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The Motivational Cost of Inequality: Pay Gaps Reduce the Willingness to Pursue Rewards

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Abstract
Factors beyond a person's control, such as demographic characteristics at birth, often influence the availability of rewards an individual can expect for their efforts. We know surprisingly little how such pay-gaps due to random differences in opportunities impact human motivation. To test this we designed a study in which we arbitrarly varied the reward offered to each participant in a group for performing the same task. Participants then had to decide whether or not they were willing to exert effort to receive their reward. Unfairness reduced participants' motivation to pursue rewards even when their relative position in the distribution was high, despite the decision being of no benefit to others and reducing reward for oneself. This relationship was partially mediated by participants' feelings. In particular, large disparity was associated with greater unhappiness, which was associated with lower willingness to work – even when controlling for absolute reward and its relative value, both of which also affected decisions to pursue rewards. Our findings suggest pay-gaps can trigger psychological dynamics that hurt productivity and well-being of all involved.

Key words: inequality, pay-gaps, motivation, effort, affect, reward
JEL Codes: D31; D91; J22

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In a system that fulfills meritocratic ideals, rewards are based solely on a person's ability to perform a task. In reality, people can often expect different rewards for similar effort due to non-meritocratic factors beyond their control, including gender (Blau & Kahn, 2007) or race (Longhi & Brynin, 2017). Such "pay-gaps" may have significant consequences to society by influencing people's motivation to exert effort in exchange for rewards. This could contribute to underachievement and low aspirations among people from disadvanted groups (Elmelech & Lu, 2004; Findlay & Wright, 1996; Uhrig, 2015; Boliver, 2013; Crawfowd, Macmillan and Vignoles, 2014; Thiele et al., 2017).

We hypothesize that arbitrary differences in opportunities to earn rewards can negatively impact not only on disadvantaged individuals, but also those offered relatively high rewards. This is because pay gaps may impact motivation via two mechanisms. On one hand, because people engage in spontaneous social comparisons and evaluate their rewards relative to those of others (Lyubomirsky & Ross, 1997; Hagerty, 2000; Boyce, Brown, & Moore, 2010; Bault et al., 2011), pay gaps can increase motivation to pursue rewards of those offered relatively high rewards and reduce the motivation of those offered relatively low rewards, irrespective of the amount offered. However, at the same time people may have a negative response to the unfairness of arbitrary distributions of rewards regardless of which side of the distribution they are at, and be less willing to pursue rewards in situations that are unfair. Indeed, it has been shown that subjects are less happy when they themselves win in a gambling task but the other subject loses, in comparison to when both subjects win (Rutledge et al., 2016). We hypothesize that such a negative reaction may have consequences beyond a person's affective state. Specifically, negative feelings can lead to apathy as well as a reduction in the subjective value of rewards (Eldar & Niv, 2015), leading to reduced motivation of all members of the group. Individuals at the bottom of the distribution could be negatively affected twice, first due to their lower relative position and second due to their reaction to unfair distribution.

Using a controlled laboratory setting, we were able to dissociate and quantify these influences, while studying them independently from other factors that are often associated with pay gaps, such as demographics or stereotypes. Participants made a series of decisions on whether to exert cognitive effort in exchange for a reward while observing the rewards offered to others for completing the same task (**Fig. 1A**). On each trial, we varied: (i) the deviation of payments in the group from an equal distribution (thereafter 'unfairness'), (ii) the relative position of the offer in the distribution (thereafter 'rank') and (iii) the magnitude of the reward (thereafter 'absolute reward'). Participants had no control over the reward's absolute, nor relative, magnitude. After viewing everyone's offers participants reported their current feelings and decided on whether to pursue the reward. We modeled the decisions to exert effort for rewards as a function of absolute reward, the offer's rank within the distribution and unfairness of the distribution. This allowed us to test whether these three factors have a unique effect on the decisions to pursue rewards. Using a mediation model we tested the hypothesis that the effects of these factors on decisions to pursue rewards were mediated by participants' affective response.

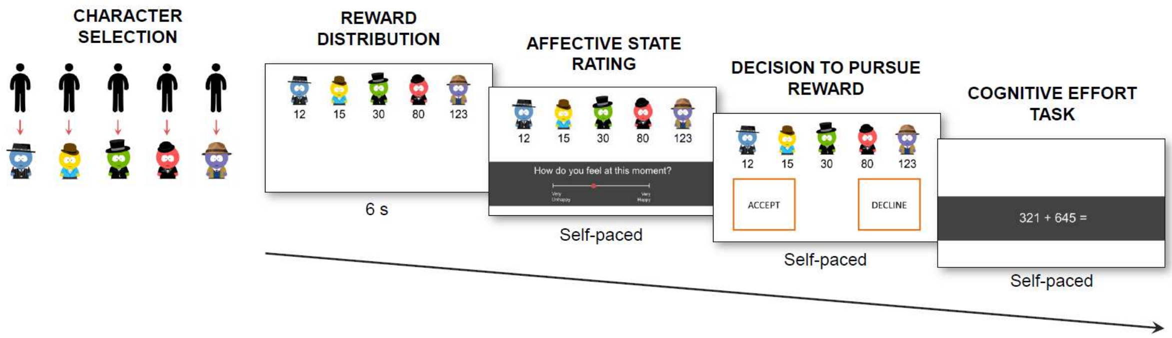

Fig. 1. Task. Participants arrived in the lab in groups of five. They were introduced to each other, and each participant selected cartoon avatar to represent them. They then retired to individual cubicles to complete the study. Each trial started with a display of all participants' reward offers. Participants then rated their current feelings and indicated whether they were willing to exert cognitive effort for their reward. If they decided to do so, they would complete three math problems. If not, they would move on to the next trial.

