Why Do I Like People Like Me?*

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Abstract

In this paper we extend the standard model of statistical discrimination to a multidimensional framework where the accuracy of evaluators depends on how knowledgeable they are in each dimension. The model yields two main implications. First, candidates who excel in the same dimensions as the evaluator tend to be preferred. Second, if two equally productive groups of workers differ in their distribution of ability across dimensions group discrimination will arise unless (i) evaluators are well informed about the extent of these differences and (ii) evaluators can take candidates' group belonging into account in their assessments.

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1 Introduction

The fact that individuals might be treated differently according to exogenous characteristics such as gender, age or race has been well documented in the literature. Most of the evidence refers to the labor market, where differences in wages or hiring and promotion that cannot be accounted for by differences in productivity have been observed.[1] In the economics literature, two distinct general sets of explanations have been proposed to explain the origin and persistence of discrimination. On the one hand, taste models, as in Gary Becker's [5] seminal work, suggest a preference-based motivation for the existence of discrimination. The difference in wages between two equally productive groups of workers arises because employers, customers or co-workers dislike interacting with employees that belong to certain groups. On the other hand, statistical models of discrimination argue that, in the presence of information asymmetries about the real productivity of workers, the group-belonging of an individual can be considered as a signal that provides additional information. In this context, taking into account an individual's group affiliation may be a rational response to its informational content. Groups of workers may differ in their expected productivity (Phelps [20], Lazear and Rosen [18]) or in the reliability of the observable signals (Aigner and Cain [1], Cornell and Welch [10]). Arrow [3] proposes an alternative model where employers' asymmetric beliefs about the human capital investments of members of different groups are self-confirming and discriminatory outcomes can be thought of as the result of a self-fulfilling prophecy. Coate and Loury [9] further formalize this approach.[2]

[1] For a survey see, for instance, Altonji and Blank [2]. Discriminatory behaviors have also been observed in housing decisions (Massey and Denton [19], lending (Hunter and Walker [16]), car selling (Ayres and Siegelman [4]) or even in the refereeing of academic papers (Blank [6], Fisher et al. [13]).

[2] For a recent review of theoretical models of statistical discrimination see Fang and Moro [12].

In this paper we extend the standard model of statistical discrimination presented by Phelps [20] introducing two novel features. First, we allow for the existence of multiple dimensions of ability. These dimensions can be understood either as different tasks that the worker needs to undertake, or as separable skills that are required to perform a single task. Second, we assume that the capability of an employer to evaluate quality at a certain dimension increases with her knowledge of that dimension.[3] This assumption is consistent with experimental evidence, where it has often been found that, in many dimensions, individuals who are less competent are also relatively less accurate at evaluating ability.[4]

Combining these features the model yields the following two predictions. First, we show that a similar-to-me-in-skills effect arises in the evaluation. Since individuals can assess knowledge more accurately at those dimensions where they are more knowledgeable, an employer who makes an optimal use of the available information will give relatively more weight to signals observed in dimensions where she is most knowledgeable. As a result, given any two equally productive candidates, the employer will tend to give a higher valuation to the candidate who excels in the same dimensions as she does. Second, the model shows that, even if members of different groups are equally productive, group discrimination might arise if groups differ in their distribution of ability across dimensions.[5] In particular, group discrim-

[3]It may be possible to rationalize this assumption within a categorical model of cognition (Fryer and Jackson [14]). According to this model, evaluators process information with the aid of "categories". If the number of categories is limited, those types of experiences that the evaluator faces less frequently are more coarsely categorized. As a result, evaluators would make less accurate predictions when confronted with such experiences. We thank an anonymous referee for making this point

[4]Knowledgeable people are more accurate in their evaluations in the field of chess (Chi [7]), physics (Chi et al. [8]), grammar (Kruger and Dunning [17]) or academic performance (Everson and Tobias [11]).

