Own experience bias in a labor market with heterogeneous rewards

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Abstract

We develop a model with which to explore discrimination and prejudice within labor markets. Our approach emphasizes the role of an individual’s own experience in the assessment of efforts of other individuals. Specifically, we consider a two stage process in which individuals first learn, through experience, whether effort is rewarded and then subsequently have to estimate the effort of others. Our theoretical results suggest that those who are not rewarded for high effort...
will underestimate the effort of other individuals while those for whom effort is rewarded will (slightly) overestimate the effort of others. We empirically test and confirm this prediction.
1 Introduction

There is a growing recognition in academic research and in the popular press of the role that unconscious bias can play in labor market discrimination. In short, an individual may be unaware that her judgment of others is influenced by, say, gender or race. Unconscious bias differs fundamentally from more conventional explanations of discrimination, such as taste-based discrimination, where the individual simply prefers one group over another, or statistical discrimination, where the individual uses observable characteristics to make unbiased inferences about unobservable characteristics. Disentangling unconscious bias from other potential sources of discrimination is, however, difficult because individuals have unique experiences and, when assessing others, may simply be making the best assessments possible given their own experiences and the information available to them. In our work we seek to isolate the effect of unconscious bias by randomly exposing individuals to different experiences. This allows us to understand whether own experience can create implicit bias.

Key to our approach is a recognition that as individuals go through their life they typically learn from personal experience the rewards for effort (at school, workplace etc.) before being in a position to make decisions about others (as manager, colleague etc.). To capture this, our model has two stages. In the learning stage an individual, who we call Alice, engages in a series of decision problems where she exerts effort in search of bonuses. This gives Alice an opportunity to learn whether effort pays for her personally. In the subsequent evaluation stage Alice is presented with the bonuses received by another individual, who we call Bob, and asked to estimate Bob’s effort. In interpretation we think of Alice as being a manager looking to appraise the past performance of Bob. Our main research question is whether the own experience of Alice biases in predictable ways her estimate of Bob’s effort.

We consider a transparent, dichotomous setting in which Alice (similarly Bob) is one of two types. For one type, called Effort Matters (EM), effort increases the probability that Alice will receive a bonus. For the other type, called Luck Matters (LM), the probability of a bonus is independent of effort. Alice is not told her type but has an opportunity in the learning stage to learn whether effort pays for her. Our theoretical results lead to testable hypotheses: If Alice is type EM then she will be systematically biased towards over-estimating the effort of Bob but this bias will be small. By contrast, if she is type LM she will be systematically biased towards under-estimating
the effort of Bob and this bias will be large. The predicted asymmetry between EM and LM types is novel and, as we shall discuss, distinguishes own-experience bias from related concepts such as the (false) consensus effect.

We test and support the predictions of the model through an experiment. The experiment, like the model, consists of two stages. In the learning stage subjects have the opportunity, over 20 periods, to earn bonuses, where the probability of a bonus depends on type and choice of the subject. In the evaluation stage of the experiment subjects are shown the sequence of bonuses received by 12 other subjects and asked to estimate the average effort choice made by each of these subjects. Our experimental results support our main hypotheses: subjects exogenously assigned type EM over-estimate the average effort of others and, on average, the bias is small; subjects assigned type LM under-estimate the average effort of others and the bias is relatively large and statistically significant.

Our results support the conclusion that those for whom only luck matters are more biased in their judgment of others than those for whom effort matters. This leads to the suggestion that those who are ‘advantaged’, that is, those who receive rewards through luck, may underestimate the effort of the less advantaged, who must input effort to have an equal or greater probability of reward. It is worth highlighting that subjects appeared on average to be good at discerning the effort choices others had made. In particular, there was a strong correlation between estimates of effort and the number of bonuses the employee had received. This suggests that subjects were relatively sophisticated in their judgments. Even so, we find evidence for own-experience bias.

That judgment of others could be biased by own experience seems natural and has significant indirect support in the psychology literature. Extensive evidence shows that people are biased in overweighting own experience because of, for example, hindsight bias (e.g. Christensen-Szalanski and Willham, 1991; Hoffrage, Hertwig and Gigerenzer, 2000), overconfidence (e.g. Dunning et al. 1990), the availability heuristic (e.g. Tversky and Kahneman, 1973, 1974), and anchoring (Furnham and Boo, 2011). Moreover, a growing literature shows evidence of projection bias, a bias towards assuming that others are similar to oneself (e.g. Ross, Greene and House, 1977; Mullen et. al. 1985; Kreuger and Clement, 1994; Breitmoser 2015). Our work introduces a new theoretical model of own experience bias and confirms that such biases can be developed in a laboratory setting.

To appreciate the wider contribution of our paper, consider the extensive
literature, field and experimental, on discrimination in labor markets (e.g. Bertrand and Mullainathan, 2004; Mobius and Rosenblat, 2006; Carlsson and Rooth, 2007; Pager, Western and Bonikowski, 2009; Charness and Kuhn, 2011; Fang and Moro, 2011; Arceo-Gomez and Campos-Vazquez, 2014; Azmat and Petrongolo, 2014). Our work is distinguished from this literature in two respects - the type of bias we study and the way we study it. We explain each in turn:

Type of bias. We consider the extent to which individuals are biased by own experience, a question of fundamental importance in understanding labor markets. This type of bias that has been largely overlooked and motivates our research. The existing literature focuses on an manager differentiating between candidates based on observable characteristics; for instance, a manager may, consciously or unconsciously, expect the productivity of a male to be higher than that of a female. In our work we look at whether a manager is systematically biased in evaluating any and all of the candidates she observes; for instance, a manager may overestimate the productivity of both male and female workers (Bordalo et al. 2019). This latter issue is the focus of our work.

Experimental approach. A crucial feature of our approach is that bias is created entirely within the lab through the random allocation of type and subsequent experience. By contrast, much of the work on discrimination looks at traits and characteristics bought from outside the lab, whether that be trust, cooperation, ability, race or gender (Castillo and Petrie, 2010; Reuben et al., 2014; Bordalo et al., 2019). Our approach creates a ‘self-contained’ environment with which to control the experience subjects are exposed to allowing us to accurately measure bias. More ‘neutral, self-contained’ lab environments are typically reserved for studying statistical discrimination (Dickinson and Oaxaca, 2014).

We proceed as follows. The model is described in Section 2. In Section 3 we provide our theoretical results and in Section 4 we report our experiment results. In Section 5 we conclude. Additional material is provided in an Appendix and Supplementary Material.

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1Her expectation may be consistent with optimal behavior given her own experience. The literature has looked to distinguish between statistical, taste-based, and implicit discrimination (e.g. Bertrand, Chugh and Mullainathan, 2005; Guryan and Charles, 2013; Ewens, Tomlin and Wang 2014).
2 The model

We describe the learning and evaluation stage in turn.

2.1 Learning stage

In the learning stage there exists a set \( \{1, \ldots, T\} \) of time periods and a set of actions \( E \subset [E_L, E_H] \), \( 0 < E_L < E_H \), where both \( E_L \) and \( E_H \) are in \( E \).\(^2\)

We interpret an action as an effort level. In each period Alice must choose an effort level from \( E \). Let \( e_t \in E \) denote the effort level chosen in period \( t \).

Having chosen an effort level, Alice learns whether she will receive a payoff bonus \( B > 0 \). Let \( b_t \in \{0, 1\} \) record whether she received a bonus in period \( t \), where \( b_t = 1 \) indicates she received a bonus and \( b_t = 0 \) otherwise.

The payoff to Alice in period \( t \) is given by

\[
    u_t = B b_t - e_t,
\]

and consists of her bonus, if any, minus the cost of effort. The total payoff of Alice over the \( T \) periods is her total payoff \( u = \sum_{t \in \mathcal{T}} u_t \).

Alice is one of two types: (1) effort matters (EM) or (2) only luck matters (LM). Each type is equally likely (and independent of the type of others).

For a type EM individual the probability of receiving the bonus is linearly increasing in the amount of effort according to the formula

\[
    \pi^{EM}(e) = \alpha e - \beta
\]

for all \( e \in E \), where \( \alpha > 0 \) and \( \beta \geq 0 \). In order to guarantee \( \pi^{EM}(e) \in (0, 1) \), we assume \( \beta \in (\max \{0, \alpha E_H - 1\}, \alpha E_L) \). Thus, for a type EM individual, the higher her effort the higher the probability she will receive the bonus. For a type LM individual the probability of receiving the bonus is independent of the effort she makes and is given by:

\[
    \pi^{LM}(e) = \gamma
\]

for all \( e \), where \( \gamma \in (0, 1) \).

In our experiment we set \( E_L = 17, E_H = 33, \alpha = 0.04, \beta = \gamma = 0.5 \) and \( B = 50 \). Thus, if Alice is of type EM the probability of her receiving the bonus is 0.82 if she chooses effort level 33 and 0.18 if she chooses effort level

\(^2\)In our experiment we will take \( E \) as the integers contained in the interval \([17, 33]\).
17. This implies her expected payoff is increasing in effort. By contrast, if Alice is type LM the probability of receiving the bonus is 0.5 independent of effort and so expected payoff is decreasing in effort. If Alice new her type it would be relatively simple for her to discern optimal effort. We explore in Section 3 what Alice should do given that she does not know her type.