RESULTS

We invited participants to the lab in groups of five. After having been introduced, they were directed to separate cubicles to complete the study. In each of 60 trials, we presented each participant the reward points offered to each of the five members of the group on that trial. Participants then rated their feelings (from very happy to very unhappy) and indicated whether they were willing to complete three math problems to earn their reward. If they decided to do so, they would complete the math problems. If they decided not to, they would move on to the next trial. The instructions emphasized that all participants would be solving the same math problems. At the end of the study, we selected one trial at random for compensation – a common procedure used to avoid the effects of reward accumulation during the task (Charness, Gneezy & Halladay, 2016). If the participant had decided not to pursue reward on that trial no bonus reward was received. If the participant decided to work for a reward on that trial, they would receive the reward offered on that trial. The decision of whether to pursue rewards did not influence the rewards offered on future trials or pay-out of other members of the group. This information was emphasized in the instructions. After the main part of the experiment, we presented all reward distributions again in the same form and order as in the first part of the study, this time asking participants about their subjective rating of how equal/unequal was each set of rewards offered.

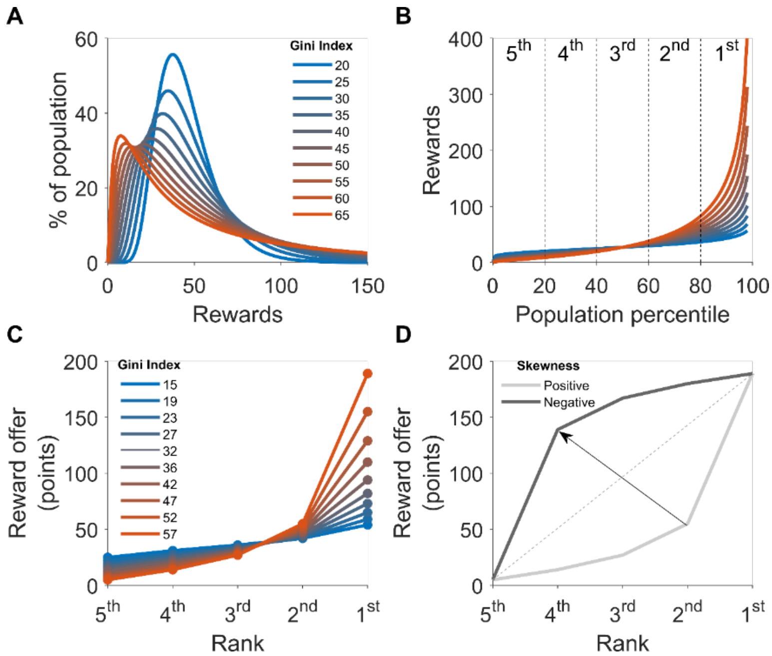

Figure 2. Reward distributions. A) We created 30 income distributions based on a log-normal probability density function (corresponding to 10 levels of Gini index uniformly distributed between 20 and 65, with 3 different median values). Log-normal distribution approximates reward distributions encountered in real-world, such as income distributions within countries (Pinkovskiy & Sala-i-Martin, 2009) and companies (Lazear & Shaw, 2007). For illustration purposes figures A, B and C show only ten of these income distributions based on only one median value. **B**) To generate rewards representative for the above distributions, we used an inverse cumulative density function of these distributions, which assigns maximal income value earned by each percent of the population. **C**) We next took an average income from each quintile of this function, with the exclusion of the top 1 percentile, resulting in five representative values for each trial. The unfairness of reward offers used in the analysis was quantified based on these five values. **D**) We transformed values from positively skewed distribution to create 30 negatively skewed reward distributions. The resulting distributions had the same range and standard deviation of rewards as the positively skewed distributions.

On each trial, we independently manipulated: (i) the deviation of payments in the group from an equal distribution (‘***unfairness***’, see methods for equation), (ii) the rank of the reward offered to each person within the group (ranging from 1 to 5 - ‘***rank***’) and (iii) the absolute reward offered (i.e., points - ‘***absolute reward***’). See methods and **Fig. 2** for details.

We conducted two experiments (N = 110 in total). The difference between the two experiments was that in one experiment the participants knew the exchange rate between reward points offered and Great British Pounds (1 point was worth £0.04), in the other experiment it was unknown and said to differ on each trial. We replicated the findings across both studies. Thus, we report here results from the combined dataset. A separate analysis of each dataset is presented in the **Supplementary Material**.

Pay gaps reduce the motivation to pursue rewards. Participants chose to pursue rewards on 54% of trials. To test whether the hypothesized factors influenced participants’ choices, we used a generalized linear mixed-effects model (GLME) predicting decisions to work for reward on every trial from unfairness level of all offers, rank of individual’s offered reward (from 1 to

5), and absolute value of the offered reward (expressed as a power function to account for diminishing marginal utility; see Methods for details). Additionally, we examined if participants reacted to reward offers differently when the minority of individuals are at the top of the distribution and the majority at the bottom or vice versa, by including in the model the signed skewness of the distribution (measured by Adjusted Pearson's Coefficient of Skewness). The possible effect of fatigue was accounted for by including trial number. All three hypothesized factors significantly influenced decisions to work in exchange for rewards. In particular, the likelihood of pursuing rewards was greater when (i) unfairness was low (β = -0.29, $p < 0.001$), (ii) rank was high (β = 0.92, $p < 0.001$) and (iii) absolute reward was high (β = 2.82, $p < 0.001$). In addition, the likelihood of pursuing rewards decreased over time (β = -1.04, $p < 0.001$), presumably due to fatigue. Skewness of the distribution did not have a significant effect (β = 0.01, p = 0.92).