[5]Following Aigner and Cain [1], we consider group discrimination as the situation where "groups that have the same average ability may receive different average pay" (pp. 178). Note that in a multidimensional framework the term *same ability* should be interpreted as meaning *same total ability* rather than *same ability at every dimension*.

ination will arise if (i) employers are not fully aware of the extent of these differences or (ii) employers are perfectly informed but cannot condition their evaluations on candidates' group-belonging. The intuition behind this result is the following. Employers will tend to give more weight to signals that have been observed in those dimensions where they are more knowledgeable. In principle this favors candidates belonging to the same group as the employer, as they are more likely to excel precisely in these dimensions. Still, a well-informed evaluator who was allowed to take into account the group belonging of candidates might adjust her priors appropriately. This would not only be efficient from an informational point of view but, as well, it would yield similar average evaluations across groups of candidates.

The model proposed in this paper differs in several ways from Phelps [20] and from other related models of statistical discrimination (Aigner and Cain [1], Cornell and Welch [10]). These models rely on the existence of some exogenous group difference in the quality of signals. Here the source of discrimination is an exogenous group difference in the distribution of quality across dimensions, but all groups are being evaluated with the same accuracy. There are also substantial differences in terms of the predictions of the model in at least two respects. First, standard models predict that among highly productive candidates, those belonging to the evaluator's group will tend to be hired but, when all candidates are relatively unproductive, those who do not belong to the employer's group will tend to be preferred, given that the observed (low) signal is a weaker indicator of their productivity. Still, up to our knowledge there is no empirical evidence supporting the latter implication, this is, the reversal of the race and gender gap for low productivity levels. In contrast, in the (multidimensional) model proposed here those candidates akin to the evaluator tend to be preferred for every level of productivity. Second, in standard models, hiding the identity of candidates eliminates discrimination. In this framework the opposite is true: evaluators will tend to prefer candidates from their own group unless they take into account candidates' group belonging. In sum, when the accuracy of evaluators at each dimension depends on how knowledgeable they are, blind evaluations may generate discriminatory outcomes.

2 The model

Let us consider the case of an individual i whose total quality q_i depends on his abilities or skills in a number D of different dimensions or fields. These fields can be understood as different tasks that the worker needs to undertake or as separable skills that are required to perform a single task. For simplicity, we will assume that candidate's total productivity is equal to the sum of his quality at each dimension $\left[q_i = \sum_{d \in D} x_{id}\right]$.

Candidates' abilities are assumed to be exogenously given and independently and normally distributed. Without loss of generality, we impose two simplifying assumptions on the population distribution of quality. First, we restrict the variance of quality to be equal across dimensions and normalize it equal to one. With this constraint we want to avoid a more general case where ability may vary systematically more along certain dimensions. Second, we assume that an individual's ability along a certain field is independent of his ability along any other dimension. In other words, the knowledge of an individual's ability in one dimension does not provide any information about his ability in any other dimension.[6] This is, $\mathbf{x}_i \to N(\mathbf{p}, \mathbf{I})$, where $\mathbf{p}$ is a Dx1 vector of mean abilities and $\mathbf{I}$ is an identity matrix.

In this multidimensional framework let us consider the case where indi-

[6] As long as there exists some kind of multidimensionality, this is, provided that quality in different dimensions is not perfectly correlated, dimensions could always be appropriately redefined such that this condition is satisfied.

viduals' total productivity is not observable but an evaluator h can observe some imperfect signal of candidates' ability at each dimension. These signals could be interpreted as the result of some tests or job interviews and their value will be a function of the candidates' true ability at each field plus an error term η which is assumed to be independently and normally distributed with zero mean and finite variance.

$$y_{id} = x_{id} + \eta_{id}^{h} \qquad \text{where } \eta_{id}^{h} \rightarrow N\left(0, \sigma_{\eta_d^h}\right)$$

Moreover, let us assume that in each dimension the accuracy of the signal is independent of the quality of the candidate: $E\left(x_{id}\eta_{id}^{h}\right) = 0$

Given the above assumptions, the evaluator will infer the quality of candidate i in dimension d as the weighted sum of the signal observed in this dimension and the distributional prior, where the weight given to the signal will depend on how accurately this signal is perceived by the evaluator:

$$E_h\left(x_{id}/y_{id}\right) = \gamma_d^h y_{id} + \left(1 - \gamma_d^h\right) p_d \tag{1}$$

where $\gamma_d^h = \frac{E_h(x_{id}y_{id})}{E_h(y_{id}y_{id})} = \frac{1}{1+\sigma_{\eta_d^h}}$ and the conditional expected total productivity is equal to:

$$E_h\left(q_i/y_{i1}, ..., y_{iD}\right) = \sum_{d \in D} \left[\gamma_d^h y_{id} + \left(1 - \gamma_d^h\right) p_d\right]$$

This is, employer h will take relatively more into account those signals that she observes in fields where she can assess information more accurately.

