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July 9, 2019

Abstract

Competing in the labor market requires job-seekers to evaluate the competitiveness of themselves and of others. Will their evaluations of others be more objective and their evaluations of themselves be more biased? Will successful and unsuccessful job-seekers in the same labor market engage in different patterns while making their evaluations? We design a laboratory experiment to study the dynamics of job-seeking strategies and individuals’ belief updating in a labor market. Our experimental treatments feature the decision-making and the evaluation of competitiveness of oneself versus of others. The probability of being accepted for a job depends on external shocks as well as the individuals’ ability ranking. We find that subjects are less likely to evaluate others’ competitiveness as high as their own in the same situation. Subjects are more inclined to attribute failure to external shocks and attribute success to their own competitiveness. Estimation results from a reinforcement learning model show that, compared to decision-making for others, subjects have a higher tolerance for failure and remain in applying for unsuitable jobs for longer periods when seeking jobs for themselves. Our findings provide evidence for the presence of self-serving attributional bias when individuals’ self-image affects their economic decisions.

Keywords: Decision-making for others; Labor market experiment; Belief updating; Belief elicitation; Reinforcement learning; Self-serving attribution bias

JEL Classification: C91; D83; D91

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1 Introduction

When job-seekers search for jobs in the labor market, they typically have to evaluate the competitiveness of themselves and of others. A job-seeker has to consider if he is qualified for the job’s requirements and if he is more qualified than other job-seekers. The job-seeker updates his evaluation dynamically based on his job-seeking history, namely, the positions for which he has applied and the application outcomes. A traditional way to model the belief-updating process is that, regardless of who is evaluating the situation or the job-seeking history, rational decision-makers would follow the Bayes rule. But in reality, will the evaluations of others be more objective and the evaluations of oneself be more biased given the same situation? Will successful and unsuccessful job-seekers in the same labor market engage in different patterns while adjusting their evaluations over time?

Many cultures around the world have some version of the saying “on-lookers see most of the game.” Such a saying suggests that people tend to make less irrational decisions and form more objective assessments of relevant information when they are actually “outside” the situation. For example, when evaluating his own competitiveness, a job-seeker might not be as objective as he would be in evaluating that of others. One possible explanation emphasizes the presence of self-image when people evaluate situations related to themselves (Wray and Stone (2005), Zhang et al. (2018)), whereas on-lookers are not affected by this factor. In this paper, we design a laboratory experiment to explore whether being a “on-looker” would make a job-seeker more objective. Our experimental treatments feature decision-making and evaluation of competitiveness for oneself versus for others. The comparison between treatments helps identify the role of self-image in the evolution of job-seeking strategies and the belief-updating process.

Apart from the self-image effect, successful or unsuccessful application outcomes also matter to one’s evaluation. The observation that people usually attribute positive experiences to their own high ability while attributing negative experiences to external randomness has been documented in the psychological literature as the “self-serving attributional bias” (Zuckerman (1979), Keith and Constantine (1999), Mezulis et al. (2004)). In our experiment, jobs are offered to job-seekers with certain probabilities, depending on external randomness as well as the job-seekers’ relative competitiveness. With this setup we intend to examine the self-serving attributional bias alongside the “lookers-on” effect, in order to obtain a comprehensive view of the job-seekers’ evaluation dynamics.

The laboratory setting allows us to precisely measure job-seekers’ “perception” of the
labor market. We borrow the design from existing work on over-confidence and forecasting (Clark and Friesen [2003], Falk et al. [2006b], Clark and Friesen [2009]), and add another treatment involving decision-making and evaluating the competitiveness of others. In either treatment, we elicit subjects’ beliefs about their own or others’ relative competitiveness, respectively. With the experimental data, we examine the dynamic pattern of subjects’ job-seeking strategies and the changes in subjects’ beliefs. We find that subjects are less likely to evaluate others’ competitiveness as high as their own in the same situation. Meanwhile, when evaluating themselves, subjects are more inclined to attribute failure to external randomness of the labor market and success to their own competitiveness. This result provides support for the presence of the self-serving attributional bias.

Our regression analyses based on the belief data shed light on the dynamic pattern of subjects’ evaluation on their competitiveness over time, yet the results do not directly indicate changes in job-seeking strategies in subsequent periods. In order to predict subjects’ next move in the labor market based on their job-seeking histories, we use a re-parameterized reinforcement learning model to quantitatively examine subjects’ strategy switches. Specifically, we model subjects’ successful or unsuccessful job-seeking outcomes as flows of positive/negative stimulus; a strategy switch would be triggered if the cumulative stimuli exceed certain thresholds. Using this model, we are able predict when a successful job-seeker will start searching for higher-paying positions, or when an unsuccessful job-seeker would downgrade his search and switch to apply for lower-paying positions. In addition, the comparison of the estimation results between treatments allows us to examine whether the triggers for strategy switches differ when subjects make decisions on behalf of others.

Estimation results from the reinforcement learning model show that, compared to the case of decision-making for others, subjects have a higher tolerance for failure and remain in applying for unsuitable jobs for longer periods when seeking jobs for themselves. Moreover, upon successful application outcomes, subjects are more slowly in switching application strategies and less likely to upgrade the search for better-paying positions when they make decisions on behalf of others. The results indicate that job-seekers are more willing to build confidence on one’s own competitiveness instead of on others’. Our findings provide supportive evidence for the influence of the self-image on job-seekers’ decisions in the labor market.

The rest of paper is organized as follows. Section 1.1 reviews the related literature. Section 2 presents the model and theoretical results. Section 3 presents the experimental design, treatments and the laboratory procedure. Section 4 discusses the experimental
findings. In particular, we use a re-parameterized reinforce learning model to estimate the learning effect for subjects’ strategy switches across treatments. Section 5 concludes. Laboratory instructions are included in the online appendix.

1.1 Related Literature

Our study is in the context of job-seeking decisions on the labor market. Theoretical literature on undirected search models (Mortensen (1970), Mortensen (2010), Pissarides (1984)) and on directed search models (Delacroix and Shi (2006), Menzio and Shi (2010)) construct the labor market equilibrium depending on the labor market tightness[1] or the employment probability for each position, which are known to the job-seekers on the market. The resulting wage distribution is either degenerate, or dispersed because of productivity differences (van den Berg and Ridder (1998)). This assumption is permissible if we focus on the property of the steady-state equilibrium. On the other side, if we examine the efficiency of search on an individual basis, and allow a discrepancy between the actual and self-estimated labor market tightness, we could expect inefficient job-search behavior due to the discrepancy.