2.2 Evaluation stage

In the evaluation stage we can think of Alice as a manager looking at the performance record, CV, of the employee Bob. By this point both Alice and Bob have completed the learning stage. The learning stage was identical for both Bob and Alice in terms of fundamental parameters. But crucially it is highly unlikely they had the same individual experience. As we shall see, own experience is crucial to our approach.

Alice observes whether Bob obtained bonuses in periods $t$ to $T$ for some $t > 1$. We refer to the sequence $\{b_t, ..., b_T\}$ as the CV of Bob. Note that Alice does not observe the effort of Bob or bonuses before period $t$. The question we shall address is what Alice infers about the effort of Bob and whether this inference depends on her own experience. We assess Alice’s evaluation of Bob based on her prediction of Bob’s average effort. To formalize this let $\bar{e}$ denote the average effort of Bob (in periods $t$ up to $T$) and let $g$ denote Alice’s estimate of Bob’s effort (in periods $t$ up to $T$). We set the payoff of Alice according to a threshold measure of accuracy. Specifically, she receives payoff $Y$ if $|\bar{e} - g| \leq k$, for an exogenous threshold $k > 0$, and receives 0 otherwise.\footnote{One could imagine more complex quadratic scoring rules for rewarding accuracy. The threshold measure has the advantage of simplicity particularly for experimental subjects.} In measuring accuracy we will also discuss prediction error $\bar{e} - g$ and absolute prediction error $|\bar{e} - g|$.

A brief comment on the interpretation of Alice’s objectives when she looks at Bob’s CV seems apt. There is no moral sense in which high effort is ‘better’ than low effort (which is reflected in our experiment instructions). Bob is simply responding to exogenously given incentives. Carrying this logic forward we should not think of Alice as wanting to reward employees who chose high effort in the past. What she wants to do is correctly interpret the background of Bob.
3 Theoretical analysis

In this section we outline some theoretical benchmarks around which to judge the behaviour and inferences of Alice. Recall that our objective is to see how Alice’s judgment of others (in the evaluation stage) may be biased her own experience (in the learning stage). We, therefore, focus on two basic issues: (1) what can we expect Alice to experience in the learning stage and (2) how may this experience bias her estimate of Bob’s effort. We consider these two issues in turn.

3.1 Learning stage

Recall that Alice does not know her type. Let $p_0 \in (0, 1)$ denote the probability that she initially assigns to being type EM. A strategy determines an action in each period $t$ for any plausible history $h_t = (e_1, b_1; \ldots; e_t, b_t)$. Once we know history $h_T = (e_1, b_1; \ldots; e_T, b_T)$ the total payoff $u = \sum_{t \in T} u_t$ is determined. With a slight abuse of notation let $u(h_T)$ denote total payoff given history $h_T \in H_T$. For any strategy $s$ and initial belief $p_0$ it is possible to determine the probability distribution over the set of outcomes. Let $\Pr (h_T \mid s, p_0)$ denote the probability of outcome $h_T$ given strategy $s$ and initial belief $p_0$. The objective of Alice in the learning stage is to choose a strategy $s$ that maximizes expected total payoff,

$$U(s) = \sum_{h_T \in H_T} \Pr (h_T \mid s, p_0) u(h_T). \quad (1)$$

Through experience Alice can update her beliefs on own type. Let $p_t$ denote the probability she assigns to being type EM given history $h_t$. It is optimal for Alice to update her beliefs over time using Bayes rule.\footnote{If $Pr(b_t \mid \star)$ denotes the probability of $b_t$ given Alice is type $\star$ then
$$p_t = \frac{p_{t-1} \Pr (b_t \mid type \ EM)}{p_{t-1} \Pr (b_t \mid type \ EM) + (1 - p_{t-1}) \Pr (b_t \mid type \ LM)}.$$
Where $Pr (b_t \mid type \ EM) = b_t (\alpha e_t - \beta) + (1 - b_t) (1 + \beta - \alpha e_t)$ and $Pr (b_t \mid type \ LM) = b_t \gamma + (1 - b_t) (1 - \gamma)$.

\footnote{The set $H_T$ need not be finite but, for any strategy $s$ and initial belief $p_0$, the set of outcomes that can occur with positive probability is finite.}} Doing this, $p_t \geq p_{t-1}$ if and only if

$$b_t (\alpha e_t - \beta) + (1 - b_t) (1 + \beta - \alpha e_t) > b_t \gamma + (1 - b_t) (1 - \gamma).$$
This yields an important cut off effort level

\[ e^* := \frac{\beta + \gamma}{\alpha}. \]

Alice would optimally increase the probability she assigns to being type EM if and only if either (1) \( e_t > e^* \) and \( b_t = 1 \) or (2) \( e_t < e^* \) and \( b_t = 0 \). Thus, if Alice puts in high effort and is successful then, according to Bayes rule, she increases the probability she assigns to being of type EM. If she puts in low effort and is unsuccessful then she similarly increases the probability she assigns to being type EM. Otherwise she increases the probability she assigns to being type LM.

3.1.1 Optimal strategy in the learning stage

In maximizing expected total payoff Alice, in period \( t \), has to trade off two potentially competing objectives: (1) maximize expected payoff in period \( t \), and (2) maximize information about type to enable a more informed choice in periods \( t+1, t+2, ..., T \). In general, there may be a conflict between these two objectives.\(^6\) To make the problem more tractable (and our experiment design more transparent) we chose parameter values so that there is no conflict between the two objectives. The optimal strategy for Alice is then to simply maximize expected payoff each period. This is captured in our first result, proved in an appendix.

**Proposition 1:** Suppose that \( (\beta + \gamma)/\alpha = (E_H + E_L)/2 \) and \( \gamma = 1/2 \). Then Alice can maximize expected total payoff in the learning stage by choosing, in any period \( t \in \{1, ..., T\} \), action \( E_H \) if \( p_{t-1}\alpha B \geq 1 \) and \( E_L \) if \( p_{t-1}\alpha B < 1 \).

To illustrate Proposition 1 consider the parameter values we use in our experiment (\( \beta = \gamma = 0.5, \alpha = 0.04, E_L = 17, E_H = 33 \)). The optimal strategy dictates Alice choose \( E_L \) if \( p_{t-1} < 0.5 \) and \( E_H \) if \( p_{t-1} > 0.5 \). If Alice uses the optimal strategy then expected effort relatively quickly converges on the ‘correct’ effort level for type (see supplementary material and Figure 1 to follow). That is, effort converges towards 33 if Alice is type EM and 17 if type LM.

\(^6\)For instance, it could be that Alice should choose \( E_L \) to maximize her expected period 1 payoff but choose \( E_H \) in order to better learn her type and maximize expected payoff in future periods.
3.1.2 Extremeness aversion

Abundant evidence suggests that many people are averse to choosing extreme options (Neumann, Bckenholt and Sinha 2016). We, therefore, explore what happens if Alice deviates from the optimal strategy by choosing effort levels other than the extremes $E_H$ and $E_L$. We begin by introducing the following definition. Alice’s strategy is said to be belief responsive if in any period $t \in \{1, ..., T\}$, she chooses an action $e_t \geq e^*$ if $p_{t-1} \alpha B \geq 1$ and action $e_t \leq e^*$ if $p_{t-1} \alpha B < 1$. If a strategy is belief responsive then Alice is learning from past experience whether to choose ‘high’ or ‘low’ effort.

To illustrate consider a belief responsive strategy in which Alice chooses $E_H - y$ and $E_L + y$ in any period $t$, for some value $y \geq 0$. If $y = 0$ we have the optimal strategy. The larger is $y$ then the higher the extent of extremeness aversion. The speed of convergence in beliefs and actions will be critical to our experimental design. Figure 1 plots the proportion of periods in which Alice chooses effort on the right side of $e^*$ for her type, i.e. $E_H - y$ if type EM and $E_L + y$ if type LM. We give the proportion over all periods and from period $\bar{t}$ onwards. Provided $y$ is not too large the proportion of choices on the right side of $e^*$ remains relatively high.\(^7\)

3.1.3 Summary from learning stage

The optimal strategy in the learning stage requires Alice to update her beliefs using Bayes rule and to choose ‘extreme’ effort levels $E_H$ and $E_L$. In reality, and in the lab, neither of these is likely to hold. We know that individuals deviate from Bayes updating and exhibit extremeness aversion. This, though, is not crucial to our model. The key feature driving our model is that Alice, by the time she reaches the evaluation stage, has a good idea, conscious or not, of the type she is. Our analysis shows that if Alice behaves optimally then she quickly learns type. Extremeness aversion and failure to use Bayes updating will clearly slow learning, but we can still reasonably expect Alice to have a good idea of own type by the evaluation stage.

\(^7\)Alice will see a significant loss in payoff from extremeness aversion. To illustrate consider $y = 3$. If Alice is type LM then choosing 20 costs them 3 more than choosing 17. Similarly, if of type EM the probability of getting the bonus drops from 0.82 to 0.7 if Alice chooses effort 30 rather than 33. This is a drop in expected bonus of 6 which is only partly compensated by spending 3 less on effort.
Figure 1: Proportion of choices that are 'correctly' above 25 for a type $E_H$ and below 25 for a type $E_L$.

3.2 Evaluation stage

Since Alice does not observe the bonuses of Bob between period one and period $t-1$ she cannot recreate Bob’s learning process. She can still, however, infer something about his type and effort from his CV. In this section we derive a benchmark threshold based on Alice having an unbiased prior of the type of Bob. We then introduce own experience bias.