2.1 Similar-to-me-in-skills effect

Let us define an evaluation as being complex if an evaluator's relative ability to assess quality is positively related to her own quality. In a context where, without loss of generality, D is equal to two, an evaluation is complex if, given an evaluator h:

$$x_{h1} > x_{h2} \Longrightarrow \sigma_{\eta_1^h} < \sigma_{\eta_2^h}$$

It easily follows that when the evaluation is complex, an evaluator who makes an optimal use of the available information will give a larger weight to those signals that have been observed in that dimension where her own ability is larger. This is,

$$x_{h1} > x_{h2} \Longrightarrow \gamma_1^h > \gamma_2^h \tag{2}$$

As a result, faced with two equally productive candidates i and j, evaluator h will tend to give a higher evaluation to the candidate who excels in the same dimension where she herself is best. More precisely,

Proposition 1 *Similar-to-me-in-skills effect*

$$q_i = q_j,\ x_{h1} > x_{h2}\ \&\ x_{i1} > x_{j1} \Rightarrow E_h\left[q_i\right] > E_h\left[q_j\right]$$

Proof. The difference in the expected quality of the two candidates is equal to:

$$E_h\left[q_i\right] - E_h\left[q_j\right] = E_h\left[\sum_{d=1,2}\left(\gamma_d^h y_{id} + \left(1-\gamma_d^h\right)p_d\right)\right] - E_h\left[\sum_{d=1,2}\left(\gamma_d^h y_{jd} + \left(1-\gamma_d^h\right)p_d\right)\right] =$$

$$= \sum_{d=1,2}\left(\gamma_d^h x_{id} + \left(1-\gamma_d^h\right)p_d\right) - \sum_{d=1,2}\left(\gamma_d^h x_{jd} + \left(1-\gamma_d^h\right)p_d\right) = \sum_{d=1,2}\gamma_d^h\left(x_{id} - x_{jd}\right)$$

which is positive since $x_{i1} - x_{j1} = x_{j2} - x_{i2} > 0$ and, by (2), $\gamma_1^h > \gamma_2^h$. ■

2.2 In-group bias

We investigate whether the existence of the above similar-to-me-in-skills effect can generate an in-group bias. Let us consider that individuals may belong to two different groups g_1 and g_2 defined according to gender, age, or some other easily observable and exogenous characteristic. Let us assume that candidates' total productivity is independent of group belonging:

$$E\left[q_i/i \in g_1\right] = E\left[q_j/j \in g_2\right] \tag{3}$$

This assumption does not prevent the possibility that members of the two groups tend to excel in different dimensions. More particularly, let us represent the existence of group-related variations in the distribution of quality in the following way:

$$x_{id} = p_d^{(g)} + \mu_{id} \qquad d = 1, 2; i \in g$$

where $p_d^{(g)}$ is the expected ability in dimension d of individuals in group g and μ is assumed to be normally and independently distributed with zero mean and variance equal to one. For simplicity, we consider the case where the distribution of quality across groups is symmetric and group g_1 has a higher mean in dimension one.

$$p_1^{(g_1)} = p_2^{(g_2)} = p_1 > p_2 = p_2^{(g_1)} = p_1^{(g_2)} \tag{4}$$

In our analysis we consider two possible scenarios. First, evaluators observe both candidates' signals of quality and also their group belonging. Second, we study the case where employers may take into account candidates' observable signals of quality but cannot observe candidates' group belonging.