Similar results are obtained when using particpants' subjective ratings of unfairness rather than an objective calculation (subjective inequality: β = -0.22, $p < 0.001$; rank: β = 0.81, $p < 0.001$; absolute reward: β = 2.84, $p < 0.001$; fatigue: β = -1.02, $p < 0.001$; skewness: β = -0.20, $p < 0.001$). Note, that the difference is that here skeweness is significant. However model comparison based on the Bayesian Information Criterion (BIC), indicated that the objective measure of unfairness provided a better fit (BIC = 3662) than the subjective measure (BIC = 3778), possibly due to the noisiness of the latter.

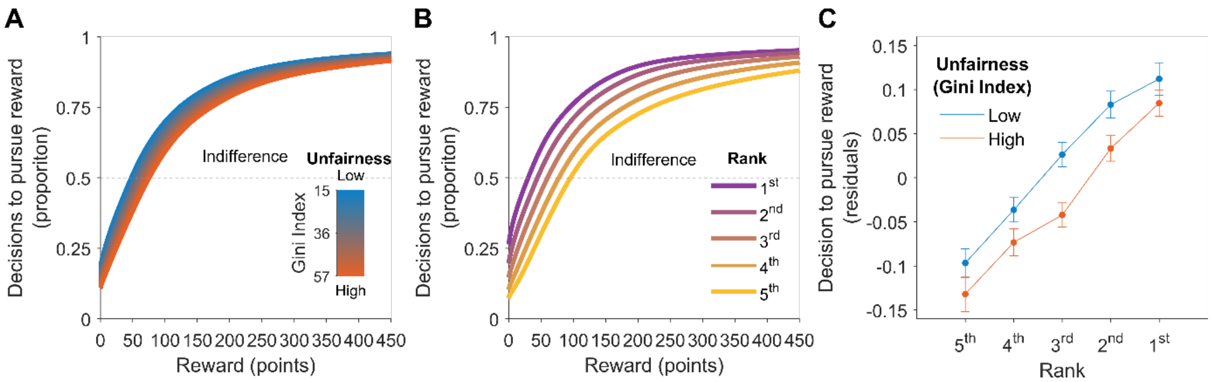

Fig. 3. Motivation to pursue rewards is higher when distribution of rewards is fair; rank (relative value) is high, and absolute reward is high. To illustrate the effect of factors influencing the motivation to pursue rewards, we plotted the probability of participants' decision to pursue rewards from a GLME model predicting choice from reward magnitude and either different levels of **(A)** unfairness or **(B)** rank. **(C)** We also plotted average residuals for the five rank categories and two levels of unfairness from a GLME model predicting choice just from absolute reward and trial number. We observe that participants are more likely to decide to pursue rewards when **(A, C)** rewards are fairly distributed and **(B, C)** when the rank is high than low. Error bars = SEM.

To illustrate the impact of unfairness, we calculated each participant's probability of pursuing rewards at different levels of unfairness and reward magnitudes (based on the estimated fixed and random effects from a GLME model predicting decision to pursue rewards only from these two factors, setting the other factors to 0). The estimated probabilities were then averaged over participants (**Fig. 3A**). As can be observed, for the same reward magnitude, participants were more likely to pursue rewards when unfairness was low rather than high. The indifference point (i.e., the reward magnitude for which participants choose to pursue rewards with 50% probability) was 27.5 points greater for the highest level of unfairness than for the lowest level.

Next, we plotted the likelihood of pursuing rewards for each reward magnitude across the five offer ranks, using the same method as above. As can be observed in **Fig. 3B** the likelihood of pursuing rewards was greater when the rank of the offer is high than when it was low for the same absolute value of the reward. For the lowest rank, participants required an additional 66.4 points to be indifferent on whether to pursue reward than for the highest rank.

To illustrate the effect of unfairness and rank in isolation from the reward magnitude, we plotted the residuals from the above GLME model with the effect of unfairness and rank set to 0. These residuals were then divided into five ranks and two levels of unfairness (high and low based on a median split; **Fig. 3C**). This exercise demonstrates that participants were less likely to pursue rewards when unfairness was high (red line) than low (blue line) across different ranks. Moreover, participants were more likely to pursue rewards when the rank of their reward offer was high than when it was low, across different levels of unfairness.

While large unfairness in the group had a negative effect on motivation, it may be that when looking downwards at the less fortunate, large unfairness might increase motivation. To test for this possibility, we added to the above GLME model two covariates for each subject and trial: the sum of distances between the participant and everyone below them (advantageous inequality), and the sum of the distances between the participant and everyone above them (disadvantageous inequality). While all three main effects from the original model remained significant (unfairness: $\beta = -0.33$, $p < 0.001$; rank: $\beta = 0.87$, $p < 0.001$; absolute reward: $\beta = 2.67$, $p < 0.001$), neither upward ($\beta = -0.04$, $p = 0.67$) nor downward ($\beta = -0.29$, $p = 0.08$) comparisons significantly influenced the willingness to work. In other words, while the relative ranking of a participant's pay offer affects motivation, as does the general level of unfairness, once we account for these two factors, having people's pay be at a greater distance from others' in either direction does not additionally impact their willingness to pursue rewards.

