).[17] The regressor 'Position in the line' takes value 1, 2 or 3 if a human participant is first, second or third in the line in a given period.

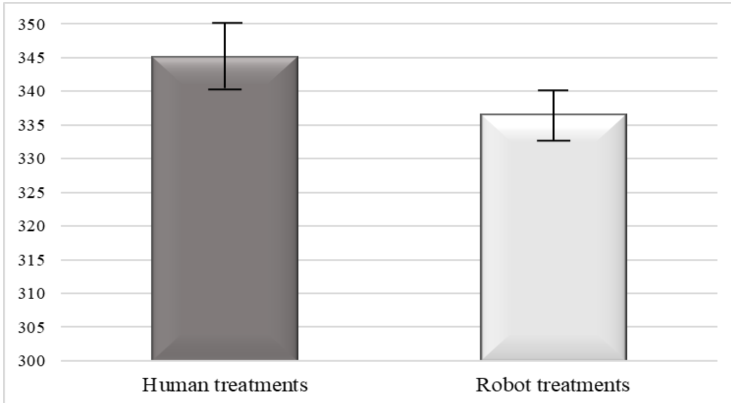

FIGURE 3. Production by treatment.
Average individual production (with 95% confidence intervals) in cents for human participants in human and robot treatments.

In line with Figure 3, we find that individual production decreases in the presence of robots and this effect is statistically significant (see Table 2 where the 'Robot Treatment Dummy' coefficient is negative and significant, p-value = 0.024). Team pay also leads to reduced individual production, although this effect is not statistically significant. Out of the 96 participants involved in the two team pay treatments, only two decided not to undertake the task thus spending their entire time browsing the web. No such behavior was observed under piece rate. The difference in the proportion of workers browsing the web is no different across team pay and piece rate treatments (Proportion test, p-value = 0.163).[18] These findings are in line with Conjecture 5i and suggests that our sequential task tends to limit the extent of the moral-hazard in teams' problem identified in non-sequential tasks (see Erev, Bornstein and Galili, 1993; Corgnet, Hernan-Gonzalez and Rassenti, 2015b and Section 4.5 for further details on testing Conjecture 5).

[17] This pilot was conducted to assess participants' performance on the newly-developed sequential task. This pilot used a version of the task in which periods lasted for 30 seconds more than in the current design and in which participants had 13 seconds instead of 12 seconds each turn for the current design to complete their color pattern. After observing the results of the pilot, we decided to give participants 1 second less per turn because performance rates achieved during the pilot were close to 100% which would have made it difficult to identify any differences across treatments. These pilot data showed that CRT is a good predictor of performance on the task.
[18] The two participants who only browsed the web under team pay are not included in our statistical analysis. This is why we have 10 observations (2 participants × 5 periods) less under team pay than under piece rate in Table 1. Including these two participants in the analysis does not affect the qualitative nature of our findings.

Not surprisingly, cognitive skills affect performance positively. Interestingly, participants who are assigned to a later position in the line tend to perform better. This seems to relate to the fact that one makes less mistakes once the grid has been already filled by previous workers.[19] Finally, the sequential task involves learning as individual production increases over time (see the positive and significant 'Period' variable coefficient). This is not surprising as learning has been shown to be pervasive in real-effort tasks involving cognitive skills (e.g. Charness and Campbell, 1988).

TABLE 2. Production by treatments and incentive schemes.

	Team pay & Piece rate [1]	Team pay [2]	Piece rate [3]
Constant	311.969***	315.185***	308.874***
	(6.627)	(10.873)	(8.177)
Robot Treatment Dummy	**-8.323****	**-9.561***	-7.494
	(3.686)	**(5.020)**	(5.623)
Team pay Treatment Dummy	-1.824	-	-
	(3.809)		
Cognitive skills (CRT)	5.875***	3.821*	7.738**
	(1.875)	(2.150)	(3.017)
Male Dummy	0.560	2.045	-1.701
	(4.424)	(6.049)	(7.089)
Period number	4.564***	4.457**	4.659**
	(1.257)	(1.721)	(1.938)
Position in the line	11.109***	8.074**	13.998***
	(2.230)	(3.672)	(2.065)
N	950	470	480
R^2	0.070	0.037	0.119
Prob > χ^2	0.000	0.004	0.000

Linear panel regressions for individual production. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

In line with Conjecture 1, we find that the presence of robots negatively affects individual production when pooling both piece rate and team pay treatments (see regression [1] in Table 2). The presence of robots has a negative effect under both team pay (p-value = 0.057) (see [2]) and piece rate (p-value = 0.183) (see [3]). The fact that the negative effect of robots is not statistically significant under piece rate is in line with our model according to which the magnitude of social

[19] In particular, being last in the line is an ideal position when the previous two workers have completed their task without mistakes. In such a case, one just has to click on all empty cells without having to check the actual color pattern.

incentives is expected to be stronger under team pay than under piece rate. This is particularly the case because, in our model, team pay triggers social pressure whereas piece rate does not.

We have thus far shown a negative effect related to the presence of robots in the sequential task. Next, we will detail how altruism, envy, shame and social pressure can account for this negative effect thus testing Conjectures 2, 3 and 4.

To that end, we need to classify workers as either altruistic, envious or shameful following the categorization of Bartling et al. (2009) (see Table C1 in Appendix C). Because this procedure does not classify workers in mutually exclusive categories (e.g. envious workers can also be shameful), we also use an alternative categorization (see Appendix C).[20] In the main text, we present the results for the original categorization of Bartling et al. (2009) although our findings do not qualitatively differ when considering mutually exclusive categories (see Appendix C).