The discrepancy is related to the presence of psychological or cognitive factors of job-seekers on the labor market. Ellis and Taylor (1983) investigate the role of self-esteem in the job search process, including self-evaluation, satisfaction, length of the search period, and the quality of the outcome. Zabojnik (2004) examines the tradeoff between economic incentives and protection of one’s self-image during a job search. Watson et al. (2005) discusses the relation between cognitive dissonance and earnings. Job-seekers tend to over-estimate the local unemployment rate upon their own unsuccessful job applications (Zabojnik (2004), Kunovich (2012), Cardoso et al. (2016a)). Cardoso et al. (2016b) also use the European Social Survey to examine the impact of mis-perceptions of the unemployment rate on individual wages. The authors find that a 1% gap between the perceived and the actual national unemployment rates reduces average wages by 0.4 to 0.7 %. One possible underlying reason is that pessimistic beliefs make people to be more concerned about their own employment prospects, which could lower their perceived bargaining power and reservation wages. Orland (2017) also discuss the relation between individuals’ big-five personality traits and their perceived inflation and unemployment rates. Thus, our experiment echoes the empirical studies on the relation between people’s perception of the labor market and

1A typical measure of labor market tightness is the ratio $v/u$, where $v$ is the number of vacancies posted in the labor market and $u$ is the number of unemployed. So the labor market is tighter when more firms seeking to fill positions relative to the number of potential workers looking for jobs.
The observation that cognitive biases matter in the search behavior on a labor market is closely related to people’s self-evaluation of their own ability or performance. Existing behavioral economic and psychology literature have provide supportive evidence. Niederle and Vesterlund (2007) conduct a laboratory experiment in which subjects were asked to perform a series of calculation tasks, and then to estimate their own performance ranking. The authors find a gender-difference in self-evaluation, namely male subjects are more likely to over-estimate their ranking. Falk et al. (2006a) and Falk et al. (2006b) show that people tend to wrongly estimate their performances relative to the average, and the learning speed is slow. Moreover, people with similar performance have diversified directions and magnitudes of biases. The presence of over-confidence in self-evaluated performance is also discussed in Clark and Friesen (2003), Van den Steen (2004), Moore and Small (2007) and Clark and Friesen (2009). The approach we adopt in this study is based on the design of Falk et al. (2006b). We extend their design by adding a treatment involving decision-maker for others. This treatment allows us to control for the behavioral factors that can influence the job-seeking process regardless of the role of the subjects. Moreover, we adopt a structural reinforcement learning model to examine the evolution of individuals’ application strategies, in addition to the observation regarding people’s belief-updating patterns.

The findings in our experiment suggest that the presence of self-image increases people’s reluctance to incorporate failure into their self-evaluation, and increases their willingness to update the self-evaluation upon successful experiences. This phenomenon has been documented in psychology literature as self-serving attributional bias (Zuckerman (1979), Baumeister et al. (1993), Keith and Constantine (1999), Keith and Constantine (1999), Mezulis et al. (2004)). It has been shown that people with higher levels of self-esteem tend to stick to goals higher than they are capable of for too long. In our experiment, application failures can be viewed as a threat to individuals’ self-image, and application successes serve as a positive stimulus for one’s self-image. People are more reluctant to incorporate experiences of failure into their self-evaluation, and in contrast, experiences of success are more likely to play a role in peoples’ self-image building. Existing literature also discuss the self-serving attributional bias in similar context with economic incentives, such as bargaining (Babcock and Loewenstein (1997), Loewenstein et al. (1993)) and political decision-making (Deffains et al. (2016)).

One observation of our experiment is that, when subjects make decisions for themselves, they are more likely to apply for jobs which are higher than their actual ranking groups. There is a tendency for subjects to believe that positive events will happen to them
even if the probability for such events is relatively small (25%). This observation echoes the discussion on the optimism bias and belief formation in the human brain (Weinstein (1980), Weinstein (1989), Sharot (2011), Sharot et al. (2012)). People usually expect positive events when making predictions about the future even if there is no evidence that could support such expectations (Lefebvre et al. (2017), Moutsiana et al. (2013)). Existing literature has documented the presence of the optimism bias in decisions with economic incentives (Dubra (2004), Puri and Robinson (2007)), in particular in the estimation of one’s professional success (Lovallo and Kahneman (2003)), of firms’ financial profits (Calderon (1993)), of personal finance outcomes (Arabsheibani et al. (2000), Wells (2007)). The difference between the self-serving attributional bias and the optimism bias is that the former applies to the situations where individuals need to attribute past experiences to one’s own ability, whereas the latter refers to cases in which individuals underestimate the likelihood of negative events and overestimate the likelihood of positive events.

In our experiment, in order to identify the self-image effect, we compare decision-making for oneself versus for others. In the latter, subjects were asked to estimate others’ performance based on application outcomes and make subsequent application decisions for others. The use of decision-making for others as a comparison tool is inspired by the role-playing approach in psychology. For instance, Keith and Constantine (1999) design treatments assigning different roles to subjects in order to elicit self-serving bias. This method is widely used in psychology experiments studying decision-making under risk (Zhang et al. (2018), Pollai and Kirchler (2012), Stone and Allgaier (2008)), loss aversion (Polman (2012)), performance in creative tasks (Polman and Emich (2011)), and health decisions (Petrova et al. (2016)). We introduce this methodology into an economic experiment, in which the self-assessment task is incentivized for its precision with monetary payment. Our design is also similar to that of Moore and Small (2007). The difference is that Moore and Small (2007) focus purely on subjects’ estimation one’s versus other’s performance, and we use a labor market context in which the self-assessments are based on application success or failure, incorporating both individuals’ performance and external shocks.

2 The Setup

Consider a collection of \(N\) individuals seeking job positions. Denote the set of jobs as \(\mathcal{K} = \{1, 2, ..., K\}\). Each job \(k \in \mathcal{K}\) has a payoff \(v^k\), which can be decomposed as \(v^k = w^k + f^k\) with \(w^k\) being the wage to the individual who is accepted by position \(k\) and \(f^k\) being the agency fee for the individual who serves as a job-seeking agent and whose
client is successfully accepted by position \( k \). In the case of no job agency on the market, all individuals apply for positions on their own behalf, \( f^k = 0 \) and \( w^k = v^k \).

Without loss of generality, suppose the jobs in \( K \) can be ranked by \( v^1 > v^2 > ... > v^K \), and the qualifications for the individuals’ ability are ranked from job 1 to job \( K \) accordingly. Individuals do not know their ability ranking. Let \( p = (p_1, p_2, ..., p_K) \) denote the prior probability that a typical individual belongs to each of the ranking groups.

An individual who satisfies a position’s qualification is more likely to be accepted than those who are not qualified. There is also randomness in the application process. An individual who is qualified for a position will be accepted by probability \( p^H \). An individual who is unqualified for a position will be accepted by probability \( p^L \). We assume \( p^H > p^L \).

If there were complete information; i.e. everyone knew the ability ranking of all \( N \) individuals, the first-best choice for an individual \( i \in \) ability group \( j \) is to apply for position \( j \).

In our experiment implementation, we set \( N = 8 \), \( K = 4 \), \( p^H = 0.75 \), \( p^L = 0.25 \) and \( w^k : f^k = 3 : 7 \).

### 2.1 Posterior Belief with Self-serving Attributional Bias

Consider that individual \( i \) applies for job \( k \in \{1, ..., K\} \). Let \( \gamma_j(i \in \text{group } j | \text{success in job } k) \) and \( \gamma_j(i \in \text{group } j | \text{failure in job } k) \) denote the posterior belief that individual \( i \) belongs to ranking group \( j \) after a success or a failure in applying for job \( k \), respectively. To incorporate the presence of self-serving attributional bias \([\text{Zuckerman (1979), Keith and Constantine (1999), Mezulis et al. (2004)}]\), we use \( \lambda_s \) and \( \lambda_f \) to denote the bias parameters affiliated with the assessment that \( i \) belongs to a ranking group or higher:

\[
\begin{align*}
\gamma_j(i \in \text{group } j | \text{success in job } k) &= \frac{p_j \cdot p^H \cdot \lambda_s}{\sum_{i=1}^{k} p_i \cdot p^H \cdot \lambda_s + \sum_{i=k+1}^{K} p_i \cdot p^L} \\
\gamma_j(i \in \text{group } j | \text{failure in job } k) &= \frac{p_j \cdot (1 - p^H) \cdot \lambda_f}{\sum_{i=1}^{k} p_i \cdot (1 - p^H) \cdot \lambda_f + \sum_{i=k+1}^{K} p_i \cdot (1 - p^L)}
\end{align*}
\]

Note that the posterior belief reduces to the standard Bayesian posterior when \( \lambda_s = \lambda_f = 1 \).