3.2.1 Benchmark threshold

Suppose that if Bob is type EM then he chooses $E_h$ in each period $t > t$ where $e^* < E_h \leq E_H$. Also suppose that if he is type LM he chooses $E_l$ in each period, where no assumptions are imposed on $E_l$. Then if Bob is of type EM the likelihood of obtaining the specific sequence of bonuses in his CV is\(^8\)

$$\Pr(CV|EM) = \prod_{t=t}^{T} (\alpha E_h - \beta)^{bt} (1 + \beta - \alpha E_h)^{1-bt} = (\alpha E_h - \beta)^X (1 + \beta - \alpha E_h)^{M-X}.\$$

\(^8\)Recall that the manager observes the sequence of bonuses in each period. If she only observed that the bonus was given $X$ times, the likelihood would be different because there are multiple ways of getting $X$ bonuses.
If he is of type LM, then irrespective of the effort he chooses, the likelihood of his CV is

\[
\Pr(CV|LM) = \prod_{t=1}^{T} \gamma^{b_t}(1 - \gamma)^{1-b_t} = \gamma^X (1 - \gamma)^{M-X}.
\]

Note that the above expressions only depend on the number of bonuses, \(X\), and not the full CV, \(\{b_1, \ldots, b_T\}\). In the following we, therefore, focus on \(X\).

Recall that \(Y\) is the payoff to Alice if she correctly estimates Bob’s effort within \(k\). The expected payoff of Alice if she estimates Bob’s effort is

\[
\mathbb{E} = \mathbb{E}_h \Pr(EM|X) + \mathbb{E}_l \Pr(LM|X).
\]

So, if \(\Pr(EM|X) > 0.5\) it is optimal to infer Bob is type EM and estimate \(g = \mathbb{E}_h\). If \(\Pr(EM|X) < 0.5\) then it is optimal to infer Bob is type LM and estimate \(g = \mathbb{E}_l\). Suppose that Alice has prior belief \(p_A\) that Bob is type EM. Then we get \(\Pr(EM|X) > 0.5\) if and only if \(X > X^*(p_A)\) where\(^9\)

\[
X^*(p_A, \mathbb{E}_h) := \frac{M \ln (1 - \gamma) - \ln (1 + \beta - \alpha \mathbb{E}_h) + \ln (1 - p_A) - \ln (p_A)}{\ln (1 - \gamma) - \ln (1 + \beta - \alpha \mathbb{E}_h) + \ln (\alpha \mathbb{E}_h - \beta) - \ln \gamma}.
\]

If Alice has an unbiased prior then \(p_A = p_0 = 1/2\). From this we suggest the following rule for inferring type and choice.

**Benchmark Threshold**: If \(X > X^*(p_0, \mathbb{E}_h)\) Alice infers that Bob was of type EM and chose effort \(\mathbb{E}_h\) in each period. If \(X \leq X^*(p_0, \mathbb{E}_h)\) Alice infers that Bob was of type LM and chose effort \(\mathbb{E}_l\) in each period.

The benchmark threshold provides a relatively simply way to estimate Bob’s effort. For instance, for the parameter values of our experiment we obtain the benchmark threshold of \(X^*(p_0, \mathbb{E}_h) = 6.7\). So, an employee with 7 or more bonuses would be inferred as type EM who chose \(\mathbb{E}_h\) in each period and an employee with 6 or less bonuses a type LM who chose \(\mathbb{E}_L\) each period. We shall see shortly (and discuss more in the supplementary material) that the

\(^9\)Given the margin of error \(k\) it is optimal to estimate within \(k\) of \(\mathbb{E}_h\).

\(^{10}\)We use Bayes rule

\[
\Pr(EM|X) = \frac{p_A \Pr(X|EM)}{p_A \Pr(X|EM) + (1 - p_A) \Pr(X|LM)} = \frac{1}{2}.
\]
benchmark threshold provides an accurate way of estimating Bob’s effort. In particular, while it is possible to come up with more complex strategies to infer effort these alternative strategies hardly improve accuracy at all.\footnote{With the parameter values we have in our experiment, the benchmark threshold gives us a 75% accuracy compared to a theoretical maximum of 78% accuracy. See the supplementary material for more information.}

### 3.2.2 Own experience bias

The benchmark threshold is based on (a) Alice having an unbiased prior belief \( p_A = p_0 \) on the probability that Bob is of type EM, and (b) knowing the effort level, \( E_h \), that Bob will choose if type EM. As we discussed in the introduction there are good reasons to expect that Alice may have a prior unconsciously biased by her own experience. We, thus, consider the possibility she exhibits own experience bias and overweights the probability others are the same type as her.\footnote{This can be related to the law of small numbers, where a small sample is overweighted in importance (Rabin 2002). Connections with the false-consensus effect will be discussed more later.} We capture this as deviations in \( p_A \) from \( p_0 \) influenced by beliefs, \( p_T \), about herself.

In our context, own experience bias can be modelled as Alice using a threshold model but with a biased prior.

**Own Experience Bias:** If Alice is type EM she has a biased prior \( p_A > p_0 \) and if type LM she has biased prior \( p_A < p_0 \). In either case, if \( X > X^*(p_A, E_h) \) Alice infers that Bob is of type EM and chose effort \( E_h \) in each period. If \( X \leq X^*(p_A, E_l) \) Alice infers that Bob is of type LM and chose effort \( E_l \) in each period.

Own experience bias (as we have defined it) says that Alice behaves in accordance with the benchmark threshold except \textit{she starts with a biased prior}. Her prior is more biased the further it deviates from \( p_0 \). Our next result shows that own experience bias leads to fundamental changes in Alice’s estimate of the effort of Bob. To formalize this let \( \tau(b, p_A) \) denote Alice’s estimate of Bob’s effort using the benchmark threshold with prior \( p_A \) when Bob has CV of \( b = \{b_T, \ldots, b_T\} \). Note that estimates with the benchmark threshold, \( \tau(b, p_0) \), provide our key benchmark for comparison.

**Proposition 2:** Suppose Bob used a belief responsive strategy in the learning stage and the Alice exhibits own experience bias. (1) If \( p_A > p_0 \) then
Alice is biased towards over-estimating the effort of Bob, \( \overline{e}(b, p) \geq \overline{e}(b, p_0) \).

(2) If \( p_A < p_0 \) then Alive is biased towards under-estimating the effort of Bob, \( \overline{e}(b, p_A) \leq \overline{e}(b, p_0) \).

In interpretation, Proposition 2 means that if Alice is type EM and suffers from own experience bias she will have a tendency to overestimate the effort of Bob. If she is type LM then she will have a tendency to underestimate the effort of Bob. To put some context on this consider Figure 2 which illustrates the consequences of bias for predicting the effort of Bob (with \( E_h = 33 \)). On the horizontal axis we plot the prior belief of Alice. On the vertical axis we measure prediction accuracy in four different dimensions, threshold measures \( k = 1, 2 \), error and absolute error. Recall that an unbiased prior is \( p_A = 0.5 \). As we move away from this unbiased prior accuracy begins to fall.\(^\text{13}\)

### 3.2.3 Asymmetric bias

We can see in Figure 2 an apparent asymmetry in which having a prior above 0.5 results (generally speaking) in less of a drop in accuracy than a prior below 0.5. In interpretation this means the own experience bias of a type EM would appear to have less of an effect than the own experience bias of a type LM.\(^\text{14}\) To put some numbers to this suppose that the prior beliefs of a type EM are uniformly distributed between \( p_0 \) and 1 and those of a type LM between 0 and \( p_0 \). Or, alternatively, suppose that prior beliefs are a triangular distribution with peak at 0.5.\(^\text{15}\) Then we get the prediction accuracy summarized in Table 1. As you can see type EM bias has less consequence than type LM bias, particularly in terms of ‘error’.

The asymmetry predicted between EM and LM types allows us to more generally pinpoint the difference between the own experience bias that we have introduced and the false-consensus effect (or anchoring effect) that is familiar in the literature. The false-consensus effect maps own action to biased estimates about others actions (see Engelmann and Strobel 2012 for a definition). In our setting this would equate to Alice estimating that Bob chose a similar effort level to her. So, if Alice chose effort level \( E_H \) in every

\(^{13}\)The ‘lumpiness’ in the figures reflects the integer nature of the threshold.

\(^{14}\)There are exceptions to this. For instance, prior \( p_A = 0.2 \) is, on average, more accurate than prior \( p_A = 0.8 \).

\(^{15}\)So, for a type EM the distribution is proportional to \( 1 - p_A \) and for a type LM proportional to \( p_A \).
period then she would estimate a higher effort level for Bob than if she chose effort level \( E_L \) in every period. Own experience bias, by contrast, maps own type to a biased belief about others types. So, if Alice is type EM she overestimates the probability Bob is type EM and if she is type LM she overestimates the probability Bob is type LM. This then indirectly influences her estimate of Bob’s effort.