4.2. Altruism (Conjecture 2)

To assess the impact of robots on the positive effect of altruistic concerns on effort provision, we make use of the social preferences elicitation test we collected in our post-experiment survey (see Appendix A). We define an *altruism index* as the number of decisions in which participants chose the allocation that maximizes the other person's payoff over all four decisions (see Bartling et al. 2009; Corgnet, Espín and Hernan-Gonzalez, 2015). Using a median-split led us to categorize workers as being altruistic whenever they chose to maximize the other person's payoff in at least 3 out of 4 decisions. According to this definition, we categorize 43.7% of the participants as being altruistic.[21]

We start by testing Conjecture 2i assessing the effect of altruistic concerns on the production of workers in a team pay work environment without robots as in the model of Rotemberg (1994)

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[20] We restrict our analysis to altruism and inequality aversion of the type modeled in Fehr and Schmidt (1999) and identified using the test of Bartling et al. (2009). Our approach to social preferences does not claim to be exhaustive as more extensive social preferences categorizations can be used. For example, Kerschbamer (2015) identifies nine archetypes of distributional preferences (note that using a similar method as Kerschbamer (2015), Kerschbamer, Sutter and Dulleck, (2017) focus only on five archetypes of social preferences: selfish, efficiency loving, spiteful, inequality averse and inequality loving). One can thus see our endeavor as studying whether the presence of robots affects the strength of the main social preferences categories. If this is the case then our analysis suggests this might also be the case for a broader range of social preferences.

[21] Our findings are robust to considering a stricter definition of altruism according to which only those who maximize the other person's payoff in all four decisions would be defined as being altruistic. In that case, only 11.1% of the participants comply with the definition.

(see Table B1 in Appendix B). We find that altruism tends to lead to higher effort provision under team pay in line with Conjecture 2i.[22]

In Figure 4, we show that the production of altruistic workers is negatively and significantly affected by the presence of robots under team pay (see left panel, p-value = 0.001, MWW) whereas it is not so for non-altruistic workers (see right panel, p-value = 0.927). These findings are in line with Conjecture 2ii.

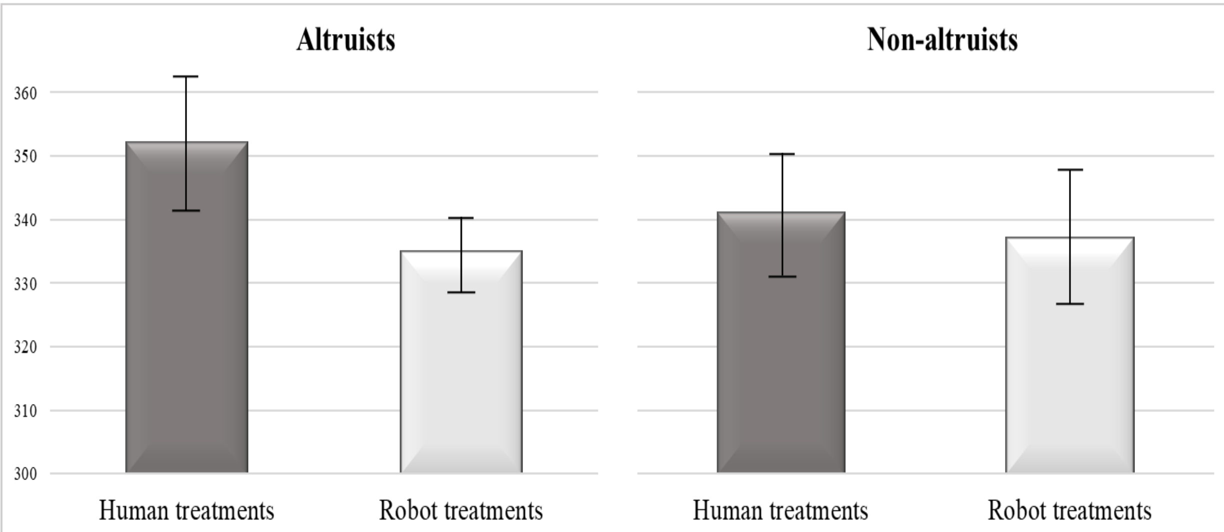

FIGURE 4. Production and altruism.
Average individual production (with 95% confidence intervals) in cents under team pay for human participants in human and robot treatments in the case of altruists (left panel) and non-altruists (right panel). Participants are categorized as being altruistic or not using a median split.

In Table 3, we show, in line with Conjecture 2ii, that the negative effect of the presence of robots on human performance is statistically significant for the case of altruists whereas it is not so for non-altruists. This is the case because the 'Robot Treatment Dummy' is negative and significant for the regression using individual production as dependent variable when considering only altruist humans (see regression [1]) whereas the 'Robot Treatment Dummy' is not significant for the case of non-altruists (regression [2]). Under piece rate, the 'Robot Treatment Dummy' is not significant for the case of altruistic workers in line with Conjecture 2iii.

[22] Under piece rate, altruism (regardless of the measure used in Table B1 in Appendix B) does not affect individual production significantly.

TABLE 3. Production and altruism.

	Team pay		Piece rate	
	Altruists [1]	Non-altruists [2]	Altruists [3]	Non-altruists [4]
Constant	311.823***	321.730***	307.581***	309.059***
	(25.127)	(18.271)	(18.461)	(15.228)
Robot Treatment Dummy	**-15.820*** **	-5.951	-6.414	-7.873
	(5.989)	(12.938)	(9.482)	(5.643)
Cognitive skills (CRT)	1.945	4.720	8.110*	7.874***
	(4.048)	(5.038)	(4.136)	(2.878)
Male Dummy	8.784	-4.422	-2.264	-1.462
	(8.097)	(7.390)	(7.571)	(10.060)
Period number	4.305**	4.672	4.275	4.975**
	(1.964)	(3.254)	(3.124)	(2.155)
Position in the line	9.441	6.613*	15.610***	12.944***
	(7.652)	(3.503)	(5.188)	(2.872)
N	215	255	200	280
R^2	0.084	0.026	0.146	0.102
Prob > χ^2	0.000	0.004	0.000	0.000

Linear panel regressions for individual production. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level. Participants are categorized as being altruistic or not using a median split.