**Proposition 1.** For ranking groups \( k \) and above; i.e. \( \forall j \in \{1, ..., k\} \), the self-serving attribution biased posterior belief that individual \( i \) belongs to group \( j \) increases more than the Bayesian posterior after an application success in \( k \), and decreases less than the Bayesian
posterior after an application failure in $k$.

For ranking groups $k+1$ and below; i.e. $\forall \ell \in \{k+1, ..., K\}$, the self-serving attributional-biased posterior belief that individual $i$ belongs to group $\ell$ decreases more than the Bayesian posterior after an application success in $k$, and increases less than the Bayesian posterior after an application failure in $k$.

Proposition 1 compares individuals’ belief-updating patterns with and without the self-serving attributional bias. Given the posterior beliefs, rational individuals choose job-seeking strategies to maximize their expected payoffs. Next, we examine the dynamics of individuals’ strategy changes given the differences in their belief-updating patterns. Specifically, we investigate how individuals adjust their job-seeking strategies based on their job-seeking histories, following the literature of reinforcement learning models (McAllister (1991), Roth and Erev (1995), Erev and Roth (1998)).

2.2 A Modified Reinforcement Learning Model for Job Switch

We employ the following reinforcement learning model to examine the pattern of individuals’ strategy switches in response to positive vs. negative job-seeking outcomes. Specifically, we estimate how many consecutive unsuccessful/successful applications it takes before an individual decides to apply for a lower-paying/higher-paying job. The intuition of the model is as follows. Each individual has a “confidence account” that receives a positive stimulus when the application is successful and a negative stimulus when the application fails. If the value of the “confidence account” reaches an upper or lower bound, it triggers a strategy switch; the individual switches to apply for other jobs in the following period. In our model, we use the differences between individual’s realized payoffs and expected payoffs as the stimulus.

Our model follows the labor market setting specified at the beginning of section. Individuals can choose from a set of jobs, $\mathcal{K}$, to apply for in each period. In the experiment we set $|\mathcal{K}| = 4$. In each period, if individual $i$ is employed by the job he applies for, he will receive the corresponding payoff in that period and his payoff is zero if not employed. Individual’s ranking remains the same across periods. Define the stimulus coming from

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2It is worth noting that the reinforcement learning model is generally used to model the learning process in multi-player interactive games. Essentially, one can view the employment process in our labor market setting as a coin-flipping “natural player” with the coin’s probability of coming up head unknown to individuals. In this way we adapt the reinforcement model to our labor market game here.
individual $i$’s application to job $j$ in period $t$ with a payoff $v$ as $R_i(v, t, j)$:

$$R_i(v, t, j) = v - E_{ijt-1}[v]$$

where $E_{ijt-1}[v]$ is the expected payoff from job $j$ after the application in period $t - 1$. The actual payoff from an application is either the wage of the job, $w^j$, if employed, or 0 if not employed. Since individual $i$’s subjective probability of getting employed is between $p^L$ and $p^H$, the expected wage from a new application should be positive but smaller than $w^j$. As a result, individual $i$ receives a positive stimulus if a new application is successful, and a negative stimulus if the application is unsuccessful.

Define $q_i^k(t)$ as individual $i$’s **assessment** for job $k$ at the start of period $t$. The assessment quantitatively measures the value of individual $i$’s “confidence” for job $k$ at the start of period $t$. If one applies for job $j$ at period $t$, depending on the application result, one would get either a positive or a negative stimulus, as defined above, added to the his assessment for job $j$. Additionally, application to a certain job $j$ would also bring some positive/negative stimuli for all other jobs besides $j$. The update of $q_i^k(t)$ can be modelled recursively as:

$$q_i^k(t + 1) = q_i^k(t) + f(k, j) \times R_i(v, t, j)$$

where $j$ is the job that individual $i$ applies for at period $t$, and $k \in K = \{1, 2, 3, 4\}$. We define a **similarity function** $f(k, j)$ between job $k$ and job $j$, following the idea of Sarin and Vahid (2004). The function captures how the result of application to job $j$ would affect one’s confidence on job $k$. The similarity function $f(k, j)$ is specified as:

$$f(k, j) = \begin{cases} 1 & \text{if } k = j \\ \delta^{|j-k|} & \text{if } k \leq j \\ -\delta^{|k-j|} & \text{if } k \geq j \end{cases}$$

So whenever an individual succeeds in applying for a job, the confidence on that job and all higher-paying job gets boosted, and vice versa. Under this specification, each individual has four assessments corresponding to the four jobs. The assessment $q_i^1(t), q_i^2(t), q_i^3(t), q_i^4(t)$ will be updated at the end of period $t$. Meanwhile, we define the initial assessments for each job as $q_i^0, q_i^2, q_i^3, q_i^4$, which is shared by all individuals of the same ranking group. Individuals from different ranking groups have different sets of initial assessments, though all assessments follow the same recursive updating rule.

For each job $k$, we define an upper bound and a lower bound: when the assessment
exceeds the upper bound, an individual would switch to apply for the higher-paying job in the adjacent tier, such as switching from job 2 to job 1 in the next period; when the assessment falls below the lower bound, an individual would switch to apply for the lower-paying job in the adjacent tier, such as switching from job 3 to job 4 in the next period. For job 1, we denote its lower bound as $u_{12}$; i.e. when $i$’s assessment $q_{i}^{1}(t + 1)$ falls below $u_{12}$, he would switch to job 2 in period $t + 1$. Similarly, we denote the upper bounds and lower bounds as $u_{21}, u_{23}$ for job 2, $u_{32}, u_{34}$ for job 3, and the upper bound for job 4 as $u_{43}$. Obviously, there is no upper bound for job 1 and no lower bound for job 4 in our setting. The upper and lower bounds are shared by all individuals of the same ranking group. Note that our model only allows individuals’ job-seeking strategies to switch between adjacent job tiers. We do not consider strategy jumps such as switching from job 1 to job 3.

Based on the upper bounds and lower bounds, we could predict the strategy switch for individual $i$ at the end of period $t$, given that he applies for job $j$ at period $t$. Formally, we define a prediction function as:

$$ g_{i}(j, t) = \begin{cases} 1 & q_{i}^{j}(t + 1) \geq u_{j(j+1)} \\ 0 & u_{(j+1)j} \leq q_{i}^{j}(t + 1) \leq u_{j(j-1)} \\ -1 & u_{(j+1)j} \geq q_{i}^{j}(t + 1) \end{cases} \quad (1) $$

where 1 refers to individual $i$ applying for a higher-paying job in period $t + 1$, $-1$ refers to individual $i$ applying for a lower-paying job in period $t + 1$, and 0 refers to individual $i$ staying unchanged in period $t + 1$.

Finally, we define the actual job switch of individual $i$ in period $t$ as:

$$ h_{i}(t) = \text{job applied}_t - \text{job applied}_{t+1} $$

Now we have constructed a model describing individuals’ learning process. In our model, we replace beliefs with the assessment function, and simplify the strategy switches as the result of the assessment function reaching the corresponding upper or lower bound. As a result, given one’s application history, our model would be able to predict whether one would switch to another job in the next period. In the estimation, we estimate the set of parameters so that our prediction $g_{i}(j, t)$ is as close to $h_{i}(t)$ as possible.