There are two practical things to observe about the difference between the false consensus effect and own experience bias. First, there is no reason, a-priori, to expect any asymmetry in terms of false-consensus effect. Type EM’s should be as biased upwards as type LMs are downwards. As we have seen, however, own experience bias (which is symmetrical in terms of type)


<table>
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<th>Scenario</th>
<th>$k = 1$ (%)</th>
<th>$k = 2$ (%)</th>
<th>Error</th>
<th>Absolute</th>
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<td>77</td>
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<td>2.82</td>
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<td>71</td>
<td>-1.30</td>
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<tr>
<td>LM bias peaked</td>
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<td>74</td>
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<td>3.26</td>
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</table>

Table 1: Accuracy of inferences with the benchmark threshold and own experience bias where priors are uniformly distributed or peaked at $p_A = 0.5$

can lead to asymmetry in which one type is more biased than another in estimating effort. Second, the false-consensus effect has nothing to say on how the manager should interpret the CV of the employee. It simply says that Alice will estimate Bob chose 'like her'. By contrast, own experience bias influences the way the manager interprets the CV.

To expand on this latter point, if Alice is type LM and suffers own experience bias then she essentially becomes desensitized to Bob’s CV because, in her experience, bonuses are luck. Only if Bob has a ‘very large’ number of bonuses does she infer this might be because of effort. On the other hand, if Alice is type EM she becomes over-sensitive to the CV of Bob. In her experience bonuses are due to effort and so an employee with bonuses must have worked hard. Own experience bias, thus, changes the way in which a manager responds to the CV of an employee in a way that is distinct from the simple upward or downward bias we might expect with the false-consensus effect.

### 3.2.4 Extremeness aversion and own-experience bias

In the preceding discussion we implicitly took it as given that Alice knows $E_h$.$^{16}$ This allowed us to focus on the bias that come comes from $p_A \neq p_0$. Here we consider what happens if Alice does not know $E_h$. Let $E_h^A$ denote Alice’s prediction of $E_h$.$^{17}$ We compare estimated effort if Alice uses her threshold $X^*(p_A, E_h^A)$ with that obtained using the benchmark threshold $X^*(p_0, E_h)$.

$^{16}$For this discussion the value of $E_l$ is not relevant.

$^{17}$We assume that this prediction is not influenced by the CV of Bob.
**Proposition 3**: The value of $X^*(p_A, E_h^A)$ is weekly increasing in $E_h^A$ and weekly decreasing in $p_A$.

Let us consider different applications of Proposition 3. First, suppose that $E_h^A > E_h$ meaning Alice under-estimates Bob’s extremeness aversion. Then it is ‘self-correcting’ for Alice to have $p_A > p_0$.

The intuition behind Proposition 3 is that extremeness aversion means the threshold for inferring that Bob is type EM becomes lower than the benchmark threshold. In other words the number of bonuses we should expect Bob to have if he is type EM and works hard is lower, because Bob is not doing enough to maximize his chances of getting the bonus. EM own experience bias also lowers the threshold for inferring Bob is type EM and so works ‘in the right direction’. By contrast LM own experience bias works in the opposite direction. In this case only a large number of bonuses is seen as evidence of high effort and that is unlikely to be observed if Bob is deviating from the optimal strategy. To illustrate the size of this bias Table 2 details the error if Bob uses the optimal strategy (this is the same as Table 1) or uses a belief responsive strategy with effort 20 and 30 or 23 and 27. We can see that LM bias increases while EM bias decreases.

Let $A^{PE}(p_A, E_h^A, E_l^A)$ and $A^{APE}(p_A, E_h^A, E_l^A)$ denote the expected prediction error and expected absolute prediction error, where the expectation is taken over all possible CVs under the assumption that Bob uses a belief responsive strategy with effort levels $E_h$ and $E_l$. The following result shows that EM own experience bias is partly self-correcting in that a little bit of bias counteracts Alice not not fully understanding Bob’s strategy. LM own experience bias, however, gets worse.

### 3.2.5 Summary of evaluation stage

We have focused on Alice using a threshold strategy in which she infers that Bob chose high effort if he received more than a threshold level of bonuses and chose low effort otherwise. A threshold strategy is intuitive and simple and will also come very close to being optimal if the threshold is set at the right level. We modelled own experience bias as Alice having a biased prior on the probability that Bob is type EM. This, in turn, influences the threshold Alice uses. In particular, we have suggested that if Alice is type LM then she may have a too high threshold because ‘in her experience’ bonuses were due to luck. Similarly, if she is type EM then she may have a too low a threshold.
The key prediction that comes out of our model is that Alice will be less biased in her estimates of Bob’s effort if she is type EM than if she is type LM. While this prediction is somewhat dependent on specific parameters and modelling assumptions the basic intuition behind it seems sound and generalizable. Specifically, if Alice is type LM then we can think that she becomes ‘desensitized’ to bonuses on the CV and so fails to pick up that Bob may have put in high effort. If Alice is type EM, by contrast, she is sensitive to bonuses on the CV. This means she may overestimate the effort of Bob, because she underestimates how lucky some people can be, but overall she will be relatively accurate. This prediction will be explored in our experiment.

### 4 Experiment

We performed an experiment that basically recreates the decision making environment described so far. The experiment consisted of two distinct parts, with the instructions for Part 2 not given until after Part 1 was completed. The instructions given to the experiment subjects are available in supplementary material. Here we detail the most salient features.

In Part 1 of the experiment subjects were exposed to the decision making task detailed in Section 2. The parameters were $E = \{17, 18, \ldots, 33\}, \alpha = 0.04, \beta = \gamma = 0.5$. Subjects were required to choose an integer between 17

### Table 2: Accuracy of inferences with the benchmark threshold and own experience bias with a uniformly distributed prior

<table>
<thead>
<tr>
<th></th>
<th>Bob</th>
<th>Alice</th>
<th>Error</th>
<th>Absolute</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal</td>
<td>Benchmark</td>
<td>0.30</td>
<td>2.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EM bias</td>
<td>-1.30</td>
<td>3.60</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LM bias</td>
<td>3.01</td>
<td>3.87</td>
<td></td>
</tr>
<tr>
<td>20 or 30</td>
<td>Benchmark</td>
<td>2.73</td>
<td>6.15</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EM bias</td>
<td>0.62</td>
<td>6.27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LM bias</td>
<td>5.45</td>
<td>6.90</td>
<td></td>
</tr>
<tr>
<td>23 or 27</td>
<td>Benchmark</td>
<td>4.75</td>
<td>7.69</td>
<td></td>
</tr>
<tr>
<td></td>
<td>EM bias</td>
<td>2.34</td>
<td>7.68</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LM bias</td>
<td>6.74</td>
<td>7.83</td>
<td></td>
</tr>
</tbody>
</table>
and 33, with a critical cutoff value of $e^* = 25$. Also, we set $T = 20$ and so the task lasted for 20 periods. In each period subjects were able to see the complete history of their effort level and the bonus so far. Note that the language used in the experiment was deliberately neutral and so made no mention of effort or employment etc.

In Part 2 of the experiment subjects were put in the role of a manager estimating the effort level of employees. They were shown the sequence of bonuses received by an employee in the last 10 periods, i.e. $\bar{t} = 11$. We shall continue to call this the CV of the employee. The subject was then asked to estimate the average effort level of the employee over these 10 periods. A subject saw a total of 12 employees, one at a time. Let us emphasize that the employees were genuine in the sense that each employee corresponded to a subject randomly chosen (without replacement) from that particular experimental session. Again, the language used in the experiment was neutral and so terms like employee were not used.

It is important to clarify that subjects were incentivized in both Parts 1 and 2 of the experiment. The incentive structure in Part 1 was simple in that the payoff accumulated over the 20 periods was converted into money. In part 2 a subject was paid £0.50 for every employee whose average effort was within two of that estimated (i.e., we used threshold accuracy with $k = 2$). A total of 155 subjects took part in the experiment spread relatively evenly over 10 sessions. There were 77 subjects of type EM and 78 of type LM. Subjects were recruited from across the student population of the University of Kent (in the UK). The experiment took place in a computer lab using z-Tree (Fischbacher 2007). A typical session lasted around 45 minutes with an average payment of around £10.50.

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18 This means that different subjects were exposed to different CVs. There are disadvantages to this approach: for instance, a subject may be exposed to 12 similar CVs and so it becomes difficult for us to identify any bias. We believe, however, that the genuine randomness in our approach avoids any form of experimenter effect or bias that could come from selecting CVs in some way.

19 This incentive structure does not incentivize a manager to fully reveal beliefs. For example, if the manager believes the employee’s average effort was the maximum 33 then the incentive is to estimate 31. As expected, most subjects did not appear to appreciate this subtlety in the incentive structure. In particular, 87 of the subjects estimated the average effort of at least one employee to be 17 or 33. And 110 subjects estimated the average effort of at least one employee to be 17, 18, 32 or 33.
4.1 Experimental hypotheses

Based on Propositions 2 and 3 we make the following hypotheses. The first hypothesis says that managers will be biased by own type and the second that the bias will be larger for those of type LM.

**Hypothesis 1:** The estimate of employee effort is, ceteris paribus, higher if the manager is of type EM than if the manager is of type LM.

**Hypothesis 2:** managers of type LM are less accurate in estimating employee effort than managers of type EM.

In interpreting these hypotheses it is important to clarify a subtle difference between a manager’s own type and his or her experience. Manager type, in our model and experiment, is exogenously determined and not known to the manager. Manager experience by contrast is endogenously determined and clearly observed by the manager. To illustrate this difference, consider someone of type EM who consistently chooses high effort and yet gets no bonuses. We know this person is type EM and yet, given her experience, she should believe she is of type LM. Type and experience can, therefore, clash. To formalize this distinction we introduce the notion of *inferred type*. By the end of period 20 a manager will have experienced history \( h_{20} = (e_1, b_1; ...; e_{20}, b_{20}) \) and so should have beliefs \( p_{20} \) if she recursively uses equation (5). We say that a manager is inferred type EM if \( p_{20} > 0.5 \) and inferred type LM if \( p_{20} < 0.5 \). Inferred type is a good measure of own experience.