Finally, we compared the original model to two alternative models; (i) the adaptation model, which is based on an assumption that people compare their income to an average value for their reference group (Helson, 1965), and (ii) the Fehr-Schmidt inequality aversion model, which assumes that people have a separate reaction to advanteagous and disadvantageous inequality (Fehr and Schmidt, 1999). In both we include absolute reward and trial number as covariates. Bayesian Information Criterion (BIC), which simulatneously assesses model fit and parsimony showed that our original model (the 'rank-unfairness model') (BIC = 3661.9) outperformed both the adaptation model (BIC = 3765.8) and the Fehr-Schmidt inequality model (BIC = 3780.1), as well models consisting of only rank (BIC = 3681.3), only unfairness (BIC = 3687.3), or only absolute reward (BIC = 3833.4). Together, the results suggest that high unfairness, low rank and low absolute reward all have significant, negative and independent effects on the willingness to pursue rewards, and that both unfairness and relative value components are necessary to explain the reactions to unequal opportunities. We next examine whether these factors exert their effect through participants' feelings.

Feelings partially mediate the effects of pay gaps on decisions to exert effort. To examine whether feelings mediated the effects of pay gaps on decisions to pursue rewards we performed two multi-level mediation analyses. Each of the mediation analysis examined whether feelings mediate the effect of one of the factors identified above (i.e., rank or unfairness), while controlling for the absolute reward magnitude, trial number and the other factor.

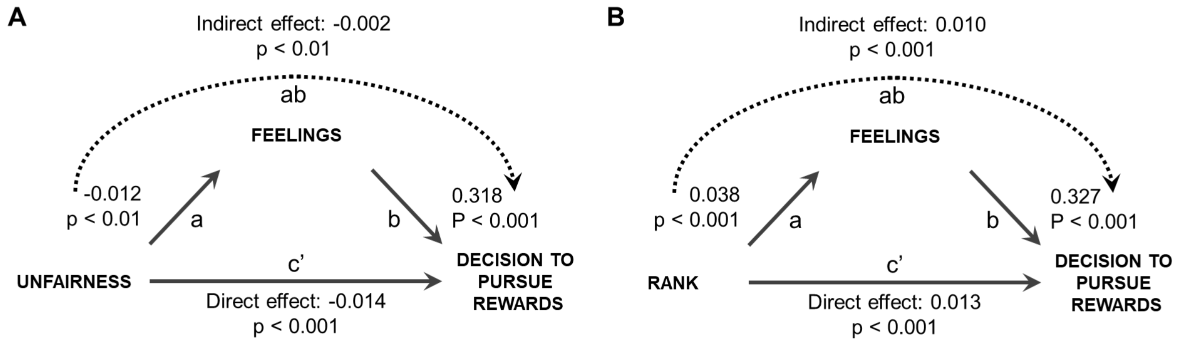

Fig. 4. Feelings partially mediate the effect of pay gaps on decisions to pursue rewards. We examined whether the effect of the two components of the motivational response to pay gaps, that is **(A)** unfairness and **(B)** rank, were mediated by feelings. In both cases, we controlled for the absolute reward, trial number and either rank (A) or unfairness (B) respectively. In both cases, we found significant indirect effect and direct effect (which represents the influence of the given factor on decision to pursue rewards, while controlling for the indirect effect), suggesting that feelings partially mediate the influence of each of the factors on decisions to pursue rewards.

We found that the effects of unfairness and rank on decision to pursue rewards were both partially mediated by feelings (see **Fig. 4**). First, as we already reported, low unfairness and high rank were related to greater likelihood to pursue rewards (total effect: *unfairness*: $\beta = -0.019$, $p < 0.001$; *rank*: $\beta = 0.029$, $p < 0.001$). This effect was partially mediated by feelings (path ab: *unfairness*: $\beta = -0.002$, $p < 0.001$; *rank*: $\beta = 0.010$, $p <0.001$) with positive feelings related to low unfairness and high rank (path a: *unfairness*: $\beta = -0.012$, $p < 0.001$; *rank*: $\beta = 0.038$, $p <0.001$). Additionally, feelings predicted decisions to pursue rewards even when unfairness and rank were accounted for (path b: *unfairness*: $\beta = 0.318$, $p < 0.001$; *rank*: $\beta = 0.327$, $p <0.001$). This suggests that incidental fluctuations of feelings, unrelated to task variables, had also a unique effect on the decision to pursue rewards. Conversely, the two task related variables had direct effect on the decision to pursue rewards that could not be accounted for by changes in feelings (path c': *unfairness*: $\beta = -0.014$, $p < 0.01$; *rank*: $\beta = 0.013$, $p <0.001$).

Subjective measure of inequality is biased by rank

Finally, we tested whether participants' *perception* of inequality was related to our objective measure of statistical dispersion of outcomes (i.e., unfairness) and participants' relative position of the received offer in the distribution (i.e., rank). To examine this, we constructed a generalized mixed effects model with participants' inequality rating as a dependent variable, and statistical dispersion and rank as independent variables. We found that both factors influenced inequality judgments. First, not surprisingly, the higher the statistical dispersion the higher the perceived inequality ($\beta = -0.26$, $p < 0.0001$). Interestingly, the higher the rank of the received offer, the more likely participants were to perceive the distribution as equal ($\beta = 0.06$, $p < 0.01$). This is despite clear instructions to rate inequlity of all offers in a distribution. These results suggest that a person's relative position in a distribution affects their assessment of how (un)equal that distribution is.