In subsection 4.3 we will present estimation results of our model using the experimental data. The group-specific parameters to be estimated are the four initial assessments $\tilde{q}_{1}, \tilde{q}_{2}, \tilde{q}_{3}, \tilde{q}_{4}$, the six bounds $u_{12}, u_{21}, u_{23}, u_{32}, u_{34}, u_{43}$ and the similarity parameter $\delta$. The
estimated initial assessments and the corresponding upper/lower bounds allow us to calculate the aggregate positive or negative stimuli that would lead one to switch to apply for a job of a different tier.

3 Experimental Design and Procedures

3.1 Treatments

Our experiment consists of two treatments, both of which involve individuals’ decision-making in the context of labor-market job applications. The result of a job application depends on a subject’s ability, which is measured by his relative performance in a real task. We use simple calculation tasks, the same as those adopted in the literature (Falk et al. (2006b), Niederle and Vesterlund (2007)). Subjects are not informed of their performance ranking. The ranking determines the probability of being accepted by different jobs for which a subject might apply.

The difference between treatments is whether the decision-makers apply for jobs for themselves or for others. We randomly assign subjects into the following two treatments:

- **Baseline treatment**: subjects apply for jobs on behalf of themselves. Subjects are not informed of the performance ranking of themselves, and are asked to report beliefs regarding their own ranking based on application results in each period.

- **Agent treatment**: each subject serves as a job-application agency and applies for a job on behalf of another randomly assigned subject (a “client”). Subjects are not informed of the performance ranking of their clients, and are asked to report beliefs regarding the clients’ ranking based on application results in each period.

The jobs differ in payoffs. In both treatments, subjects make decisions with consequences that matter to their own economic interests. In the baseline treatment, each subject receives the total payoff of a job as a wage upon successful application. In the agent treatment, the total payoff of a job is split into the client’s wage and the agent’s agency fee. We set the client’s wage and the agent’s agency fee to be proportional to each other, and monotonically increasing with higher-paying job tiers, so that the clients’ and agents’ economic incentives are perfectly aligned.
3.2 Testing Hypotheses

We are interested in the evolution of application strategies and the updating process of subjective beliefs between and within treatments. We first examine the role of self-image in individuals’ decision-making and belief-updating within each treatment. As implied by Proposition 1, individuals are more likely to attribute unsuccessful applications to external shocks on the labor market, but to attribute successful applications to their own “high abilities.” Whenever one’s self-image plays a role in the decision-making, we expect to observe a belief updating process that weighs application success and failure asymmetrically.

We then compare job-seeking strategies and belief-updating patterns between treatments. The difference between treatments features the role of self-image in one’s own decision-making. When individuals make their own application decisions and evaluate their own ability ranking, the self-image effect plays a more significant role than in the case when individuals make decisions and form beliefs for others. Hence, we would expect the disparity in the belief-updating process in response to success vs. failure to be more salient in the baseline treatment, compared to that in the agent treatment. Moreover, we would like to check if individuals tend to be more “objective” and less biased when updating beliefs about others, namely, if the belief updating process in the agent treatment follows the Bayesian benchmark more closely. In summary, we have the following test hypotheses:

**Hypothesis 1.** In both treatments, subjects’ job application strategies converge to the first-best choices across periods.

**Hypothesis 2.** Subjects’ belief updating pattern deviates from the Bayesian benchmark in the baseline treatment. Moreover, the belief updating pattern in the baseline treatment differs from that in the agent treatment.

**Hypothesis 3.** In the baseline treatment, the number of successful applications for subjects to switch to a higher-paying job is greater than the number of unsuccessful applications for subjects to switch to a lower-paying job. In the agent treatment, subjects need more successful applications of their clients to apply for a higher-paying job, and need fewer unsuccessful applications of their clients to apply for a lower-paying job.

3.3 Experiment Procedure and Belief Elicitation Design

The experiment was programmed and conducted using z-tree (Fischbacher (2007)) at XXXX Laboratory at XX University. Students with no prior experience with our experi-
ment were recruited from the undergraduate population of XX University. Our recruitment notifications were sent to students of all disciplines, and recruited subjects had diverse backgrounds, including mathematics, pure sciences, engineering, social sciences, humanities, business, economics and finance. The experiment followed a between-subject design, with half of the recruited subjects in the baseline and the other half in the agent treatment. We conducted 8 sessions with 4 sessions for each treatment.

Each session consisted of 4 rounds. Each round consisted of 1 real task and 8 periods of applications and feedback. Each round began with a real task for the purpose of determining subjects’ performance ranking. In each real task, all subjects participated in a 3-minute test in each round in which they were asked to calculate the sum of five numbers (rounds 1&2) or the product of two numbers (rounds 3&4). The numbers were randomly drawn from 0 to 100 for each subject. Subjects received piece-rate payment for every correct answer. Then we ranked all subjects from top to bottom according to the number of their correct answers, and applied a random tiebreaker in case of a tie. Subjects knew the number of their own correct answers, but were not informed of their ranking, nor given any information about others’ performance or ranking.

After the real task, subjects entered the job application stage, and were instructed to apply for one job position out of the four jobs posted. Jobs were ranked from the highest-paying one to the lowest-paying one, and recruiting standards differed accordingly. The payoff structure and recruiting standards for the baseline and agent treatments are shown in Table 1 and 2 respectively.

In the baseline (agent) treatment, applicants (clients) who were qualified had a 75% probability of being employed by the job they (their agents) had applied for, and applicants (clients) who were unqualified had a 25% probability of being employed by the job they (their agents) had applied for. In the case of no employment, applicants (clients and agents) would receive zero payoffs. In the case of employment, applicants (clients) would receive wages and agents would receive agency fees as shown in Table 2.

<table>
<thead>
<tr>
<th>Position</th>
<th>Wage</th>
<th>Qualification on Applicants’ Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Job 1</td>
<td>300</td>
<td>Top 2</td>
</tr>
<tr>
<td>Job 2</td>
<td>250</td>
<td>Top 4</td>
</tr>
<tr>
<td>Job 3</td>
<td>200</td>
<td>Top 6</td>
</tr>
<tr>
<td>Job 4</td>
<td>150</td>
<td>All applicants</td>
</tr>
</tbody>
</table>

Table 1: Payoffs and Qualifications of the Jobs: Baseline Treatment

After the application stage, subjects would enter the feedback stage, in which they were...
Position Agent Fee Wage Qualification: Clients’ Ranking
Job 1 210 90 75th percentile and higher
Job 2 175 75 50th percentile and higher
Job 3 140 60 25th percentile and higher
Job 4 105 45 All applicants acceptable

Table 2: Payoffs and Qualifications of the Jobs: Agent Treatment

informed of the employment results. Then we elicited subjects’ beliefs regarding their (their clients’) performance ranking. We conducted the belief elicitation in two steps. First, we asked the subjects to estimate the probability that they (their clients) ranked above the average. In order to elicit true subjective beliefs, we incentivized the subjects using the following quadratic scoring rule:

\[
\text{penalty}_i(x) = \begin{cases} 
((1-x) \times 10)^2 & \text{if subject i is better than average} \\
(x \times 10)^2 & \text{if subject i is worse than average}
\end{cases}
\]  

where \(x\) denotes subject i’s belief of oneself (i’s client) being better than average. Tokens would be subtracted from subjects’ accounts as the penalty for inaccurate estimation.