As one would expect, own type and inferred type are highly correlated (\( \rho = 0.76 \)). In the following we shall primarily focus on own type because it has the virtue of being exogenously determined. Hypothesis 1 and 2 are, thus, stated in terms of own type. Inferred type, while it is arguably a better measure of own experience, has the problem of being endogenously determined. This is a problem because it means we are unable to rule out the possibility that any bias we observe is being driven by individual differences. In the supplementary material we show that all the results to follow are identical if we use inferred type instead of own type. Our results are, thus, robust to how we measure own experience.

One thing we would like to highlight is that, whether we use on own type or inferred type, the focus is on the manager expecting others to face the same *incentive structure* as she does. This is different than expecting others
to have, say, the same luck as she had in obtaining bonuses. Our approach, therefore, encapsulates the idea that managers are *not* biased (controlling for type) by things like the number of bonuses they themselves received. We shall use this observation in the following to provide a further robustness check of our results.

### 4.2 Learning stage

Our focus in the experiment is on the evaluation stage and whether subjects are biased by own type. Given, however, that our predictions are based on the manager using an optimal or belief responsive strategy we briefly look at behaviour in the first part of the experiment. Figure 4 plots the distribution of choices in round 11 (where the CV begins) and round 20 (where it ends). You can see that around a third of subjects (36% in period 11 and 30% in period 20) are choosing the optimal effort level for their type with 17 and 33 the modal choices. Even so, there is evidence of extremeness aversion with choices in the intermediate range. Around two thirds of subjects are choosing high effort (more than 25) or low effort (less than 25) consistent with their type (67% in period 11 and 75% in period 20).

To look in more detail at whether subjects behaved optimally we calculated deviation from the effort level dictated by the optimal strategy. This is calculated consistent with Bayesian updating and the actual experience of the subject. Figure 5 plots total deviation (summed over periods 11 to 20) and median deviation (again, over periods 11 to 20). For comparison we provide the distribution one would expect with random choice. A total of 16 (out of 155) subjects choose the optimal strategy. We can see, however, that a large proportion of subjects are ‘close’ to the optimal strategy. Consistent with Figure 1 we find (see the supplementary information for more information) that around a third to two thirds of subjects (depending on the strictness of definition) behaved consistent with a belief responsive strategy.

The crucial thing from our perspective is that subjects responded enough to the incentives they faced that effort levels, type and bonuses are highly correlated. So from the perspective of managers in part 2 of the experiment there was, as we shall see, value in trying to interpret the CV and infer the type of employees. Indeed, there was a clear threshold in the data consistent with our theoretical model. In particular it was optimal to infer a subject with less 6 bonuses was type LM (for instance, 62% of subjects with 5 bonuses were type LM) and to infer that a subject with 6 or more bonuses was type
Figure 3: Distribution of choices in round 11 and 20 by type.
Figure 4: Distribution of absolute deviation and median deviation from optimal strategy in part 1 between periods 11 and 20.
4.3 Are estimates biased by own type?

Table 2 provides data for own effort (averaged over the last 10 periods), the estimated effort of others (averaged over the 12 employees seen) and four measures of estimate accuracy. In interpretation, therefore, we see the effort of Alice, her estimate of Bob’s effort and the accuracy of this estimate. For completeness we provide the data for both own type and inferred type. Recall that different managers were exposed to different employees. The numbers in Table 1 (and the analysis to follow) represent the actual error between estimate and effort for each manager, employee pair.

Consistent with the optimal strategy we observe subjects of type EM choosing significantly higher effort than those of type LM ($p < 0.001$ for own type and inferred type using a two-sided Mann-Whitney test of average effort with each subject as a unit of observation). Our main concern is subjects’ estimates of others effort. Because own type is uncorrelated with the type of others these estimates should not depend on own type. Consistent, however, with Hypothesis 1 we see that the average estimate of type EM’s is higher than that of type LM’s ($p = 0.026$, $0.023$ for own and inferred type respectively using two-sided Mann Whitney test). The average estimate of type EM managers was around 0.7 higher than that of type LM managers. This compares to a difference in own effort of around 3.5. Hence the size of bias is approximately one fifth of the difference in own effort.

In order to more directly see the way in which own type biases estimates of
others effort we can look at the four measures of accuracy detailed in Table 2. Note that these numbers are directly comparable to those in Table 1 derived from our theoretical model. Consistent with hypothesis 1 we find that those of type LM underestimate effort (the prediction error term is positive) while those of type EM overestimate effort. This difference is highly significant \( (p = 0.008, 0.002 \text{ two-sided Mann Whitney}) \). Consistent with Hypothesis 2 we also find that those of type EM are more accurate in estimating effort than those of type LM. Indeed, the prediction error of type LMs is nearly six times that of type EMs. The absolute prediction error \( (p = 0.052, 0.025 \text{ two-sided Mann Whitney}) \) and threshold accuracy \( (p > 0.5) \) show a much less marked difference, although this is also consistent with Table 1.

To provide a further test of Hypotheses 1 and 2 we report the results of OLS regressions with respectively own effort, average estimated effort of others, and average error as the dependent variable. For example, with own effort as the dependent variable we estimate \( e_i = a_1 + a_2 T_i + \varepsilon_i \) where \( e_i \) is subject \( i \)'s own effort (averaged over the last 10 periods), \( T_i \) is 0 or 1 depending on whether subject \( i \) was type EM or LM and \( \varepsilon_i \) is an error term. Table 4 summarizes the results. As already previewed we also report, as a robustness check, results where the bonuses of the manager are included as a dependent variable. The regressions reported in Table 4 use own type; in supplementary material we provide the analogous table for inferred type. Consistent with Hypothesis 1 the coefficient on type LM is significant and positive when estimating the effort of others. Consistent with Hypothesis 2 the average error of a type EM is indistinguishable from zero (see the constant term) while the average error of a type LM is significantly greater than zero. In summary, therefore, we find that managers of type LM underestimate the effort of others while managers of type EM are relatively unbiased.

### 4.4 The CV of the employee

Clearly we would expect the manager to base their estimate of employee effort on the CV of the employee. To help put own experience bias in context and to complete the analysis we investigate this in a little more detail. Figure 6 depicts the relationship between the number of bonuses an employee received and the average estimated effort by managers. Figure 7 complements this by depicting the actual average effort of employees. We see a positive relationship between the number of bonuses an employee received and estimated effort. Moreover, this relationship is remarkably close to the actual
relationship between the number of bonuses and effort. Own experience bias is captured by the gap between the EM and LM estimates. To put things in perspective, compare an employee with 4 bonuses to one with 7 bonuses. Average estimates of effort for the employee with 4 bonuses are 23.0 and 23.3 for managers of type LM and EM respectively. For the employee with 7 bonuses the numbers are 26.0 and 26.2. The number of bonuses clearly seem to matter more than own type. We would argue, however, that this is not an excuse to ignore own experience bias. Indeed, that subjects took account of the worker’s CV is strong evidence they understood the decision task. Despite this we still observe evidence for own experience bias.

As a final piece of evidence we exploit the panel nature of the data set and report in Table 5 the results of four random effects linear regressions with either estimated effort or estimate error as the dependent variable. For instance, we estimate $g_{in} = a_1 + a_2 T_i + a_3 X_n + \varepsilon_{in}$ where $g_{in}$ is subject $i$’s estimate of $n$’s average effort, $X_n$ is the number of bonuses of subject $n$ and $T_i$ is defined as before. Again, an appendix provides the analogous results using inferred type rather than type. The results in Table 5 provide further support for Hypothesis 1 in that own type significantly effects estimated effort.

In evaluating Hypothesis 2 some care is needed to take account of the negative coefficient for the bonuses of the employee. In particular, as you can see in Figure 7, the vast majority of employees received between 4 and

<table>
<thead>
<tr>
<th></th>
<th>Own effort</th>
<th>Estimated effort</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>26.78***</td>
<td>22.65***</td>
<td>-0.14</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(1.39)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Type LM</td>
<td>-3.52***</td>
<td>-3.18***</td>
<td>0.96**</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.62)</td>
<td>(0.38)</td>
</tr>
<tr>
<td>Own bonuses</td>
<td>-0.38***</td>
<td>-0.45</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.07)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.17</td>
<td>0.22</td>
<td>0.04</td>
</tr>
<tr>
<td>No. of obs.</td>
<td>155</td>
<td>155</td>
<td>155</td>
</tr>
</tbody>
</table>

Table 4: OLS regressions with own effort (averaged over the last 10 periods), average estimated effort of others, and average error as the dependent variable. Standard error in brackets, * indicates significant at 10% level, ** a the 5% level and *** at the 1% level.
Figure 5: manager’s estimate of average effort of employee distinguishing between own type. The number of observations is given for type EM [] and LM ()..

Figure 6: Average effort depending on the number of bonuses received. The number of observations is in brackets.
Table 5: Results of random effects linear regressions with estimated employee effort as the dependent variable. Standard errors in brackets; ***, ** and * significant at 1%, 5% and 10% level respectively.