DISCUSSION

Randomness plays a surprisingly important role in determining the barriers and opportunities encountered by individuals on their path to a prosperous life (Pluchino, Biondo, Rapisarda, 2018). Country of birth alone explains 66% of global variation in living standards (Milanovic, 2014). Other non-meritocratic factors, such as zip code (Chetty & Henderen, 2018), parental socio-economic status (Duncan & Magnuson, 2012), gender (Blau & Kahn, 2007), ethnicity (Longhi & Brynin, 2017), or a person's name (Silberzahnm & Ygknabbm, 2013) have been shown to have a significant effect on earnings, even after controlling for merit.

In the current study we investigated how decisions to pursue rewards are altered by a person's awareness that some people in their group were more lucky than others in the rewards they were offered for performing the same task. We hypothesized that the motivation to pursue rewards would be influenced by violation of the fairness principle and relative valuation of rewards. We find that an unfair distribution of rewards between group members had a negative impact on the decision to pursue rewards not only of disadvantaged individuals but also of advantaged individuals. Specifically, high unfairness was related to a reduction in the likelihood participants agreed to work for their reward irrespective of the magnitude of their reward and their relative position in the distribution. This is despite such refusal reducing the likelihood of receiving a bonus, while having no impact on the rewards received by others.

Second, the likelihood of exerting effort in exchange for reward was reduced when the rank of the offer was lower in comparison to that offered to others and vice versa (i.e., higher rank was related to greater motivation to work), irrespective of the actual magnitude of the offered reward. The third factor modulating motivation was the absolute reward itself. The fact that absolute reward magnitude exerted influence even when controlling for the level of unfairness and offer rank suggests that while people do care about the rewards of others, they only partially adapt to present social context when deciding whether to pursue rewards (Burke et al., 2016). We find that the rank-unfairness model outperforms many alternative formulations in explaining particpents' reactions to pay-gaps.

By manipulating the unfairness of offers, offer's rank and absolute reward on each trial, we were able to dissociate the influence of each of the three factors *within* the same individual. By doing so, we overcome a difficulty in studying these variables in the "real-world", where individuals with different traits or experiences may populate different parts of the distribution (Gelissen & de Graaf, 2006) - making it difficult to isolate the influence of these components from factors correlating with them, such as negative effects of stereotypes on aspirations (Migheli, 2015; Riegle-Crumb, Moore, & Ramos-Wada, 2011). Together, these findings suggest that individuals who are offered less than others are disadvantaged not only because the absolute reward they can possibly obtain is lower, but also because they might suffer from a motivational cost reducing the likelihood that they will puruse even those rewards that are within their reach. The latter may be due to lower relative value of their rewards and a demotivating effect of participating in situation that seem unfair.

Importantly, because the decisions to pursue rewards were made in private and did not affect anybody but the participant themself, the observed effect of unfairness on motivation cannot be attributed to reputation concerns (Engelmann & Fischbacher, 2009), reciprocity (Kube, Maréchal, & Puppe, 2012) or retribution motives (Suleiman, 1996). Instead, our results suggest that unfairness and rank exert their effect on motivation partially by influencing experienced feelings. We report a mediation that includes two links: the first is between each of the two factors (unfairness and rank) and negative feelings; and the second between negative feelings and a reduction in the willingness to exert effort. As for the first link, high unfairness and low rank each triggered negative feelings even when controlling for magnitude of the reward offered. The negative impact of pay gaps on feelings supports the notion that perception of unfairness is reflected in an emotional response (Rutledge et al., 2016) and thus carries a cost to one's psychological well-being. The finding that rank influenced experienced feelings is consistent with studies showing that well-being measures are influenced by a person's standing relative to others (Lyubomirsky & Ross, 1997; Hagerty, 2000; Boyce, Brown & Moore, 2010).

The second link is between feelings and the willingness to pursue rewards. Although the idea that unhappiness is related to low motivation is intuitive, there has not been conclusive evidence for it in healthy individuals (for review see: Lucas and Diener, 2003). Past studies have mostly examined the relationship between mood and performance level, rather than the decision to engage in effort altogether, and produced mixed results. While some researchers found a beneficial effect of positive mood induction on performance (Oswald, Proto & Sgroi, 2015), others found that positive and negative emotions can improve or impair performance depending on the nature of the task (Gray, 2001; Phillips et al., 2002; Dreisbach, 2006). With regards to the motivation to pursue rewards, we find that unhappiness has a negative effect. Lower happiness in our study can either index reaction to lower subjective value of rewards offered (Rutledge et al., 2014), or play a causal role in decreasing the value of rewards (Eldar & Niv, 2015). The fact that fluctuations in happiness ratings had an additional effect on motivation to pursue rewards, indepedent from the effect of variables manipulated in the task, suggests that both explanations are plausible.