The second step was to elicit subjects’ conditional beliefs in the cases of being either above or below the average. Subjects were given two parallel conditional probability questions. One question asked the subjects to state their belief that they (their clients) were among the top 2, if their (their clients’) rankings were above the average. The other question asked the subjects to report their belief that they (their clients) were among the bottom 2, if their (their clients’) rankings were below the average.

Quadratic penalty rules similar to Equation 2 applied to subjects’ inaccurate estimates for both questions. Given each subject’s (client’s) performance, only one of the two conditional probability questions would be valid. Since subjects had no information regarding their (their clients’) rankings, they understood that either case could be the valid one with a positive probability, so they had to answer both questions seriously. Subjects’ answers to the three belief elicitation questions at the feedback stage would allow us to compute their beliefs that their (their clients’) rankings were in each of the four quartiles.

Each period was finished after the feedback stage, then subjects entered the application stage of the next period. After finishing all 32 periods, subjects were asked to fill out a questionnaire about their demographic background, and a questionnaire that measured their self-confidence and self-esteem level. We used a short questionnaire containing 10 questions following the design of Charms and Rosenbaum (1960) and Day and Hamblin.
For each question, subjects were asked to choose a response that best represented themselves on a scale from “strongly disagree” to “strongly agree.”

The whole experiment lasted for 120 min. The earnings for each subject consisted of the sum of earnings from the real task, wages (wages and agency fees), minus the penalty for each round’s inaccurate estimations. Subjects were paid for their total earnings from all four rounds, at an exchange rate of 1 local currency per 120 tokens. Subjects were also paid a show-up fee of 20 local currency.

4 Experimental Findings

In total, we have 64 subjects, with 32 in the baseline and 32 in the agent treatment. Each subject participates in 32 periods of job applications and belief elicitation, so there are 2048 observations on application strategies and subjective beliefs in both treatments. Table 3 presents the summary statistics of the experiment. The agent treatment has a smaller variation in experimental earnings. By using two-sample t-test and Wilcoxon rank-sum test, we find no significant difference in both average and median earnings across the treatments.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Stat.</th>
<th>Subjects</th>
<th>Earnings</th>
<th>Self-Confidence</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Mean</td>
<td>32</td>
<td>29.600</td>
<td>31.125</td>
<td>0.719</td>
</tr>
<tr>
<td></td>
<td>Med.</td>
<td></td>
<td>26.785</td>
<td>31.50</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td></td>
<td>16.555</td>
<td>4.02</td>
<td>0.450</td>
</tr>
<tr>
<td>Agent</td>
<td>Mean</td>
<td>32</td>
<td>24.923</td>
<td>30.406</td>
<td>0.563</td>
</tr>
<tr>
<td></td>
<td>Med.</td>
<td></td>
<td>25.352</td>
<td>30.50</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td></td>
<td>6.507</td>
<td>4.389</td>
<td>0.496</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Family Income</th>
<th>Risk Preference</th>
<th>Social Preference</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>Mean</td>
<td>16801</td>
<td>534.05</td>
<td>71.07</td>
</tr>
<tr>
<td></td>
<td>Med.</td>
<td>10000</td>
<td>600</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>19402.8</td>
<td>252.22</td>
<td>22.23</td>
</tr>
<tr>
<td>Agent</td>
<td>Mean</td>
<td>18948.2</td>
<td>500</td>
<td>76.44</td>
</tr>
<tr>
<td></td>
<td>Med.</td>
<td>10000</td>
<td>600</td>
<td>72.5</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>30231.7</td>
<td>282.98</td>
<td>20.855</td>
</tr>
</tbody>
</table>

Table 3: Summary Statistics of Main Variables and Individual Characteristics
4.1 Application Strategy

In this part, we investigate the evolution path of subjects’ application strategies across periods (Hypothesis 1). We split our data by treatments, and in each treatment, we divide all the subjects into four groups, according to their ranking groups. Within each ranking group, we calculate the average of the application strategies of all subjects’ at each period. The results are shown in Figure 1.

For each group $j$, the horizontal dashed line corresponds to job $j$, which is their first-best choice. From the figure, we could see a weak trend of convergence of subjects’ application strategies to the first-best-choice in the complete-information scenario, which indicates subjects’ learning of their relative ranking over time. Specifically for ranking group 2 and 3, the paths of both treatments converge to the corresponding first-best choices. For ranking group 1, we observe such convergence only in the baseline treatment. It indicates that subjects who make application decisions for others are less likely to believe that their clients are in the top ability group. Meanwhile, the speed of convergence is slower for ranking group 4, suggesting that subjects in both treatments are reluctant to admit the fact that themselves (or their clients) are in the lowest ranking group.

Note that we have 4 rounds in a single session, and each round consists of 8 periods. After each round of the application game, another ranking test is taken and all subjects’ ranking groups might change after the new round’s ranking test. It means that the composition of subjects of Group 1 during period 1-8 might be different from that during period 9-16, 17-24 and 25-32. Yet it does not restrict us from gaining some insights about how close subjects’ average strategies are to their first-best-choice, and could also explain the cyclical fluctuations of the strategy path of some ranking groups, especially Group 3.

**Finding 1.** Subjects’ job application choices converge to the first-best choices across time for all ranking groups in the baseline treatments, and for all but the top-ranking group in the agent treatment.

To better investigate the driving forces behind these strategy paths, in the next section we examine subjects’ belief updating pattern and check whether such patterns differ between treatments.
4.2 Belief Updating and Self-serving Attribution Bias

In this subsection, we will analyze subjects’ belief-updating patterns (Hypothesis 2). In particular, we are interested in investigating: (1) whether subjects’ belief-updating process exhibits self-serving attribution bias within each treatment; i.e. whether the magnitude of the change in beliefs differs in response to application success vs. failure and (2) whether the belief updating process differs significantly between treatments.

In the following analysis, we conduct two sets of regression analyses. We first study the change in subjects’ posterior beliefs in response to application outcomes. We then examine if subjects’ belief-updating follows the Bayes rule and whether the updating pattern differs between treatments. We mainly use the belief data of subjects in both treatments. Each subject $i$, after period $t$’s application, is asked about his subjective probabilities that himself (or his client in the agent treatment) belonging to ability groups 1, 2, 3, 4. These beliefs are elicited via a scoring rule described by Equation (2). The elicited beliefs are stored as a vector: $P_i(t) = (P_{i1}(t), P_{i2}(t), P_{i3}(t), P_{i4}(t))$. 

Figure 1: Paths of Application Strategies Across Periods, by Actual Ranking Group

![Figure 1: Paths of Application Strategies Across Periods, by Actual Ranking Group](image-url)
In order to examine the belief-updating process, we define the prior belief and posterior belief in our experimental setting as subjects’ beliefs on his (or his client’s) ranking group before and after each period’s application. Since there are 4 ranking groups in a session, each subject would have 4 pairs of prior/posterior beliefs, which are the prior and posterior beliefs on being in Group 1, 2, 3, 4, respectively. Specifically, for each ranking group \( j \), we define the prior belief, denoted as \( \text{CumuExAnte}_{ij}(t) \), as subject \( i \)'s belief on himself (or his client) belonging to ability group \( j \) or better, at the start of period \( t \), which is simply \( \sum_{m=1}^{j} P_{im}(t - 1) \). Similarly, we define the posterior belief, denoted as \( \text{CumuExPost}_{ij}(t) \), as subject \( i \)'s belief on himself (or his client) belonging to ability group \( j \) or better, at the end of period \( t \), which is \( \sum_{m=1}^{j} P_{im}(t) \).