As is shown in Table C2 in Appendix C, the findings in Table 3 continue to hold when using a categorization of altruistic workers that do not overlap with envy and shame.

4.3. Envy and shame (Conjecture 3)

To test Conjecture 3, we define *envious (shameful)* workers using our social preferences elicitation test. In line with Bartling et al. (2009), an envious worker will be defined as one not willing to obtain a lower payoff than others thus choosing Option A in Decisions 3 and 4 (see Table A1 in Appendix A). By contrast, a shameful worker dislikes to obtain higher payoffs than his or her coworkers thus choosing Option A in Decisions 1 and 2. It follows that 37.4% (29.5%) of the participants are categorized as envious (shameful).[23] We also categorize as *ahead-seeking* those individuals who strive to systematically earn more money than the other participant (see Option B for Decisions 1 and 2). Using this definition, we categorize 10.6% of the workers as ahead-seeking.

[23] These are standard results for a population of university students (see e.g. Corgnet, Espín and Hernan-Gonzalez, 2015).

In line with Conjecture 3i, we show in Table B2 in Appendix B that under piece rate envious workers tend to exert higher effort than non-envious workers in human treatments (see positive and significant coefficient for ‘Envious Dummy’ in regression [1]). It is also consistent with Conjecture 3i that shameful workers underperform those who are not shameful in the piece rate human treatment (see negative and significant coefficient for ‘Shameful Dummy’ in regression [2] in Table B2).

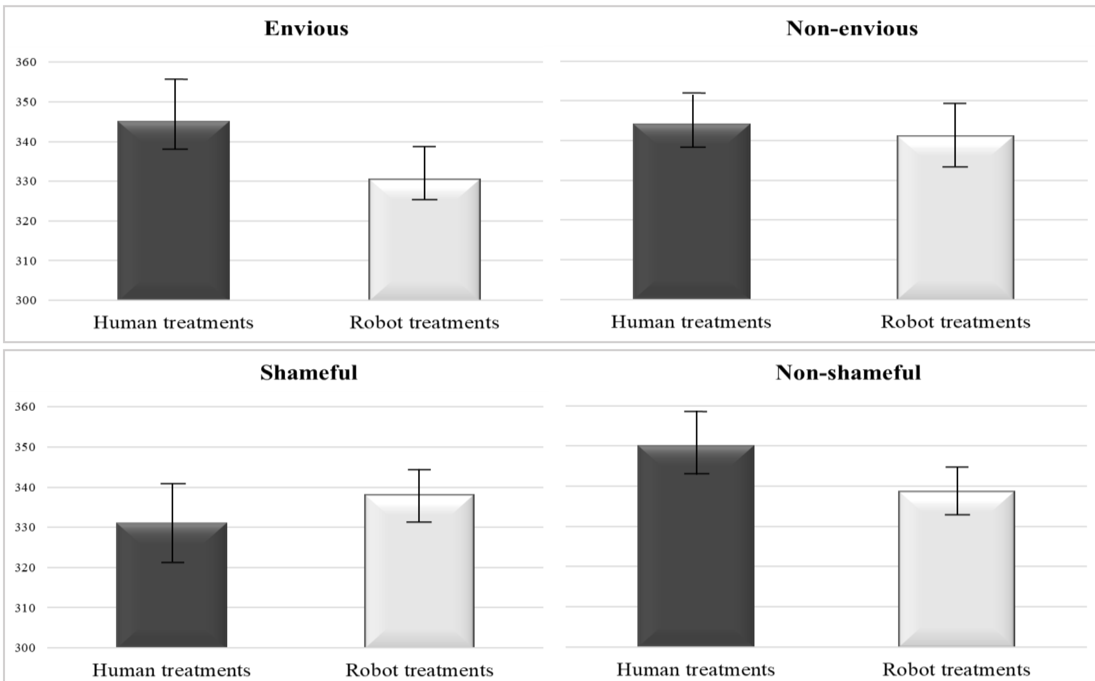

FIGURE 5. Production, envy and shame.
Average individual production (with 95% confidence intervals) under piece rate for human participants in human and robot treatments in the case of envious (upper left panel) and non-envious (upper right panel). Individual production under piece rate for human participants in human and robot treatments in the case of shameful (lower left panel) and non-shameful (lower right panel).

In Figure 5, we report graphical evidence for Conjecture 3ii as the negative effect of the presence of robots is observed for envious workers (upper left panel, p-value = 0.007, MWW) but not for non-envious workers (upper right panel, p-value = 0.712). By contrast, we observe a positive, although not significant, effect of the presence of robots for shameful workers (lower left panel, p-value = 0.223). For non-shameful workers the presence of robots seems to have a negative effect similarly to the case for envious workers (p-value = 0.035). This can be explained by the fact that many workers who are non-shameful exhibit ahead-seeking motives (18.7% of the participants in our dataset) thus working hard to surpass other humans whereas not exerting any extra effort to outperform robots (see regression [5] in Table 4 for the positive effect of ahead-seeking motives on workers' performance in human compared to robot treatments).