<table>
<thead>
<tr>
<th></th>
<th>Estimated effort</th>
<th>Error in estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>21.4***</td>
<td>22.0***</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(0.85)</td>
</tr>
<tr>
<td>Type LM</td>
<td>-0.71**</td>
<td>-0.76**</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.36)</td>
</tr>
<tr>
<td>Bonuses of employee</td>
<td>0.64***</td>
<td>-0.29***</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Bonuses of manager</td>
<td>-0.64</td>
<td>-0.06</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.07)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1860</td>
<td>1860</td>
</tr>
</tbody>
</table>

7 bonuses. The predicted error of a type EM manager falls, therefore, in the range $1.33 - 4 \times 0.29 = 0.17$ to $1.33 - 7 \times 0.29 = -0.7$. This combined effect is not significantly different to zero when the number of bonuses is 4, 5 or 6 ($p > 0.1$, F-test) but is for 7 bonuses ($p = 0.017$). In interpretation this suggests type EM managers are generally unbiased but do overestimate the effort of employees with the best CVs. The predicted error of a type LM manager falls in the range 1.19 to 0.32. This combined effect is significantly different to zero for 4, 5 and 6 bonuses ($p = 0.001, 0.002, 0.055$ respectively) but not 7 ($p = 0.44$). This suggests that type LM managers systematically underestimate the effort of employees. These results are further evidence in support of Hypothesis 2.

5 Conclusion

The relationship between effort and success in the workplace is likely to differ from one individual to another depending on the characteristics of that individual and the prevailing norms within society. To make our points, in this paper we have considered a stark dichotomy between those for whom effort matters and those for whom it does not. More generally, we can think of each individual as having a personal payoff function (relating effort and expected payoff) that represents their earning potential. If there is discrimination or
prejudice in labor markets then this will be reflected in the personal payoff function. For example, those individuals whose parents are well educated may expect a high payoff with little effort and a low rate of increase of earnings as a function of effort. These are like our type LMs in that they do not need to make any special effort to succeed. By contrast, those individuals whose parents are not well educated may expect a low payoff with little effort and a high rate of increase of earnings as a function of effort. These are like the type EMs in that success is highly dependent on effort.

Our contribution is to show that an individual’s own experience (based on their personal payoff function) can systematically influence their estimate of the effort of others. In particular, we show that type LMs are likely to underestimate the effort of type EMs. Continuing our example, individuals whose parents are well educated may underestimate the effort of individuals from less advantaged backgrounds. To equate type, as we are now doing, with readily observable characteristics like parental education, gender or race, may seem at odds with our assumption that type is unknown. Note, however, that it is the returns from effort, captured in the personal payoff function, that are assumed unknown. So, a person may simply not appreciate the different constraints that others face. For example, because of discrimination the returns to effort may systematically depend on gender, but it is only through personal experience that individuals become aware of this difference.

Our experiment is not designed to disentangle the precise cause of own experience bias. Even so, we highlight that our model makes a very particular prediction about asymmetry in the size of bias. We predict and find that type EM managers are relatively unbiased while type LM managers are more biased. This finding illustrates how our approach is distinguished from simply assuming a false-consensus effect or anchoring effect. Own experience bias, as we have defined it, posits that the Alice expects others to have faced the same incentive structure as her. This is a specific prediction. The false-consensus effect, by contrast, merely posits that Alice expects others to be ‘like her’ (Ross, Greene and House 1977, Engelmann and Strobel 2012). In our context it is ambiguous what that would mean. Arguably, the most natural interpretation would be that if Alice is lucky she expects others to also be lucky. That is different to believing others have the same incentives. Thus, while the false consensus effect and anchoring may lead to own experience bias, our approach goes somewhat deeper in probing the specific consequences of this.

Economic prosperity and equal opportunity depends on the abilities of
individuals being correctly assessed. In our model and experiment managers are merely asked to estimate the effort of employees, not make hiring decisions. Even so, it seems safe to conjecture that own experience bias will lead to inefficiency in labor markets. To illustrate this point, suppose that through happenstance, social norms may have meant that many women were disadvantaged in terms of education relative to men. Consequently, women had to work harder to get equal pay (meaning they are of type EM while men were of type LM). In this setting men may come to miss-attribute the fact that women have to work harder to obtain equal pay to lower abilities of women (rather than differences in personal payoff function), thus creating another form of bias. This would be consistent with the psychological evidence on miss-attribute of cause, most notably the finding that men have a tendency to treat success of women as due to luck (Friske 1998).

Consider the problem of identifying the best individual for a job is a major issue that has long interested economists from diverse perspectives. It arises, for example, in the job matching literature (Crawford and Knoer, 1981; Kelso and Crawford 1982), the literature on statistical discrimination in labor markets (Aigner and Cain, 1977; Phelps, 1972) and that on equalizing differences (Rosen, 1986). Even if managers are well informed and unbiased, complexities in identifying the best potential employee are considerable. If managers are biased then employees may not be assigned to positions that allow them to achieve their potential productivity. The costs of misallocation can be large (e.g. Cavalcanti and Tavares, 2016). In this paper we argue that the own experience of a manager can influence her judgement in evaluating others and lead to systematic deviations from optimal evaluations. Our theoretical model and experiment, testing the implications of the model, contribute also to this literature.

The proceeding discussion suggests that discrimination (men and women being treated differently) coupled with own experience bias can result in prejudice (men miss-attribute the cause of women’s low reward). To the best of our knowledge the idea that discrimination can cause prejudice, rather than prejudice cause discrimination, is new. As things stand the theoretical literature, primarily economic, has focused on how discrimination can arise without prejudice. See, for example statistical discrimination (Arrow 1973,1998\textsuperscript{20}), uncoordinated sorting (Schelling 2006) and social capital based discrimina-

\textsuperscript{20}Arrow (1973) introduces the notion of statistical discrimination while Arrow (1998) discusses related literature and observes that much remains to be explained.
tion (Granovetter 1998). Fascinating and informative though these insights are, prejudice does exist. Indeed the psychology literature has focused on studying the prevalence and origins of stereotyping and prejudice (Allport 1979, Friske 1998, Brown 2000). In this literature discrimination is seen to arise because of prejudice (see also Becker 1957). We believe that future work should explore the inter-connections between prejudice and discrimination. The current paper offers one framework with which to do so.

To further develop this point let us reiterate the difference between our approach and that taken in the literature on labour market discrimination. That literature addresses questions of the form: does an individual treat, say, men differently than women. Our approach, by contrast, leads to questions of the form: might men, because of their different personal experiences, make systematically different judgments compared to women. These are distinct questions that both warrant study. We would, however, strongly argue that the current literature neglects the role of own experience and so this should be a priority for future work. This claim is largely consistent with the approach advocated by Akerlof and Shiller (2010, Chapter 13), who argue that to understand poverty, and discrimination, we need to take account of the different ‘stories’ and ‘views of the world’ that blacks have compared to whites. They write that, ‘[t]he role of stories, of us versus them, of the search for self-respect, and of fairness in the lives of the poor is absent from standard economic analysis of poverty’ (page 163). We would add that it is also absent from standard economic analysis of discrimination and prejudice.

Let us finish this introduction by highlighting that the problem of identifying the best individual for a job is a major issue that has long interested economists from diverse perspectives. It arises, for example, in the job matching literature (Crawford and Knoer, 1981; Kelso and Crawford 1982), the literature on statistical discrimination in labor markets (Aigner and Cain, 1977; Phelps, 1972) and that on equalizing differences (Rosen, 1986). Even if managers are well informed and unbiased, complexities in identifying the best potential employee are considerable. If managers are biased then employees may not be assigned to positions that allow them to achieve their potential productivity. The costs of misallocation can be large (e.g. Cavalcanti and Tavares, 2016). In this paper we argue that the own experience of a manager can influence her judgement in evaluating others and lead to systematic deviations from optimal evaluations. Our theoretical model and experiment, testing the implications of the model, contribute also to this literature.
Appendix

Proof of Proposition 1

The objective of the individual is to choose an action in each period to maximize her total payoff \( u = \sum_{t \in T} u_t \). In determining the optimal strategy we consider a problem that is, in principle, very different. Specifically, we consider the individual in period \( t \geq 1 \), having observed history \( h_{t-1} = (e_1, b_1; \ldots; e_{t-1}, b_{t-1}) \), trying to maximize her payoff in period \( g \geq t \). Thus, the individual is choosing an action in each period \( t, \ldots, g \) so as to maximize payoff \( u_g \).

Suppose that \( t = g \) and so the individual simply wants to maximize her payoff in the current period. She has beliefs \( p_{t-1} \). If the individual chooses effort level \( e_t \) then her expected payoff in period \( t \) is given by

\[
E[u_t(e_t)] = p_{t-1}(\alpha e_t - \beta)B + (1 - p_{t-1})\gamma B - e_t
\]

Hence, the individual should choose \( E_H \) if \( p_{t-1}\alpha B > 1 \) and choose \( E_L \) if \( p_{t-1}\alpha B < 1 \).

Suppose next that \( t < g \) and so the individual is trying to maximize her payoff in some future period. Note that the objective in choosing an action in periods \( t, \ldots, g - 1 \) is to obtain as accurate a belief as possible, \( p_{t-1} \), before choosing effort in period \( g \). We proceed in two stages. First we show that there is a symmetry in effort choice and its effect on prior probabilities, and then we show that information is maximized by choosing either effort level \( E_L \) or \( E_H \).