Using the Bayes rule, we can calculate the Bayesian posterior beliefs conditional on application outcomes, given one’s prior belief. Again, there are 4 pairs of such beliefs:

\[
P_{ij}(t|\text{fail in applying } j^*) = \frac{(1 - p^H) \times P_{ij}(t - 1)}{\text{CumuExAnte}_{ij^*}(t) \times (1 - p^H) + (1 - \text{CumuExAnte}_{ij^*}(t)) \times (1 - p^L)}
\]

\[
P_{ij}(t|\text{succeed in applying } j^*) = \frac{p^H \times P_{ij}(t - 1)}{\text{CumuExAnte}_{ij^*}(t) \times p^H + (1 - \text{CumuExAnte}_{ij^*}(t)) \times p^L}
\]

for any \( j <= j^* \). And for any \( j > j^* \), we could change the \( p^H \) to \( p^L \) in both numerators. These are the beliefs that subjects would have if they perfectly followed the Bayes rule.

We denote the above two Bayesian posterior beliefs as \( P_{ij}(t|f_{j^*}) \) and \( P_{ij}(t|s_{j^*}) \), where \( f \) and \( s \) stands for failure or success. As shown above, subject \( i \)'s Bayesian posterior belief in period \( t \) is calculated using the Bayes Rule based on \( i \)'s own prior belief. Therefore, it represents a belief-updating process consistent with the “rational” benchmark within that period\(^3\)

We focus on a special pair of beliefs in our regression analysis. Let \( j^* \) denote the job that subject \( i \) applies for in period \( t \), and we define \( \text{exante}_i(t) \) as \( \text{CumuExAnte}_{ij^*}(t) \), which is simply \( \sum_{m=1}^{j^*} P_{im}(t - 1) \). Similarly, we define \( \text{expost}_i(t) \) as \( \text{CumuExPost}_{ij^*}(t) \), which is \( \sum_{m=1}^{j^*} P_{im}(t) \). For instance, suppose one applies for job 3 this period, then the prior and posterior beliefs we are interested in are his beliefs on himself being in ranking group 3 or better, before and after his application. In a word, the variables \( \text{exante}_i(t) \) and \( \text{expost}_i(t) \) are one’s prior and posterior belief on one’s qualification on his current target job.

For the explanatory variable, we use the above-defined Bayesian-benchmark beliefs cor-

\(^3\)In the two Bayesian belief formula, by inserting the definition of \( \text{CumuExAnte}_{ij^*}(t) \), the numerators are exactly part of the denominators.
responding to the posterior belief. If an application fails, we have BayesFail\(_i(t)\), which is \(P_{ij^*}(t|f^*)\). If an application is successful, we have BayesSucceed\(_i(t)\), which is \(P_{ij^*}(t|s^*)\). These two beliefs are the Bayesian benchmark for \(\text{expost}_i(t)\). If a subject updates his belief in a Bayesian manner, then \(\text{expost}_i(t)\) should equal either one of the two Bayesian benchmark, depending on the application outcomes.

Finally, we have three key dummy variables, result\(_i(t)\), agent and gender\(_i\), which take on a value of 1 when application by subject \(i\) in period \(t\) is successful, the treatment is agent treatment and the subject \(i\) is female, and 0 otherwise. We denote the three variables as \(r_{it}\), \(A\) and \(g_i\). With all variables defined as above, we conduct the following two sets of linear regressions:

\[
\text{expost}_i(t) = \alpha + \beta \ast \text{exante}_i(t) + \gamma \ast r_{it} + \delta \ast r_{it} \ast A + \theta' C_i
\]  \hspace{1cm} (3)

\[
\text{expost}_i(t) = \alpha + \eta_1 \ast \text{BayesFail}_i(t) \ast (1 - r_{it}) + \eta_2 \ast \text{BayesSucceed}_i(t) \ast r_{it} + \\
\quad \zeta_1 \ast \text{BayesFail}_i(t) \ast (1 - r_{it}) \ast A + \zeta_2 \ast \text{BayesSucceed}_i(t) \ast r_{it} \ast A + \\
\quad \kappa_1 \ast \text{BayesFail}_i(t) \ast (1 - r_{it}) \ast g_i + \kappa_2 \ast \text{BayesSucceed}_i(t) \ast r_{it} \ast g_i + \theta' C_i
\]  \hspace{1cm} (4)

where \(C_i\) is a vector of control variables of subject \(i\), including age, social preference (higher value for more selfishness), risk preference (higher value for more risk-seeking) and other demographic variables. The corresponding questionnaires are included in the online appendix.

In Regression Equation (3), we test (1) whether subjects’ posterior beliefs respond to application results in the correct direction, and (2) if there is any response differences between treatments, given the same set of prior beliefs. In Regression Equation (4), we examine (1) whether the posterior beliefs are consistent with the Bayesian beliefs, and (2) whether the pattern of (in)consistency differs in response to different application outcomes between treatments.

Table 4 shows the results of Regression Equation (3). Coefficients of the main explanatory variables are significant, and the signs of the coefficients are as expected. First, subjects’ posterior beliefs are generally higher if the prior belief is high (\(\beta > 0\)). Second, subjects’ posterior beliefs increase in response to application success and decrease in response to application failure (\(\gamma > 0\)). It indicates that subjects are gaining/losing confidence after positive/negative outcomes. Third, the coefficients of variables riskpreference and socialpreference are both significantly positive, indicating that subjects who are more risk-seeking or more selfish tend to have higher posterior beliefs.
Table 4: Subjects’ Posterior Beliefs in Response to Application Result

Moreover, the coefficient of the interacting term $r_{it} \times A$, $\delta$, is significantly negative. It implies that, when evaluating others instead of oneself, given the same prior belief and the same application success, the posterior belief does not increase as high as that in the baseline treatment. Two possible mechanisms could be the driving force behind this observation: (1) subjects are generally more “strict” in the agent treatment upon observing others’ success and less likely to attribute the success to other’s high ability, and (2) if subjects attribute their clients’ application success to high ability ranking, they would at the same time admit
that they themselves probably have a lower ranking since their clients are competing with them in the same session. More discussion on the possible implications of this result is included in the Section 5.

![Table 5: Subjects’ Posterior Beliefs vs. Bayesian Posterior](image)

Notes: (1) The variables BayesFail\(_i(t) \times (1 - r_{it})\) and BayesSucceed\(_i(t) \times r_{it}\) are the Bayesian posterior belief calculated using Bayes rule from the subject \(i\)’s actual prior belief in period \(t\) (actual posterior belief in period \(t - 1\)), and represent the benchmark beliefs for Bayesian-rational subjects upon observing application failure or success. (2) Standard errors are in parentheses, clustered at individual subject level. (3) Significant level: *** \(p < 0.01\), ** \(p < 0.05\), * \(p < 0.1\).
Table 5 shows the results of Regression Equation (4). Coefficients of the main explanatory variables are significant and the signs are as expected. In neither treatments, subjects update their beliefs exactly following the Bayesian benchmark. In the baseline treatment, whenever the Bayesian posterior increases by 1% upon a successful application, the subjects only increase their posterior by roughly 0.7%, and when the Bayesian posterior decreases by 1% upon an unsuccessful application, the subjects only decrease the posterior by roughly 0.5%. This generally means that subjects adjust their beliefs in a smaller magnitude compared to the Bayesian benchmark. Neither do they build up confidence as quickly as a Bayesian-rational decision-maker upon success, nor do they lose confidence as quickly as a Bayesian-rational decision-maker upon failure.