In Table 4, we confirm Conjecture 3ii by showing that the negative effect of the presence of robots on individual production (see variable 'Robot Treatment Dummy' which is negative and significant) under piece rate holds for envious workers but not for non-envious workers (see regressions [1] and [2]). In line with Conjecture 3ii, shameful workers tend to work more in the presence of robots, although the 'Robot Treatment Dummy' fails to reach statistical significance (p-value = 0.195) (see regression [3]). Non-shameful workers tend to react negatively to the presence of robots although to a lesser magnitude than envious workers (see regression [4]). Our categorization of social preference types (see Table C1 in Appendix C) is such that envious (shameful) workers may also be shameful (envious). Not surprisingly, when we consider only shameful (envious) workers who are not categorized as envious (shameful), the statistical significance of our findings improves further (see Table C3 in Appendix C). Finally, in line with Conjecture 3ii, ahead-seeking workers exert higher effort in the piece rate human treatment than in the piece rate robot treatment (see regression [5]).

In regression [6] we also show that under piece rate the presence of robots does not affect individual production for workers who are both envious and shameful. These workers are referred to as *egalitarian* by Bartling et al. (2009). This is in line with our model because egalitarian workers both dislike disadvantageous payoff inequality (they are envious) and advantageous payoff inequality (they are shameful) (see Fehr and Schmidt, 1999; Bartling et al. 2009) so that the positive effect of envy on effort provision is likely to be at least partly offset by the negative effect of shame.[24]

In Table B3 in Appendix B we confirm Conjecture 3iii by showing that the presence of robots does not affect individual production under team pay for envious as well as for shameful workers.[25] In Table C4 in Appendix C we replicate the results in Table 4 using an exclusive categorization of social preference types.[26]

[24] For the two effects to fully cancel out, it would have to be the case that workers are as shameful as envious.

[25] Because of an insufficient number of workers categorized as ahead-seeking (40) under team pay, we do not report the results of the regression for ahead-seeking workers in Table B3 in Appendix B.

[26] Unlike Table 3, we do not conduct regressions for shameful (non-shameful) and egalitarian workers because such social preference types cannot be identified by our mutually exclusive social preferences categorization (see Table C1 in Appendix C). Also, we do not have enough ahead-seeking workers in our mutually exclusive categorization to conduct a regression only with those workers.

TABLE 4. Production and social preference types.

Piece rate treatments	Envious [1]	Non-envious [2]	Shameful [3]	Non-shameful [4]	Ahead-seeking [5]	Egalitarian [6]
Constant	316.544***	305.994***	278.116***	325.519***	314.756***	303.028***
	(18.375)	(9.722)	(10.798)	(10.301)	(22.405)	(21.129)
Robot Treatment Dummy	**-18.560*** **	0.244	8.152	-12.728*	**-28.264*** **	-4.735
	(6.774)	(6.223)	(6.294)	(6.837)	**(7.344)**	(13.095)
Cognitive skills (CRT)	7.330*	8.489**	12.424***	5.814	14.464*	8.925
	(3.854)	(4.244)	(3.876)	(3.627)	(7.633)	(9.602)
Male Dummy	-4.509	-3.095	-0.230	-5.455	-13.728	-14.176
	(11.797)	(6.545)	(7.603)	(6.935)	(10.994)	(9.931)
Period number	4.769*	4.600**	8.196***	3.114	8.175**	6.818
	(2.803)	(2.007)	(2.455)	(2.390)	(3.309)	(4.493)
Position in the line	14.273***	14.000***	12.785***	14.406***	12.735*	15.546***
	(3.858)	(4.128)	(3.320)	(2.470)	(7.152)	(5.403)
N	205	275	145	335	85	70
R^2	0.113	0.142	0.262	0.098	0.213	0.142
Prob > χ^2	0.000	0.000	0.000	0.000	0.000	0.000

Linear panel regressions for individual production. Robust standard errors clustered at the session level are in parentheses.
*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

In the next section, we test Conjecture 4 assessing the extent to which humans can exert stronger social pressure than robots.

4.4. Social pressure (Conjecture 4)

In Figure 6, we report, in line with Conjecture 4, that a human's performance is improved more substantially when another human rather than a robot is observing their performance. This figure reports individual production for human workers who are positioned second in the line because this is the only position for which a human worker can either be followed only by a human or only by a robot.[27] Importantly, this social pressure effect is much more pronounced for team pay (p-value < 0.001, MWW) which is when one's performance readily affects another human's earnings than for piece rate (p-value = 0.969).

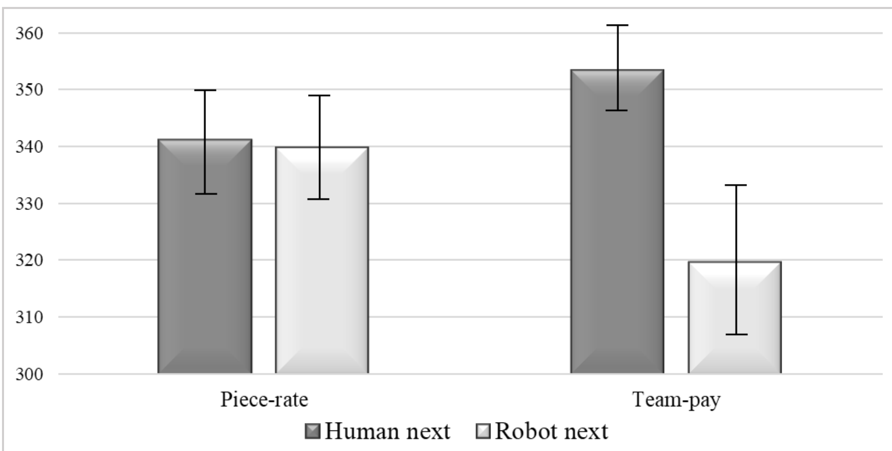

FIGURE 6. Production and social pressure.
Average individual production (with 95% confidence intervals) in cents for human participants in robot treatments who are followed by either a human or a robot.