While our study examines reaction in a controlled laboratory setting it may have implications for people's decisions and reactions outside the lab. We speculate that negative feelings caused by arbitrary reward disparities might be one reason why disadvantaged individuals are more likely to suffer from anxiety and depression (González et al., 2010; Piccinelli & Wilkinson, 2000; Lee et al., 2017). Furthermore, decreased motivation caused by unfairness and low relative position might make upward mobility particularly difficult, contributing to sustained poverty among disadvantaged groups (Elmelech & Lu, 2004; Findlay & Wright, 1996; Uhrig, 2015). As such, the motivational phenomenon described in this study might constitute yet another example of a poverty-trap, that is a situation where having worse prospects triggers additional mechanisms ensuring that a person remains poor. It also suggests that any observed signs of decreased motivation among disadvantaged groups might be situational, rather than stemming from characteristics of these groups, and thus could be a potential target of interventions.

In our study it was made clear to particpents that they had no control over the magnitude of the rewards offered. In contrast, in many everyday situations there is ambiguity about the role of randomness in success. Previous studies have shown that in such ambiguous situations, those who are advantaged are more likely assume that their economic position is a result of talent and effort, while those who are disadvantaged assume it is a result of external circumstances (Hunt, 2004; Kluegel and Smith, 1986). Interestingly, we also observed position-dependent subjectivity. In particular, we found that those who were offered relatively high rewards estimated inequlity as lower than those who were offered relatively low rewards.

While past studies have suggested people are generally averse to unfair distributions of rewards, here we uncover their consequences beyond distribution preferences (Fehr & Schmidt, 1999; Dawes et al., 2007) or impact on affective state (Tricomi et al., 2010; Rutledge et al., 2016). We show that unequal pay and opportunity have a negative influence on the motivation to work for rewards of not only disadvantaged individuals but also of others around them. Our findings provide an empirical framework for considering the impact of pay opportunity gaps on individuals, organizations, and societies, suggesting they can trigger psychological dynamics that hurt the productivity of all involved.

METHODS

Participants. One hundred and ten participants from University College London subject pool were recruited to take part in two experiments: sixty in experiment 1 (mean age 22.1[3.2], age range 18 – 35; 38 women) and fifty in experiment 2 (mean age 21.4[2.0]; age range 18 – 35; 34 women). Across two experiments, 67% of participants originated from Western countries. The average self-identified political orientation was 3.52(1.38) on a scale ranging from 1 (extremely right wing) to 7 (extremely left wing) and was not significantly different from the centre of the scale ($t(87)=0.12$, $p = 0.91$). All participants started with an initial endowment of £10 and were paid an additional bonus based on their decision to accept or reject reward offers in exchange for performing a cognitive task in one randomly selected trial. Participants who accepted all reward offers were excluded from the data analysis as we could not identify the factors influencing their decisions due to lack of behavioral variability, beyond the fact that they were maximizing their bonus reward at the end (eight subjects in experiment 1 and seven subjects in experiment 2), leaving 52 and 43 participants in each experimental sample respectively. None of the subjects rejected all offers. All participants provided written informed consent. The experiment was approved by the UCL ethics committee.

Procedure

Overview. We invited participants to the lab in groups of five. To easily identify themselves during the task, they were asked to choose a cartoon avatar that would represent them in the study. A randomly drawn lot number determined the order of choosing avatars. Participants were informed that each person will be offered a different reward on each trial and that these rewards were randomly decided on each trial by a computer program. Next, participants retired to separate cubicles where they were given additional instructions.

Participants first completed one practice trial. There were 60 trials in total. On each trial, participants observed the rewards offered to all five participants for 6 seconds then rated their feelings (self-paced) and decided whether to pursue the reward (self-paced). Below we detail each part of the task.

Incentive structure. Bonus reward was contingent on the participant's decision to pursue reward. Participants were informed that at the end of the task a computer program would choose one trial at random for payment – a common procedure that was shown to reproduce the behavioural results of many decision-making experiments that paid for all trials, while reducing the unwanted reward adapatation and accumulation effects (Charness, Gneezy & Halladay, 2016). If participants selected to pursue reward on that trial, they would receive the amount equal to the number of points displayed on that trial. In Experiment 1 participants were aware that each point was worth £0.04. In Experiment 2, the exchange rate of points with £ was unknown to the participants and varied randomly from trial to trial ranging from £0.001 to £0.08. We employed this manipulation to minimize adaptation and comparisons to rewards offered on past trials. Bonus reward could range from £0 to £18.64 in Experiment 1 and from £0 to £37.28 in Experiment 2 if the participant decided not to pursue reward on the randomly selected trial no bonus was paid out. Consequently, rejecting a reward offer decreased the likelihood of receiving a bonus at the end of the task. There was no contingency between participants' decisions or performance and reward offers in subsequent trials. Neither did decisions throughout the task influence the pay-outs of other participants. This was conveyed in the task instructions and participants had to pass comprehension checks, ensuring that they understood the details of the task.

Distribution of reward offers. We created 60 different distributions in total and presented them in random order. We generated 30 reward distributions based on a log-normal probability density function. Log-normal distribution was chosen as it fits closely real-world income structures within firms (Lazear & Shaw, 2016) and countries (Pinkovskiy & Sala-i-Martin, 2009). To vary the levels of reward magnitude range and statistical dispersion we used a combination of 3 different median values (0.55, 1, 1.45) and 10 different standard deviations, corresponding to values of the Gini coefficient varying uniformly from 20 to 65 (**Fig. 2**), resulting in 30 different distributions. Log-normal distributions are always positively skewed. To generalize our findings, we also included 30 negatively skewed distributions that were a mirror-image of the positively skewed distributions by applying the following transformation of representative values:

$$x_{positive} = \{x_1, x_2, x_3, x_4, x_5\}$$
$$x_{negative} = \left|x_{positive} - max\left(x_{positive}\right)\right| + \min\left(x_{positive}\right)$$

Where x_n is subject *n* payment offer in each trial, $x_{positive}$ and $x_{negative}$ are payment offers of all participants in trials with positively and negatively skewed distributions, respectively.