The same pattern also appears in the agent treatment. An interesting observation is that subjects in the agent treatment adjust their beliefs in an even smaller magnitude than those in the baseline treatment. Upon a successful application, subjects in the baseline treatment increase their posterior belief faster than those in the agent treatment, which is consistent with the strategy path shown in Figure 1. Although in both treatments subjects update their posterior beliefs in a smaller magnitude than the Bayesian benchmark, subjects' belief updating in the baseline treatment is closer to the Bayesian benchmark.

It is worth noting that \( \eta_1 < \eta_2 \); i.e. subjects’ posterior beliefs change by a larger magnitude upon positive application outcomes. In other words, upon successful applications, subjects’ belief updating is closer to the Bayesian benchmark. The asymmetry in confidence building supports the presence of self-serving attribution bias. Interestingly, we also observe a similar pattern of asymmetry in the agent treatment \( (\eta_1 + \zeta_1 < \eta_2 + \zeta_2) \). The magnitude of such asymmetry are similar between treatments, which indicates the existence of self-serving attribution bias in both treatments.

To summarize, subjects change their beliefs in larger magnitude in the baseline treatment and upon an application success. Subjects in the baseline treatment incorporate application failure and success into the belief updating process asymmetrically; so do the subjects in the agent treatment. The possible mechanism is that failure is not interpreted as a result of lower ranking, but as bad luck; i.e. even with a 75% employment probability, subjects tend to attribute application failure to the 25% unemployment probability. Meanwhile, subjects are more likely to attribute application success to their own high ability ranking.

A minor point is that the coefficients of variables \textit{riskpreference} and \textit{socialpreference} are both significantly positive, indicating that subjects who are more risk-seeking or more
selfish tend to have higher posterior beliefs. We find no significant gender effect in either set of the regression analysis.

**Finding 2.** Subjects do not follow the Bayes Rule when updating their beliefs regarding their own or their clients’ ability ranking in either treatment. In the agent treatment, subjects’ beliefs change in a smaller magnitude compared to the Bayesian benchmark. In the baseline treatment, the changes in subjects’ posterior beliefs are closer to the Bayesian benchmark upon both successful and unsuccessful applications, though still in a smaller magnitude than the Bayesian benchmark.

**Finding 3.** Subjects’ belief-updating pattern exhibits self-serving attribution bias. In both treatments, the increments of beliefs after application successes are larger than the decrements after application failures. The closeness between the actual beliefs and Bayesian benchmark changes; such changes upon different types of events follow such an order: one’s own success > others’ success > one’s own failure > other’s failure.

### 4.3 Reinforcement Learning Model Estimation

Subsection 4.2 shows the difference of the belief-updating pattern within and between treatments. We observe that subjects are more reluctant to admit their own failure in the context of job-seeking. In subsection 2.2 we introduce a structural framework of job-switch following the literature of reinforcement learning. In this subsection, we adopt this framework to quantitatively evaluate how many application failures one would generally experience before losing confidence and not sticking to his current application choice (Hypothesis 3). Using the model, we are able to predict whether a subject would switch his target job upwards or downwards in the next period, given his application history. Below we present the estimation procedure, results, and the behavioral interpretation.

In our estimation, we first predict if a subject is going to switch job in the next period using Equation (1), and then compare it with the actual job switch of that subject. The optimization problem is to minimize the squared loss of prediction function:

$$ e = \sum_{j=1}^{4} \sum_{i \in S_j(t)} \sum_{t} [g(j,t) - h_i(t)]^2 $$

where $S_j(t)$ refers to the subset of subjects who apply to job $j$ in period $t$. Since the initial assessment levels $q_1, q_2, q_3, q_4$ might not be the same across different ranking groups, we run the estimation for each ranking group separately. For each treatment and each ranking
group \{1, 2, 3, 4\}, we estimate 11 parameters (4 initial assessment levels, 6 upper and lower bound parameter and the \(\delta\) of the similarity function) by minimizing the loss function specified above. Full estimation results are available in Table 8 in the Appendix, and the parameters most relevant to each group is presented in Table 6.

<table>
<thead>
<tr>
<th>Key Parameters</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>(q_1^0), (u_{12})</td>
<td>(u_{21}), (q_2^0), (u_{23})</td>
<td>(u_{32}), (q_3^0), (u_{34})</td>
<td>(u_{43}), (q_4^0)</td>
</tr>
<tr>
<td>Agent</td>
<td>174.6, 178.6</td>
<td>708.6, 114.3, 3.7</td>
<td>1082.9, 71.4, -67.1</td>
<td>725.7, 93.4</td>
</tr>
</tbody>
</table>

Table 6: Estimation Results of the Reinforcement Learning Model with Strategy Similarity

In Table 6, each job’s initial assessment and lower/upper bounds only apply to subjects of the corresponding group who take the job as their first-best choices. For instance, for subjects belonging to group 2 in the baseline treatment, the first-best choice is job 2 and the estimated initial assessment is \(q_2^0 = 41\). The upper and lower bounds for switching job applications are \(u_{21} = 777\) and \(u_{23} = -387\). That is, subjects in group 2 update their \(q_2(t)\) starting from a value of 41; they switch to applying for job 1 if \(q_2(t)\) increases above 777 after several positive stimuli, or switch to applying for job 3 if \(q_2(t)\) decreases below -387 after several negative stimuli.

To better understand how many application successes/failures would lead one to switch to applying a higher-paying/lower-paying job, in Table 7 we calculate the difference between the value of initial assessment and the upper/lower bound of each group, and then divide it by the job’s payoff level (wage in the baseline treatment, agency fee in the agent treatment):

\[
\frac{u_{kk-1} - q_0^0}{u^k}, \frac{u_{kk+1} - q_0^0}{u^k}
\]

The two quantities capture the number of consecutive successes (with positive sign (+)) or consecutive failures (with negative sign (−)) a subject in group \(k\) would typically experience before he switches to job \(k-1\) or \(k+1\). For example, after an application failure in job 2, the subject’s actual payoff is 0, while job 2 could have provided a payoff of 250 if the subject were successfully employed. If one has anticipated a full payoff of 250 from the job, the maximum negative stimuli equals the forgone payoff, 250. The amount of negative stimuli he needs to trigger a downward job switch is \(q_2^0 - u_{23} = 41 - (-387) = 428\). So the ratio equals 1.712, meaning that the subject in group 2 sticks to applying for job 2 until he experiences an average of 1.712 application failures before switching to applying for job 3.