In Table 5, we show that, in line with Conjecture 4i, being followed by a human rather than a robot leads to an increase in humans' production under team pay (see 'Human Next Dummy' which takes value one if a human worker is followed by another human in the line and value zero otherwise, regression [1]). In line with Conjecture 4ii, the 'Human Next Dummy' is not significant for the case of piece rate (see regression [2]) suggesting that the positive social pressure effect of humans' presence is not observed in that case.

[27] A human worker who is first in the line would always be followed by one human as well as one robot (in different orders) thus preventing us to directly test Conjecture 4.

TABLE 5. Production and social pressure.

	Team pay [1]	Piece rate [2]
Constant	298.410***	318.860***
	(18.682)	(16.215)
Human Next Dummy	**35.492*** **	5.407
	(9.092)	(8.599)
Cognitive skills (CRT)	3.587	5.073
	(4.725)	(6.997)
Male Dummy	1.176	-4.927
	(14.411)	(11.961)
Period number	4.608***	6.357***
	(1.071)	(1.818)
N	68	80
R^2	0.262	0.111
Prob > χ^2	0.000	0.002

Linear panel regressions for individual production for robot treatments and for humans in the second position in the line. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

In Table 5, we have considered cases in which the human worker in the second position is either followed by another human or not. Because we consider robot treatments, a second-position worker who is (not) followed by a human is necessarily preceded by a robot (human). As a result, the positive and significant 'Human Next Dummy' in regression [1] implies that, for a second-position worker, the effect of being observed by a human rather than a robot (social pressure) is significantly more positive than any effect of observing the performance of a human rather than a robot (peer pressure). These findings are in line with the works of Mas and Moretti (2009) as well as Corgnet, Hernan-Gonzalez and Rassenti (2015b).

4.5. Piece rate versus team pay (Conjecture 5)

In Table 1 (regression [1]), we already provided support for Conjecture 5i as workers were found not to exert a significantly lower level of effort under team pay than under piece rate. This finding is consistent with a large body of empirical works revealing limited support for the moral hazard in teams' problem (e.g. Homans 1953, 1954; Manz and Sims 1993; Bewley, 1999). Our work shows that the extent of shirking in teams crucially hinges upon workers' social motives. An implication of our model is that moral hazard in teams will be most pronounced in the absence of social incentives (Conjecture 5ii). To test Conjecture 5ii, we first need to identify those workers who do not exhibit social preferences. We define *selfish* workers as those systematically picking the allocation of money that maximizes their own payoff in the social preference test of Bartling et al. (2009) (see Table C1 in Appendix C). Selfish workers cannot be categorized as either altruistic, envious or shameful.[28] To test Conjecture 5ii, we thus conduct the same regression as in Table 1 for the case of selfish workers who are last in the line so that both social preferences and social pressure are muted (see Table B4 in Appendix B). We report a negative and marginally significant effect of team pay on individual production (see "Team pay Treatment Dummy" coefficient in Table B4, p-value = 0.089) providing some support for the existence of a moral hazard in teams problem when social incentives are muted.

4.6. Discussion

Our findings show that social incentives play an important role in understanding why humans behave differently when surrounded by other humans than when surrounded by robots. Because social incentives have a positive effect on work effort, the presence of robots affects workers' motivation negatively thus leading to what can be seen as a "rage against the machine". Rather than a negative reaction ("rage") to the presence of robots, our findings could be interpreted as humans reacting to the presence of other humans while being indifferent to robots. This is exemplified by the fact that envious humans would "race" against other humans while not doing so against robots.

An alternative explanation for the negative effect of the presence of robots on human performance is to argue that, regardless of social incentives, workers feel negatively toward robots leading them to experience more stress, less work satisfaction thus lowering their motivation to perform (see Bartneck et al. 2005; Syrdal et al. 2009). However, this type of explanation is not consistent with our data regarding the affective response of human workers to the different treatments measured using the valence, arousal, and dominance scores of Self-Assessment Manikin (Bradley and Lang, 1994) (see Appendix A). We find that human and robot treatments do not differ, regardless of the dimension we consider (all p-values > 0.10 for the nine Rank Sum Tests comparing self-reported arousal, pleasure and dominance at the beginning, in the middle and at the end of the experiment).

[28] However, some selfish individuals (12.2% in our sample) are also categorized as ahead-seeking.

5. Conclusion

Employment contracts are most often highly incomplete leaving aside crucial features of one's job definition. In such context, social incentives operating by means of social preferences and social pressure have been proposed as solutions to free riding issues in firms. Our contribution was to highlight the magnitude of social incentives as well as study their interaction with monetary incentives. To that end, we developed a new experimental paradigm featuring a real-effort sequential task in which social incentives could be muted or heightened by controlling whether one would interact with humans or robots. We wanted to assess the extent to which workers being given the same compensation scheme, either piece rate or team pay, would be affected by the mere presence of robots. We found that human performance was significantly lower in the treatments in which humans interacted with robots than when they only interacted with humans. This result was obtained despite the fact that monetary incentives were kept constant across treatments and robots were calibrated to perform as well as an average human worker in the human treatments. We tested and supported our conjectures that such negative reaction to the presence of robots was due to the weakening of social incentives in the robot treatments.