To generate reward offers representative of the above distributions, we used an inverse cumulative density function of these distributions which assigns maximal pay value earned by each percent of the population. We next took an average pay from subsequent 20 percentiles of this function, with the exclusion of top 1 percentile, resulting in 5 values reflecting an average pay of each 20% of the population. The last percentile was excluded as it approaches infinity. Unfairness was quantified based on these 5 representative values. To introduce variability to the middle pay (that otherwise would be the same for all distributions generated from the same median value) we additionally subtracted a number between 0 and 9 from each representative value in each distribution (in each distribution the same number was subtracted for each value). This resulted in the pay offers shown in Supplementary Table 1.

Feelings ratings. After presenting the reward offers participants rated how happy they felt by clicking on a continuous sliding scale ranging from very unhappy to very happy. The slider started in the middle of the scale on every trial.

Inequality ratings. The second task started immediately after the first. Participants were informed that they will have to judge how equal the pay distribution was on a scale varying from very unequal to very equal. We used 60 income distributions from the first task and displayed them in the same form and order.

Math task. Participants then indicated if they wanted to pursue reward on that trial. If they decided to pursue reward, they would solve a math task. Otherwise, they immediately proceeded to a new trial. The task comprised of solving three math problems. Each problem required adding two 3-digit numbers. To ensure equal difficulty of math problems throughout the task, each addition had exactly two carryovers (sum of ones, tens or hundreds greater than 10). E.g., problems included sums like 118 + 197. If participants provided an incorrect answer, they had to solve an additional problem. Participants continued until they got three problems correct. On average 89% of attempts were correct, and it took subjects 17 seconds (SD = 7.56s) on average to solve each problem.

Data analysis

All the analyses were performed using MATLAB 2017b software.

Dependent variables. Feelings ratings were transformed to range from 0 to 1, with 0 indicating a low score (i.e., very unhappy). Decisions to exert effort were coded as categorical variables, with 1 indicating accepting a reward offer and 0 indicating rejecting the reward offer.

Independent variables.

To account for a possibility of diminishing marginal utility of each additional awarded point, we tested if the effect of reward magnitude was better expressed as a linear or a power function (as it is in the prospect theory: Tversky & Kahneman, 1992):

$$Reward\ magnitude\ utility = \ {x_i}^{\rho}$$

Where x is the reward offer, and ρ represents parameter describing the curvature of the reward function, ranging from 0 to 1 (at which point it is linear). To fit the above function, we estimated nonlinear mixed-effects model with stochastic Expectation-Maximization algorithm (Delyon, Lavielle, & Moulines, 1999). The ρ value maximizing the R^2 of the model describing the relationship between reward magnitude and motivation to pursue rewards (including the variables listed in the section below) was equal to 0.43, suggesting a non-linear relationship between absolute reward and its value, and was subsequently used in all analyses.

Participant's offer rank was normalized to range from 0 to 1 as follows:

$$Rank_t = \frac{i-1}{n-1}$$

Where i is the reward offer index in a set of offers ordered from lowest to highest and n is the number of participants in the group (in our case 5). The above rank measure assigns 1 to the person with the best offer, 0 to the person with the lowest offer, and 0.5 to the person with the intermediate offer.

Unfairness were measured as Gini coefficient, calculated as follows:

$$Unfairness = \frac{\frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|x_i - x_j\right|}{2\bar{x}}$$

Where n is the number of participants in the group, $x_i$and $x_j$is the reward offers received by each person, and $\bar{x}$ is the mean reward offer.

Advantaegous and disadvantageous inequality in the Fehr-Schmidt model were calculated as follows (Fehr and Schmidt, 1999):

$$Advantaegous\ inequality = \sum_{j=1}^{n} max\left|x_i - x_j, 0\right|$$

$$Disadvantageous\ inequality = \sum_{j=1}^{n} max\left|x_j - x_i, 0\right|$$

Where x_i is an individual's payment offer and x_j are payment offers received by other group members.

Skewness was measured as Adjusted Pearson's Coefficient of Skewness, calculated as follows:

$$Adjusted\ Pearson's\ Coefficient\ of\ Skewness = \frac{\sqrt{n(n-1)}\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{(n-2)\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2}\right)^3}$$

Where $\bar{x}$ is the average reward offer, n is the number of participants in the group, x_i is the reward offer received by each person.

To obtain standardized coefficients in the Generalized Linear Mixed Effects Model, all variables were z-scored prior to the analyses.

Generalized linear mixed-effects model. To account for within-subject correlations of responses related to repeated measures in our design, we used Generalized Linear Mixed Effects (GLME) model approach, in which fixed effects describe group-level effects and random effects describe idiosyncrasies specific for an individual. The GLME model included decisions to pursue rewards as the categorical dependent variable. The independent variables were unfairness (measured as gini coefficient), rank (normalized to range from 0 to 1, for lowest and highest rank respectively), reward magnitude (expressed as a power function). All variables were standardized prior to the analysis. Following methodological recommendations by Barr and collegues (2013), all models included fixed and random effects for intercept and all independent variables.