Symmetry: Take as given beliefs \( p_{t-1} \). Let \( E_M = (E_H + E_L)/2 = e^* \). We will compare effort level \( e_t > E_M \) with effort level \( e'_t = E_M - (e_t - E_M) = 2E_M - e_t \). We want to show that the probability distribution over beliefs \( p_t \) is the same whether the individual chooses \( e_t \) or \( e'_t \). In other words, both \( e_t \) or \( e'_t \) provide the same information. This implies that the individual’s expected payoff in period \( g \) is the same if she chooses effort level \( e_t \) or \( e'_t \) in period \( t < g \).

Suppose the individual chooses effort level \( e_t > E_M \). Two events can occur:

(a) The individual receives the bonus, \( b_t = 1 \). This happens with probability

\[
p_{t-1}\Pr(b_t = 1|EM) + (1 - p_{t-1})\Pr(b_t = 1|LM) = p_{t-1}(\alpha e_t - \beta) + (1 - p_{t-1})\gamma
\]
and yields
\[ p_t = \frac{p_{t-1} (\alpha e_t - \beta)}{p_{t-1} (\alpha e_t - \beta) + (1 - p_{t-1}) \gamma}. \] (3)

(b) The individual does not receive a bonus, \( b_t = 0 \). This happens with probability
\[ p_{t-1} (1 + \beta - \alpha e_t) + (1 - p_{t-1}) (1 - \gamma) \]
and yields
\[ p_t = \frac{p_{t-1} (1 + \beta - \alpha e_t)}{p_{t-1} (1 + \beta - \alpha e_t) + (1 - p_{t-1}) (1 - \gamma)}. \] (4)

Now suppose the individual chooses effort level \( e'_t \). Two events can occur:
(c) The individual does not receive a bonus, \( b_t = 0 \). This happens with probability
\[ p_{t-1} (1 + \beta - \alpha e'_t) + (1 - p_{t-1}) (1 - \gamma) \]
and yields
\[ p_t = \frac{p_{t-1} (\alpha e_t - \beta)}{p_{t-1} (\alpha e_t - \beta) + (1 - p_{t-1}) \gamma}. \] (5)
Note that this outcome exactly coincides with that of (a).
(d) The individual receives the bonus, \( b_t = 1 \). This happens with probability
\[ p_{t-1} (\alpha e'_t - \beta) + (1 - p_{t-1}) \gamma \]
and yields
\[ p_t = \frac{p_{t-1} (1 + \beta - \alpha e_t)}{p_{t-1} (1 + \beta - \alpha e_t) + (1 - p_{t-1}) (1 - \gamma)}. \] (6)
Note that this outcome exactly coincides with that of (b).

We have shown that the distribution over values of \( p_t \) is exactly the same whether the individual chooses effort level \( e_t \) or \( e'_t \) (because outcomes (a) and (c) are equivalent and (b) and (d) are equivalent). Given the objective of maximizing payoff in period \( g > t \) the individual is, therefore, indifferent between choosing effort \( e_t \) or \( e'_t \).

**Information:** Without loss of generality we can now focus on the individual choosing an effort level \( e_t > E_M \). The comparison we shall make is that between effort level \( e_t \) and \( e'_t > e_t \). We will show that the individual’s
expected payoff in period \( g \) is higher, ceteris paribus, if she chooses effort level \( e'_t \) in period \( t < g \) compared to \( e_t \).

Suppose that the individual is of type LM. Then her payoff is maximized in period \( g \) if she chooses effort level \( e_g = E_L \). We have seen that she will do that if \( p_{g-1} \alpha B < 1 \). Her payoff is, thus, increasing in the probability \( \Pr \left( p_{g-1} < \frac{1}{\alpha B} \right) \). Similarly if the individual is of type EM her payoff is increasing in the probability \( \Pr \left( p_{g-1} > \frac{1}{\alpha B} \right) \). We, therefore, need to show that choosing effort level \( e'_t > e_t \) increases the expected probability that \( p_{g-1} \) is the right side of \( 1/\alpha B \).

This situation is a statistical game, in the sense of Blackwell and Girshick (1954). The individual has the choice of performing experiment \( e'_t \) or experiment \( e_t \). Note that

\[
\Pr \left( b_t | EM \right) - \Pr \left( b_t | LM \right) = (\alpha e - \gamma - \beta) (2b_t - 1).
\]

is increasing in \( e \). Choosing effort level \( e'_t \) allows, therefore, a more accurate belief \( p_t \) and, therefore, \( p_{g-1} \) than choosing \( e_t \). This means that experiment \( e'_t \) is more informative than experiment \( e_t \) (see Definition 12.2.1 of Blackwell and Girshick 1954). From this we can conclude that the expected payoff in period \( g \) is maximized, ceteris paribus, by choosing \( E_H \), or \( E_L \) in period \( t \).

We are now in a position to prove the Proposition. Suppose that in period 1 the individual chooses \( E_L \) if \( p_0 < 1/\alpha B \) and chooses \( E_H \) otherwise. We know that this maximizes payoff in period 1. Moreover, we know that, it ceteris paribus, maximizes expected payoff in period 2, 3, ..., \( T \). The individual cannot, therefore, do any better. This argument can be repeated in period 2. Specifically, suppose that in period 2 the individual chooses \( E_L \) if \( p_1 < 1/\alpha B \) and chooses \( E_H \) otherwise. We know that this maximizes payoff in period 2. Moreover, we know that, it ceteris paribus, maximizes expected payoff in period 3, 4, ..., \( T \). Again, therefore, the individual cannot do any better. Repeating this argument for periods 3 to \( T \) gives the desired result.

\[\blacksquare\]

**Proof of Proposition 2**

From equation (2) we can see that

\[
\frac{dX^*}{dp_A} = C \left( \frac{1}{1 - p_A} - \frac{1}{p_A} \right)
\]

where \( C > 0 \) is a constant that depends on \( \gamma, \beta, \alpha \) and \( E_H \). Thus \( dX^*/dp_A < 0 \) and \( X^*(p_A) \) is a decreasing function of \( p_A \).
Suppose that the manager is type EM and so \( p_A > p_0 \). Then \( X^*(p_A) < X^*(p_0) \) and so the manager has a lower threshold than the benchmark threshold. If \( X < X^*(p_A) \) then \( \bar{v}(b,p_A) = \bar{v}(b,p_0) = E_L \). If \( X > X^*(p_0) \) then \( \bar{v}(b,p_A) = \bar{v}(b,p_0) = E_H \). If \( X \in (X^*(p_A), X^*(p_0)) \) then \( \bar{v}(b,p_A) = E_H > \bar{v}(b,p_0) = E_L \). Thus, for any \( X \) we have \( \bar{v}(b,p_A) > \bar{v}(b,p_0) \) giving the desired result. A similar logic treats the case of \( p_A < p_0 \).

Proof of Proposition 3

Suppose that the only information Alice has about Bob is the number of bonuses \( X \) that Bob received from period \( t \) to \( T \). Suppose also that Bob knows his own type and has a belief responsive strategy where he chooses \( e^* < E_h \leq E_H \) if type \( EP \). Then it is optimal for Alice to use the benchmark threshold

\[
X^*(p_A = p_0, E_h) = \frac{M (\ln (1 - \gamma) - \ln (1 + \beta - \alpha E_h)) + \ln (1 - p_A) - \ln (p_A)}{\ln (1 - \gamma) - \ln (1 + \beta - \alpha E_h) + \ln (\alpha E_h - \beta) - \ln \gamma}
\] (7)

We first consider how the optimal threshold changes if Bob uses a belief responsive strategy. Setting \( p_A = 0.5 \) and \( \gamma = 0.5 \) we get that

\[
\frac{dX^*(0.5, E_h)}{dE_h} \propto (\alpha E_h - \beta) (\ln(\alpha E_h - \beta) - \ln(1 + \beta - \alpha E_h)) - (\ln(1 - \gamma) - \ln(1 + \beta - \alpha E_h)).
\] (8)

Set \( x = \alpha E_h - \beta \). Then equation (8) can be written,

\[
\frac{dX^*(p_A, E_h)}{dE_h} \propto x \ln(x) + (1 - x) \ln(1 - x) - \ln(0.5) \geq 0
\] (9)

where the equality is strict for all values of \( x \) other than 0.5. This tells that if Bob has a belief responsive strategy with \( E_h < E_H \) then the benchmark threshold is lower, \( X^*(p_0, E_h) < X^*(p_0, E_H) \), than if Bob used the optimal strategy.

We next consider the threshold Alice will use if she has own experience bias. Recall that

\[
\frac{dX^*(p_A, E_H)}{dp_A} = C \left( -\frac{1}{1 - p_A} - \frac{1}{p_A} \right) < 0.
\]

Thus, for any \( E_h < E_H \) there exists \( p_A > p_0 \) such that

\[
|X^*(p_0, E_h) - X^*(p_A, E_H)| < |X^*(p_0, E_h) - X^*(p_0, E_H)|.
\]
It follows that Alice’s estimates will be more accurate with belief \( p_A \) than unbiased prior \( p_0 \). If \( p_A < p_0 \) then estimates will be less accurate than with unbiased prior \( p_0 \).

**Optimal strategy of the manager**

In the following we assume that the employee Bob uses the optimal strategy, as detailed in Section 3. Given this assumption we can determine the optimal strategy of the manager Alice in determining the average effort of Bob. Key will be the beliefs of Bob. At the beginning of period \( t \) Bob will have beliefs \( p_{t-1} \). Let \( \hat{p} = p_{t-1} \).