Our findings provide causal evidence for the key role of social incentives at work thus supporting the earlier claim of a series of theoretical works in the incentives literature (e.g. Kandel and Lazear, 1992; Rotemberg, 1994; Bartling and von Siemens, 2010; Dur and Sol, 2010). Our results are of high relevance not only for incentive theory but also for the literature on social preferences. In particular, our findings show that other-regarding preferences can have a positive effect on effort provision whether they are categorized as prosocial (altruism) or antisocial (envy) (see e.g. Zizzo and Oswald, 2001; Kimbrough and Reiss, 2012). Our work thus suggests an evolutionary reason for the prevalence of both prosocial and antisocial motives as they can both fuel cooperation depending on whether rewards are defined at the individual or group level. Our argument complements previous works putting forward the evolutionary forces behind prosocial motivations in social dilemmas (see Boyd et al. 2003; Sobel, 2005; Silk and House, 2015).

Our findings also contribute to Organizational Economics by highlighting that, whenever firms implement new organizational designs, they should take into account the possible negative effect of automation on the strength of social incentives. The stark effects reported here are, however, likely to represent a lower bound as we did not consider all dimensions of social incentives leaving aside issues of social interaction (e.g. Dur and Sol, 2010), reciprocity and trust (e.g. Charness and Rabin, 2002; Casadesus-Masanell, 2004; Sobel, 2005; Segal and Sobel, 2007; Ramalingam and Rauh, 2010), norms (e.g. Danilov and Sliwka, 2017), identity (see Akerlof and Kranton, 2000; Dugar and Shahriar, 2012), prosocial organizations and the role of firm missions (e.g. Dur and Zoutenbier, 2014; Banuri and Keefer, 2016; Carpenter and Gong, 2016; Besley and Ghatak, 2018) as well as prosocial punishments (see Fehr and Gächter, 2000, 2002; Carpenter et al. 2009). More generally, social incentives are likely to be even more prevalent in actual work settings in which workers can communicate with their coworkers. In addition, our experiment was conducted with University-educated young adults who have been shown to be more at ease with new technologies and automation (Adecco, 2012; OECD, 2016) suggesting that mature workers could react even more negatively to the presence of robots.

To our knowledge, ours is the first study to identify and quantify the negative effect of automation on social incentives. Doing so, we highlight the crucial role of social incentives in alleviating moral hazard in teams. This confirms the conjecture that the prevalence of team pay (e.g. Ledford, Lawler and Mohrman, 1995; Parker, McAdams and Zielinski, 2000; Lazear and Shaw, 2007) and more generally low-powered incentives (Chiappori and Salanié, 2000) can be explained by the strength of social incentives. Our findings can thus explain the overwhelming success of team pay observed in field studies (Dumaine, 1990, 1994; Hamilton, Nickerson and Owan 2003; Hansen 1997; Ichniowski et al. 1996; Ichniowski, Shaw and Prennushi 1997; Kruse 1992; Manz and Sims 1993). In sum, an apparently weak form of incentives can be strengthened by the social context and thus become the best-available option.

Our findings also provide causal evidence for the argument of Milgrom and Roberts (1990), Roberts (2004) and Brynjolfsson and Migrom (2013) that the effectiveness of payment practices crucially hinges on complementary organizational design features and human resource practices. Our research thus fills a gap identified by Lazear and Oyer (2013, p. 508) regarding the lack of empirical support for the relevance of complementarities across human practices:

> "*That is, team-based productivity may be more important when firms invest in selecting employees carefully, training people in the system, and other practices. Testing this idea is empirically challenging, however, because measuring productivity is difficult, and human resource practices are adopted endogenously*."

Answering the call of Lazear and Oyer (2013), our findings put forth that team incentives are effective when social incentives prevail which is when a team is composed of altruistic workers and does not involve robots.

Future research should investigate further the interaction between social incentives and organizational design. For example, it remains to be seen whether social incentives will become increasingly important as the workplace becomes more automated. To alleviate the negative effect of the presence of robots at work while keeping intact its many benefits (Autor, 2015), developing robots which will be able to trigger social preferences and induce social pressure seems critical (see Hall, 2017). The evidence collected by Deming (2017) may also suggest an alternative strategy that consists in recruiting workers who are especially sensitive to social incentives.

Our work shows that, because social incentives are remarkably effective, there are negative externalities of replacing humans by robots on the morale of the workforce. On the top of that, managers who themselves respond to social incentives may be reluctant to hire robot subordinates because this might weaken their own motivation.

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Appendix A. Instructions

Sequential Task

Instructions are available here: http://www.goo.gl/Hg5jXn and as a supplementary material of the submitted manuscript.

Survey

Cognitive Reflection Test (5 Minutes)

Taken from Frederick (2005):

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? ____ cents
[Correct answer: 5 cents; intuitive answer: 10 cents]

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes
[Correct answer: 5 minutes; intuitive answer: 100 minutes]

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____ days
[Correct answer: 47 days; intuitive answer: 24 days]

Social Preferences (Barling et al. 2009)

You will be asked to make a series of choices in decision problems. For each line in the table below (Table A1), please state whether you prefer Option A or Option B. Notice that there are a total of 4 lines in the table but just one line will be randomly selected for payment. Each line is equally likely to be chosen, so you should pay equal attention to the choice you make in every line. After you have made all your decisions a number between 1 and 4 will be randomly selected by the computer. This number determines which line is going to be paid. Your earnings for the selected line depend on which option you chose: if you chose Option A in that line, you will receive $2 and the other participant who will be matched with you will also receive $2. If you chose Option B in that line, you and the other participant will receive earnings as indicated in the table for that specific line. For example, if you chose B in line 2 and this line is selected for payment, you will receive $3 and the other participant will receive $1. Similarly, if you chose B in line 3 and this line is selected for payment, you will receive $2 and the other participant will receive $4. Note that the other participant will never be informed of your personal identity and you will not be informed of the other participant's personal identity. After you have made all your decisions, the computer will randomly draw a number to determine which line is going to be paid. Then the computer will randomly and anonymously match you with another participant in the experiment. While matching you with another participant, the computer will also randomly determine whose decision to implement. If the computer chooses your decision to implement, then the earnings to you and the other participant will be determined according to your choice of A or B. If the computer chooses the other participant decision to implement, then the earnings will be determined according to the other participant choice of A or B.