---

4The consecutive successes/failures here are in the sense of net application successes or failures. For example, if a subject from group 2 has experienced one application failure and three application successes,
Table 7: Numbers of Net Successes and Failures Needed Before Switching Job Application Strategies

<table>
<thead>
<tr>
<th></th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch Direction</td>
<td>1 → 2</td>
<td>2 → 1</td>
<td>2 → 3</td>
<td>3 → 2</td>
</tr>
<tr>
<td>Baseline</td>
<td>-1.93</td>
<td>2.95</td>
<td>-1.71</td>
<td>3.49</td>
</tr>
<tr>
<td>Agent</td>
<td>0.15</td>
<td>2.38</td>
<td>-0.44</td>
<td>5.06</td>
</tr>
</tbody>
</table>

Compared to the agent treatment, when subjects apply for jobs for themselves, they are more reluctant to switch to lower-paying positions, and experience more negative stimuli before switching target for lower-paying jobs. In the baseline treatment, it takes more application failures for one to finally have a lower enough assessment to apply for a lower-paying job. Meanwhile, subjects in group 3 and 4 of the baseline treatment, compared to their counterparts in the agent treatment, switch to apply for higher-paying positions after only a few application successes, indicating that they are very hasty to go for better-paying jobs. These findings are consistent with the discussion in the self-serving attribution bias literature, suggesting that people are more likely to incorporate positive events into the evaluation of their own ability, while are less likely to absorb negative information from unsuccessful experiences. When people make decisions for others, it is more easily for them to downgrade the evaluation of others and to switch to applying for lower-paying positions.

Finding 4. The estimation of the reinforcement learning model shows that, compared to the baseline treatment, subjects undergo fewer unsuccessful applications before switching to applying for a lower-paying job, and experience more successful applications before switching to applying for a higher-paying job on behalf of their clients in the agent treatment.

---

he has a net success of 2 since the failure and one of the successes cancel out. All numbers in Table 7 represent the net successes/failures needed for one to switch his target job to a better-paying/worse-paying one.

We would like to provide an explanation for the seeming anomaly in Column 1 → 2 of Table 7. In the agent treatment, the sign of the value 0.15 means that an average of −0.15 times of application failure are needed for an agent who has applied to job 1 in previous periods to switch to applying for job 2. In fact this is not counter-intuitive. The estimation result actually indicates that when agents evaluate the ability ranking of their clients, they seldom place their clients into the top tier of all ranking groups. In the agent treatment, it is frequently observed that agents apply for Job 1 at most once. One possible driving force is that, if a subject believes that his client belonging to the top tier of all subjects, he has smaller chance to be in the same tier himself. Therefore, the positive sign of 0.15 is consistent with the presence of the self-image effect.
5 Concluding Remarks

The Bayes rule is a commonly-used tool when economic theorists model rational decision-makers’ belief-updating process. In order to investigate whether individuals’ self-image would play a role in the deviation of actual belief from the Bayesian-updating pattern, we conduct a laboratory experiment with a simulated labor market. We find that subjects generally deviate from the Bayesian-updating pattern and exhibit self-serving attribution bias in the job-seeking process. Subjects adjust their beliefs by a larger magnitude upon an application success and by a smaller magnitude upon an application failure.

Since there exists other behavioral factors that might affect subjects’ behavior in the baseline labor market, we also conduct an agent treatment where subjects seek job positions on behalf of others. By comparing the belief updating pattern between the two treatments, we are able to control for the behavioral factors that can influence the job-seeking process regardless of the role of the subjects. By comparing the two role-playing treatments, we find that when subjects seek job positions for themselves, they are more likely to switch their application targets to the better-paying positions. In the agent treatment, subjects also adjust their beliefs asymmetrically upon others’ application success vs. failure. Our findings may provide insights into economic or financial decision-making environments similar to the context in our study.

It is worth noting that individuals’ self-image could play a role in the agent treatment as well. One potential mechanism is that subjects are competing with others in the same labor market where providing high evaluations for their clients means a higher probability that they themselves belong to a lower ability group. This strategic concern could potentially harm subjects’ own self-image and make subjects more reluctant to give high evaluations to their clients. Fortunately, this self-image effect works in the same direction as the effect we identified in the baseline treatment. We expect that further research will disentangle the effects of one’s self-image under other economic or social settings, such as individual vs. partner decision-making in household finance, business or organizational decision-making, etc. Furthermore, we expect to see how such a role-playing method could be adopted in settings with strategic interactions, so that more individual-specific behavioral factors could be identified in the corresponding environments.

Finally, we also recognize that the statistical analyses conducted in the empirical section suffer from a small-sample issue, though the issue does not prevent us from obtaining insights about the basic pattern of individuals’ belief-updating and strategy dynamics in
this laboratory labor market. In general, our regression analyses are able to provide strong evidence that supports our main empirical findings. We would expect more statistical significance in our structural model parameters should we have more data, yet we would expect a similar consistency pattern between the regression analyses and the structural estimation results. Hopefully, such a role-play treatment can be applied in experiments with larger scales in future research that involves decision-making with economic incentives.
6 Appendix

6.1 Proofs

Proof. of Proposition 6. Without loss of generality, consider individual $i$ applies for job $k \in \{1, \ldots, K\}$ (or $i$’s agent applies for job $k$ on $i$’s behalf). For the ease of notation, we also use $\{1, \ldots, K\}$ to denote the ranking groups of all individuals. Let $p_k$ denote the prior belief that $i$ belongs to group $k$, with $\sum_{i=1}^{K} p_i = 1$.

For ranking groups $k$ and above; i.e. $\forall j \in \{1, \ldots, k\}$, the posterior belief for each group $j$ increases more than the Bayesian posterior after a success in $k$:

$$\gamma_j(i \in \text{group } j | \text{success in job } k) = \frac{p_j \cdot p^H \cdot \lambda_s}{\sum_{i=1}^{k} p_i \cdot p^H \cdot \lambda_s + \sum_{i=k+1}^{K} p_i \cdot p^L} > p_j$$

if and only if $p^H > p^L$ and $\lambda_s > 1$. For ranking groups $k + 1$ and below; i.e. $\forall \ell \in \{k + 1, \ldots, K\}$, the posterior belief for each group $\ell$ decreases more than the Bayesian posterior after a success in $k$:

$$\gamma_\ell(i \in \text{group } \ell | \text{success in job } k) = \frac{p_\ell \cdot p^L}{\sum_{i=1}^{k} p_i \cdot p^H \cdot \lambda_s + \sum_{i=k+1}^{K} p_i \cdot p^L} < p_\ell$$

On the other side, for ranking groups $k$ and above; i.e. $\forall j \in \{1, \ldots, k\}$, the posterior belief for each group $j$ decreases from the prior, but the decrement is less than the decrement in Bayesian posterior after a failure in $k$:

$$\gamma_j(i \in \text{group } j | \text{failure in job } k) = \frac{p_j \cdot (1 - p^H) \cdot \lambda_f}{\sum_{i=1}^{k} p_i \cdot (1 - p^H) \cdot \lambda_f + \sum_{i=k+1}^{K} p_i \cdot (1 - p^L)}$$

if and only if $p^H > p^L$ and $1 < \lambda_f < (1 - p^L)/(1 - p^H)$. For ranking groups $k + 1$ and below; i.e. $\forall \ell \in \{k + 1, \ldots, K\}$, the posterior belief for each group $\ell$ increases from the prior, but
the increment is less than the increment in Bayesian posterior after a failure in k:

\[
\gamma_\ell(i \in \text{group } \ell|\text{failure in job } k) = \frac{p_\ell \cdot (1 - p^L)}{\sum_{i=1}^{k} p_i \cdot (1 - p^H) \cdot \lambda_f + \sum_{i=k+1}^{K} p_i \cdot (1 - p^L)} < \frac{p_\ell \cdot (1 - p^L)}{\sum_{i=1}^{k} p_i \cdot (1 - p^H) + \sum_{i=k+1}^{K} p_i \cdot (1 - p^L)} \text{ and } > p_\ell
\]

6.2 Other Figures and Tables

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Table 8: Estimation Results of the Reinforcement Learning Model with Strategy Similarity: All Parameters
References