To illustrate the size of the effect of unfairness and rank we plotted predicted values of the above GLME model across different levels of unfairness (**Fig 3A**) and separately, across different ranks (**Fig 3B**), with the effect of trial number, rank (only for **Fig 3A**) and unfairness (only for **Fig 3B**) set to 0. To illustrate the effect of unfairness and rank in isolation from reward magnitude (**Fig 3C**), we estimated the probability of pursuing rewards on each trial from a GLME model including absolute reward and trial number (with other factors fixed to 0). We then calculated the residuals, by subtracting observed decisions and their predicted probability. We categorized residuals into 5 ranks and two levels of unfairness (based on the middle value of the tested range) and calculated the average residual value for each participant within each category and plotted the averages over participants within each category.

Mediation analysis. We used a multilevel mediation analysis approach (Kenny, Korchamaros, & Bolger, 2003), which nests trial-level observations within upper-level units (individual participants), similarly to the GLME approach described above. The analysis was performed using M3 Mediation Toolbox for MATLAB (Wager et al., 2008). Bootstrapping approach, a non-parametric method based on resampling with replacement, was used to estimate the significance of the effects, using the standard 10000 samples (Hayes, 2009). To control for the fact that independent variables in our design were correlated and ensure that the conclusion of the mediation analysis relates specifically to the investigated variable, each mediation model was performed on residuals from a GLME model regressing out the effect of the variable not tested. That is regressing out trial number, and: (i) reward magnitude and rank for the mediation model describing the effect of unfairness, or (ii) reward magnitude and unfairness for the mediation model describing the effect of rank; on both feelings and decisions to pursue rewards.

OPEN PRACTICES STATEMENT

Neither of the experiments reported in this article was formally preregistered. Data and code are available in the Github repository, https://github.com/affective-brain-lab/Gesiarz_unfairness_motivation upon publication.

CONTRIBUTIONS

F.G., J.E.D, and T.S. designed the experiments. F.G. collected and analyzed the data with guidance from T.S. F.G and T.S wrote the intial manuscript draft with edits from J.E.D. All authors approved the final version of the manuscript.

COMPETING INTERESTS

The authors declare no competing interests.

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SUPPLEMENTARY INFORMATION

Table S1. Distributions of payment offers between participants (expressed in points) for each trial presented in the experiment

Rank				
5th	4th	3rd	2nd	1st
25	31	36	42	54
22	29	35	42	59
19	27	34	43	65
17	25	33	44	73
15	23	32	45	82
13	21	31	47	94
10	19	30	48	110
8	17	29	50	129
7	15	28	52	155
5	14	27	55	189
34	44	51	60	79
30	41	50	62	88
27	39	49	64	98
23	36	48	66	111
20	34	47	68	127
17	31	46	71	146
15	29	46	74	170
12	26	45	77	201
10	24	44	81	242
7	21	43	87	297
48	64	76	90	119
43	60	75	93	133
38	57	74	96	150
33	53	73	100	170
29	50	72	104	196
25	47	71	109	226
21	43	70	114	265
18	40	69	120	315
15	37	68	127	379
12	33	67	136	466
25	37	43	48	54
22	39	46	52	59
19	41	50	57	65
17	46	57	65	73
15	52	65	74	82
13	60	76	86	94
10	72	90	101	110
8	87	108	120	129
7	110	134	147	155
5	139	167	180	189
34	53	62	69	79
30	56	68	77	88
27	61	76	86	98
23	68	86	98	111
20	79	100	113	127
17	92	117	132	146
15	111	139	156	170
12	136	168	187	201
10	171	208	228	242
7	217	261	283	297
48	77	91	103	119
43	83	101	116	133
38	92	114	131	150
33	103	130	150	170

29	121	153	175	196
25	142	180	204	226
21	172	216	243	265
18	213	264	293	315
15	267	326	357	379
12	342	411	445	466

Table S2. **Influence of unfairness, rank and absolute reward on experienced feelings.** GLME model predicting self-reported feelings.

	Coefficient (SE)	**T-stat**	**P-value**
Intercept	0.45(0.015)	29.94	< 0.0001
Trial	-0.05(0.006)	-8.44	< 0.0001
Absolute reward	0.095(0.008)	11.85	< 0.0001
Rank	0.070(0.009)	8.08	< 0.0001
Unfairness	-0.011(0.004)	-3.60	< 0.0001

Table S3. GLME model predicting decisions to pursue rewards in Experiment 1 (value of points known).

	Coefficient (SE)	**T-stat**	**P-value**
Intercept	1.10(0.60)	1.83	< 0.01
Trial	-1.45(0.17)	-8.37	< 0.0001
Absolute reward	4.33(0.42)	10.27	< 0.0001
Rank	0.37(0.12)	3.13	< 0.0001
Unfairness	-0.14(0.09)	-1.98	0.058

Table S4. **GLME model of decisions to pursue rewards, Experiment II (value of points unknown).**

	Coefficient (SE)	**T-stat**	**P-value**
Intercept	0.63(0.31)	1.98	0.047
Trial	-1.05(0.11)	-9.77	< 0.0001
Absolute reward	2.84(0.22)	12.48	< 0.0001
Rank	0.91(0.10)	8.66	< 0.0001
Unfairness	-0.29 (0.22)	-4.82	< 0.0001

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