TABLE A1. Social preferences elicitation.

Decision	Option A Payoff self, Payoff other	Option B Payoff self, Payoff other
1	$2,$2	$2,$1
2	$2,$2	$3,$1
3	$2,$2	$2,$4
4	$2,$2	$3,$5

Bartling et al. (2009).

Self-assessment manikin (Bradley and Lang, 1994)

Participants took the Self-Assessment Maniking (Figure A1) right before starting the task, as well as in the middle and at the end of the task.

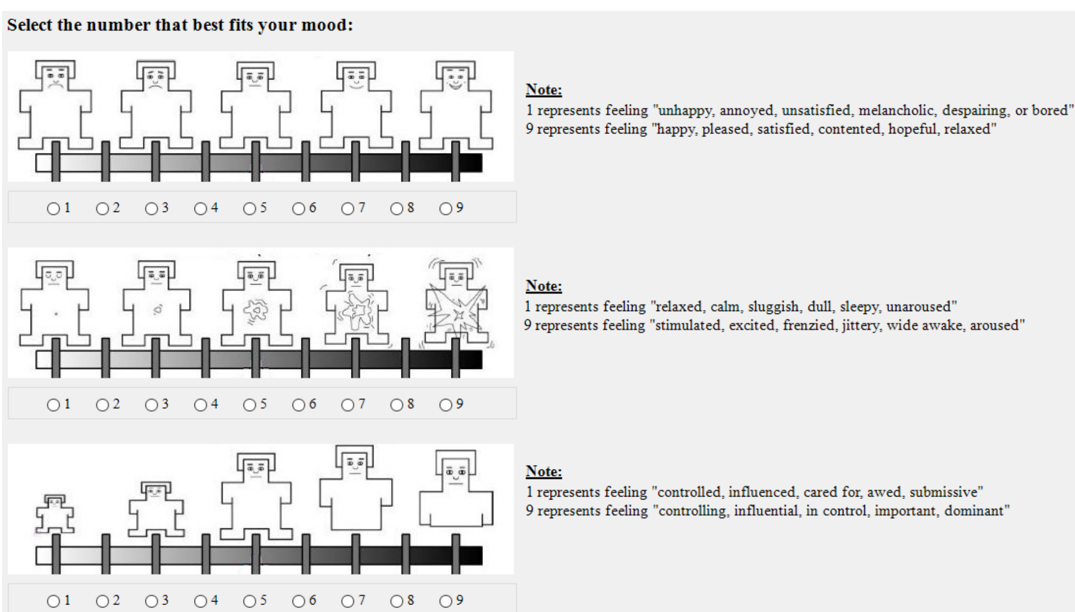

FIGURE A1. Self-assessment manikin.
Bradley and Lang (1994)

Appendix B. Additional analyses.

TABLE B1. Production and different measures of altruism.

Team pay human treatment	[1]	[2]	[3]
Constant	313.770***	331.371***	
	(15.715)	(10.662)	
Altruism Index	**9.983****	**-**	**-**
	(4.364)		
Altruism Dummy[29]	-	8.089	-
		(6.654)	
Strict Altruism Dummy	-	**-**	**19.701*****
			(1.712)
Cognitive skills (CRT)	1.866*	2.707	4.685*
	(1.050)	(2.114)	(2.710)
Male Dummy	-1.816	-1.296	-0.319
	(4.815)	(5.460)	(5.075)
Period number	1.243	1.245	1.246
	(2.031)	(2.030)	(2.030)
Position in the line	5.634	6.191	6.315
	(5.940)	(5.933)	(5.985)
N	235	235	235
R^2	0.034	0.018	0.022
Prob > χ^2	0.000	0.000	0.000

Linear panel regressions for individual production in the team pay human treatment. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

[29] This dummy takes value one if a participant's altruism index is at least equal to 3, and value zero outherwise.

TABLE B2. Production, envy and shame.

Piece rate human treatment	[1]	[2]
Constant	307.096***	323.997***
	(7.653)	(9.862)
Envious Dummy	**10.670****	-
	(5.436)	
Shameful Dummy	-	**-18.105*****
		(6.917)
Cognitive skills (CRT)	10.768***	9.717**
	(4.832)	(3.948)
Male Dummy	0.480	-3.496**
	(13.154)	(8.204)
Period number	0.510	0.510
	(2.455)	(2.450)
Position in the line	16.072	15.679***
	(2.902)	(2.970)
N	240	240
R^2	0.128	0.141
Prob > χ^2	0.000	0.000

Linear panel regressions for individual production in the piece rate human treatment. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

TABLE B3. Production, envy and shame under the presence of robots.