If Alice were to know \( \hat{p} \) then she could very accurately estimate the average effort of Bob. In particular, she can infer that \( e_t = E_L \) if \( \hat{p} < 0.5 \) and \( e_t = E_H \) if \( \hat{p} > 0.5 \). Alice then observes \( b_t \), allowing her to infer \( p_t \). From this she can infer \( e_{t+1} \) and so on. The only slight complication is if \( p_t = 0.5 \) for some \( t \geq \hat{t} - 1 \). In this instance Bob would be indifferent between choosing effort level \( E_L \) and \( E_H \) in period \( t + 1 \) and so Alice cannot know for certain his effort level. She still, however, can obtain a probability distribution over Bob’s average effort. Let \( E(\hat{p}, b_\tau, ..., b_T) \) denote Alice’s estimate of Bob’s average effort given \( \hat{p} \) and \( b_\tau, ..., b_T \).

In reality Alice does not know \( \hat{p} \). Alice can work out the probability \( \hat{p} = p \) for any \( p \) given the type of Bob, \( \Pr(\hat{p} = p|\text{typeLM}) \) and \( \Pr(\hat{p} = p|\text{typeEM}) \). Alice can also work out the likelihood of the bonuses Bob received given \( \hat{p} \) and type, \( \Pr(b_\tau, ..., b_T|\hat{p}, \text{typeLM}) \) and \( \Pr(b_\tau, ..., b_T|\hat{p}, \text{typeEM}) \). She can then calculate the probability \( \hat{p} = p \) given the observed bonuses, \( \Pr(p|b_\tau, ..., b_T) \).

The average effort of Bob can then be estimated using

\[
\sum_{p \in \Psi} \Pr(p|b_\tau, ..., b_T) E(\hat{p}, b_\tau, ..., b_T)
\]

where \( \Psi \) is the set of probabilities \( p \) such that \( \Pr(p|b_\tau, ..., b_T) > 0 \). Note that \( \Psi \) will be a finite set.

Let us now compare the optimal strategy with the simple heuristic. The simple heuristic is essentially characterized by Alice assuming \( \hat{p} = 0 \) or 1. This assumption is likely to be way off the mark. The estimates of average effort obtained on the basis of the assumption can, however, be fairly accurate. To demonstrate we can return to the example. To illustrate the inaccuracy of the assumption \( \hat{p} = 0 \) or 1 we note that if Bob uses the optimal
Table A1: Comparison of accuracy of simple heuristic with optimal strategy.

<table>
<thead>
<tr>
<th>Strategy to</th>
<th>Overall</th>
<th>Type LM</th>
<th>Type EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>71</td>
<td>58</td>
<td>83</td>
</tr>
<tr>
<td>$k = 1$ (%)</td>
<td>75</td>
<td>63</td>
<td>87</td>
</tr>
<tr>
<td>Error</td>
<td>0.66</td>
<td>-0.21</td>
<td>1.53</td>
</tr>
<tr>
<td>Absolute Error</td>
<td>3.00</td>
<td>4.26</td>
<td>1.73</td>
</tr>
<tr>
<td>$k = 2$ (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In Table A1 we compare the simple heuristic with two different optimal strategies. The first optimal strategy has the objective of minimizing error and the second of maximizing the proportion of estimates within two of the actual effort. While the optimal strategies improve on the simple heuristic in the particular domain for which they were designed the simple heuristic still does very well in comparison. Recall that subjects in our experiment were rewarded for the proportion of estimates within 2 of the actual. Using the optimal strategy rather than the simple heuristic would only have improved accuracy by 3%.

Results using inferred type

Table A2 is analogous to Table 4 reported in the main text. The only difference is that we use inferred type rather than own type. As you can see the results are almost identical. Table A3 is analogous to Table 5.

On the Benchmark Threshold

If Bob receives more than $X^*$ bonuses then Alice would optimally infer that Bob has put in high effort and conversely if Bob receives fewer than $X^*$ then
<table>
<thead>
<tr>
<th>Own effort</th>
<th>Estimated effort</th>
<th>Average error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>26.57***</td>
<td>22.29***</td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td>(1.38)</td>
</tr>
<tr>
<td>Inferred LM</td>
<td>-3.40***</td>
<td>-3.09***</td>
</tr>
<tr>
<td></td>
<td>(0.63)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>Own bonuses</td>
<td>0.39***</td>
<td>-0.42</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.07)</td>
</tr>
</tbody>
</table>

\[ R^2 \] 0.17 0.22 0.03 0.03 0.04 0.05

| No. of obs. | 155 | 155 | 155 | 155 | 155 | 155 |

Table A2: OLS regressions with own effort (averaged over the last 10 periods), average estimated effort of others, and average error as the dependent variable. Standard error in brackets, * indicates significant at 10% level, ** at the 5% level and *** at the 1% level.

<table>
<thead>
<tr>
<th>Estimated effort</th>
<th>Error in estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>21.4***</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
</tr>
<tr>
<td>Inferred type LM</td>
<td>-0.70**</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
</tr>
<tr>
<td>Bonuses of employee</td>
<td>0.64***</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
</tr>
<tr>
<td>Bonuses of manager</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>1860</td>
</tr>
</tbody>
</table>

Table A3: Results of random effects linear regressions with estimated employee effort as the dependent variable. Standard errors in brackets; *** , ** and * significant at 1%, 5% and 10% level respectively.
Alice can optimally infer that Bob put in low effort. For the parameter values of our model, we obtain

\[ X^* = 6.7. \]

If Bob is of type EM and choose effort \( E_H \) in each period then the likelihood of obtaining the specific sequence of bonuses in his CV is

\[
\Pr(X|EM) = \prod_{t=1}^{T} (\alpha E_H - \beta)^{b_t} (1 + \beta - \alpha E_H)^{1-b_t} = (\alpha E_H - \beta)^X (1 + \beta - \alpha E_H)^{M-X}.
\]

If he is of type LM and chose effort \( E_L \) then the likelihood of obtaining \( X \) bonuses is

\[
\Pr(X|LM) = \prod_{t=1}^{T} \gamma^{b_t} (1 - \gamma)^{1-b_t} = \gamma^X (1 - \gamma)^{M-X}.
\]

Recall that \( Y \) is the payoff to Alice if she correctly estimates Bob’s effort within \( k \). The expected payoff of Alice if she estimates Bob’s effort is \( g = E_H \) is \( Y \Pr(EM|X) \) and her payoff is she estimates \( g = E_L \) is \( Y \Pr(LM|X) \). Suppose that Alice has the correct prior belief \( p_0 = 0.5 \). Then, if \( \Pr(EM|X) > 0.5 \) it is optimal to infer Bob is type EM and estimate \( g = E_H \). If \( \Pr(EM|X) < 0.5 \) then it is optimal to infer Bob is type LM and estimate \( g = E_L \). Setting \( \Pr(EM|X) = 0.5 \) gives us the threshold for the number of bonuses:\( ^{23} \)

\[ X^* := \frac{M (\ln (1 - \gamma) - \ln (1 + \beta - \alpha E_H)) + \ln (1 - p) - \ln (0.5)}{\ln (1 - \gamma) - \ln (1 + \beta - \alpha E_H) + \ln (\alpha E_H - \beta) - \ln \gamma}. \]

If Bob did not know his type (or was not using the optimal strategy) then Alice can potentially do better. For example, if she observes a seemingly non-random sequence of bonuses, such as five periods in a row with a bonus and

\[ ^{21} \text{Recall that the manager observes the sequence of bonuses in each period. If she only observed that the bonus was given } X \text{ times, the likelihood would be different because there are multiple ways of getting } X \text{ bonuses.} \]

\[ ^{22} \text{Given the margin of error } k \text{ it is optimal to estimate within } k \text{ of } e_H. \]

\[ ^{23} \text{We use Bayes rule} \]

\[
\Pr(EM|X) = \frac{\Pr(X|EM)}{\Pr(X|EM) + \Pr(X|LM)},
\]

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then five without a bonus, it may be apt to increase her belief Bob is of type EM.

We compare, however, the Benchmark Threshold with more complex alternatives below and show that the potential gains from greater complexity are very small.\textsuperscript{24} The Benchmark Threshold, therefore, particularly given its ease of use, provides an excellent way for Alice to estimate Bob’s effort.

\textsuperscript{24}With the parameter values we have in our experiment, the simple heuristic gives us a 75\% accuracy and the optimal strategy a 78\% accuracy. See Table A1 in the Appendix.
Our experimental findings also add to a sizable literature looking at beliefs in decision making tasks (e.g. Davis, 1987; Huck and Weizsacker, 2002; Costa-Gomes, Huck and Weizsäcker, 2014; Dickinson and Oaxaca, 2014). In this literature, evidence of subjects believing others will be ‘like them’ is not uncommon (e.g. Fischbacher and Gächter, 2010) and may reflect a false-consensus effect of overweighting own choice (e.g. Engelmann and Strobel 2012). 

References


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An issue within this literature is whether information moderates existing bias. Castillo and Petrie (2010) and Reuben et al. (2014) find information eliminated and moderated, respectively, racial and gender bias. Engelmann and Stobel (2012) find that the false-consensus effect disappears if information is available at no cost. Recall that in our case own-experience bias is observed despite giving information about Bob through the ‘CV’.

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