Team pay treatments	Envious [1]	Shameful [2]
Constant	328.477***	352.943***
	(26.605)	(16.780)
Robot Treatment Dummy	5.291	4.914
	(10.916)	(8.358)
Cognitive skills (CRT)	11.026***	4.120
	(3.482)	(3.577)
Male Dummy	-17.794	-6.785
	(16.431)	(16.204)
Period number	2.958	-1.572
	(1.991)	(2.590)
Position in the line	9.491	2.967
	(6.029)	(7.625)
N	150	135
R^2	0.075	0.022
Prob > χ^2	0.000	0.042

Linear panel regressions for individual production in team pay treatments. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

TABLE B4. Production and selfish workers

All treatments (Workers who are last in the line)	Selfish [1]
Constant	354.953
	(21.020)
Robot Treatment Dummy	-14.013
	(8.507)
Team pay Treatment Dummy	**-17.387***
	(10.259)
Cognitive skills (CRT)	5.119
	(1.427)
Male Dummy	-2.780
	(15.027)
Period number	5.119***
	(1.427)
N	158
R^2	0.059
Prob > χ^2	0.000

Linear panel regressions for individual production of selfish workers. Robust standard errors clustered at the session level are in parentheses. *** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

Appendix C. Social preferences categorization

The mutually exclusive categorization shown in Table C1 is such that for each of the workers categorized as belonging to a given social preference type in column [1] we only keep those who cannot be categorized as belonging to any other social preference type in column [1]. Alternatively, we could have applied the technique developed of Kerschbamer (2015) to categorize workers in nine mutually exclusive types. However, we do not have enough observations to perform this procedure proficiently. This is the case because our conjectures lead us to focus on specific social preference types for specific treatments. Even when using our mutually exclusive categorization of workers across only five social preference types (see Table C1) we are not able to conduct all the analyses we performed with our original categorization (see Table C4).

TABLE C1. Social preferences categorization.

Social preference types (% of workers per category)	Bartling et al. (2009)[30]	Mutually exclusive categorization
	[1]	[2]
Altruism	44.3%	31.3%
Envy	37.0%	13.0%
Shame	29.7%	0%
Ahead-seeking	13.0%	5.7%
Selfish	47.4%	10.4%

[30] We define altruistic workers as choosing the maximization of the other's payoff in at least three out of the four decisions presented in Table A1 in Appendix A. Envious (shameful) workers choose Option A in Decisions 3 and 4 (1 and 2). Ahead-seeking workers choose Option B in Decisions 1 and 2.

TABLE C2. Production and altruism (mutually exclusive categorization).

	Team pay		Piece rate	
	Altruists	Non-altruists	Altruists	Non-altruists
	[1]	[2]	[3]	[4]
Constant	294.612***	321.646***	353.630***	299.945***
	(32.582)	(15.707)	(28.688)	(10.467)
Robot Treatment Dummy	**-19.219*****	-3.186	-23.843	-3.421
	(6.813)	(10.048)	(15.481)	(5.070)
Cognitive skills (CRT)	2.808	4.593*	2.277	9.409***
	(3.742)	(2.361)	(4.116)	(2.753)
Male Dummy	6.864	1.103	-12.932	0.275
	(9.046)	(7.600)	(11.926)	(8.645)
Period number	6.125**	3.738	1.131	5.966***
	(1.780)	(2.755)	(4.720)	(1.698)
Position in the line	17.967**	3.871	17.114***	12.571***
	(8.115)	(4.048)	(6.595)	(2.434)
N	170	300	125	355
R^2	0.177	0.143	0.145	0.143
Prob > χ^2	0.000	0.000	0.000	0.000

Linear panel regressions for individual production using a mutually exclusive categorization of social preferences. Robust standard errors clustered at the session level are in parentheses.

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

TABLE C3. Production, envy and shame (mutually exclusive categorization).

Piece rate treatments	Envious (but not shameful) [1]	Shameful (but not envious) [2]
Constant	328.732***	280.624***
	(20.397)	(16.341)
Robot Treatment Dummy	**-25.198*** **	**20.467***
	(7.890)	**(11.388)**
Cognitive skills (CRT)	8.819*	12.424***
	(4.597)	(3.651)
Male Dummy	-7.617	-11.001
	(11.356)	(13.274)
Period number	3.757	9.667***
	(3.834)	(1.352)
Position in the line	13.771***	11.534***
	(3.201)	(3.571)
N	135	75
R^2	0.126	0.592
Prob > χ^2	0.000	0.000

Linear panel regressions for individual production in piece rate treatments. Robust standard errors clustered at the session level are in parentheses.

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

TABLE C4.- Production and social preference types (mutually exclusive categorization).[31]

Piece rate treatments	Envious	Non-envious	Envious & ahead seeking	Non-envious & non-ahead seeking
	[1]	[2]	[3]	[4]
Constant	302.911***	305.994***	328.732***	300.628***
	(7.866)	(9.722)	(20.397)	(8.535)
Robot Treatment Dummy	-18.235	-5.816	**-25.197*** **	-0.352
	(17.035)	(6.222)	**(8.790)**	(5.572)
Cognitive skills (CRT)	3.626	8.577**	8.819*	9.000***
	(7.413)	(3.401)	(4.597)	(3.186)
Male Dummy	-10.539	-1.642	-7.618	-1.773
	(15.634)	(6.381)	(11.356)	(6.707)
Period number	-1.040	5.594***	3.757	5.014**
	(5.563)	(1.893)	(3.834)	(2.079)
Position in the line	19.323***	13.755***	13.771	14.041***
	(4.908)	(2.234)	(3.201)	(2.903)
N	70	410	135	345
R^2	0.139	0.135	0.126	0.143
Prob > χ^2	0.000	0.000	0.000	0.000

Linear panel regressions for individual production in piece rate treatments for the case of the mutually exclusive categorization of social preference types. Robust standard errors clustered at the session level are in parentheses.
*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level.

[31] Unlike Table 3, we do not conduct regressions for shameful (non-shameful) and egalitarian workers because such social preference types cannot be identified by our mutually exclusive social preferences categorization (see Table C1). Also, we do not have enough ahead-seeking workers in our mutually exclusive categorization to conduct a regression only with those workers.