2.2.1 Non-blind evaluations

If employers observe that employees belonging to certain groups tend to perform better on certain dimensions, employers will take into account this information in their evaluations. In this set up, evaluators estimate candidates' quality in a similar way as in (1). Given that $y_{id} = x_{id} + \eta^h_{id}$, it follows that in each dimension the relationship between quality and signal, net of the group effect, will be equal to $x_{id} - p_d^{(g)} = \gamma_d^h \left(y_{id} - p_d^{(g)} \right) + u_{id}$. Thus, $E_h \left(x_{id} \right) = E_h \left[\gamma_d^h y_{id} + \left(1 - \gamma_d^h \right) p_d^{(g)} \right]$ where $\gamma_d^h = \frac{Var(\mu_{id})}{Var(\mu_{id}) + Var\left(\eta^h_{id}\right)} = \frac{1}{1+\sigma_{\eta^h_d}}$.

If the evaluator can condition her evaluation on the observed signals and on the group belonging of candidates, then any two equally productive candidates tend to obtain the same valuations independently of group belonging.

Proposition 2 *Non-blind evaluations yield non-discriminatory outcomes*

$$E_h \left[p_{id} / \, i \in g_1 \right] = p_d^{(g_1)}; E_h \left[p_{jd} / \, j \in g_2 \right] = p_d^{(g_2)} \Longrightarrow E_h \left(q_i / i \in g_1 \right) = E_h \left(q_j / j \in g_2 \right) \qquad d = 1, 2$$

Proof.

$$E_h \left(q_i / i \in g_1 \right) - E_h \left(q_j / j \in g_2 \right) =$$

$$E_h \left[\sum_{d=1,2} \left(\gamma_d^h y_{id} + \left(1 - \gamma_d^h \right) p_{id} \right) / i \in g_1 \right] - E_h \left[\sum_{d=1,2} \left(\gamma_d^h y_{jd} + \left(1 - \gamma_d^h \right) p_{jd} \right) / j \in g_2 \right] =$$

$$= \sum_{d=1,2} \left(\gamma_d^h p_d^{(g_1)} + \left(1 - \gamma_d^h \right) p_d^{(g_1)} \right) - \sum_{d=1,2} \left(\gamma_d^h p_d^{(g_2)} + \left(1 - \gamma_d^h \right) p_d^{(g_2)} \right) = \{ by \, (3) \} = 0$$

■ In summary, if well-informed employers may condition their evaluation on the group belonging of candidates, the outcome of evaluations will be independent of employers' group belonging.

2.2.2 Blind evaluations

Let us consider the case when evaluators cannot observe candidates' group belonging. Without loss of generality, we will assume that it is common knowledge that there are two groups of equal size $[P(i \in g_1) = P(i \in g_2)]$. Evaluators will infer candidates' group belonging based on the observed signals. In particular, if the evaluator h observes signals y_{i1} and y_{i2}, her best guess about candidate i's group belonging to group l is given by:

$$P_h(i \in g_l / y_{i1}, y_{i2}) = \frac{P_h(y_{i1}, y_{i2}/i \in g_l) * P(i \in g_l)}{\sum\limits_{k=1,2} P_h(y_{i1}, y_{i2}/i \in g_k) * P(i \in g_k)} = \frac{P_h(y_{i1}, y_{i2}/i \in g_l)}{\sum\limits_{k=1,2} P_h(y_{i1}, y_{i2}/i \in g_k)}$$

Based on the observed signals and the inferred group belonging, evaluator h will estimate the quality of candidate i as follows:

$$E_h(q_i / y_{i1}, y_{i2}) =$$

$$= E_h\left[\sum_{d=1,2}\left(\gamma_d^h y_{id} + \left(1-\gamma_d^h\right) p_{id}\right) / y_{i1}, y_{i2}\right] = \sum_{d=1,2}\left(\gamma_d^h y_{id} + \left(1-\gamma_d^h\right) E_h(p_{id}/y_{i1}, y_{i2})\right)$$

$$\text{where } E_h(p_{id} / y_{i1}, y_{i2}) = P_h(i \in g_1/y_{i1}, y_{i2}) * \left(p_d^{(g_1)} - p_d^{(g_2)}\right) + p_d^{(g_2)}$$

If signals are not fully informative about candidates' group belonging, candidates that belong to the evaluator's group tend to be favored.[7]

Proposition 3 *Blind evaluations yield discriminatory outcomes*

$$P_h(i \in g_2/i \notin g_2) > 0; P_h(j \in g_1/j \notin g_1) > 0 \Longrightarrow E_h(q_i/i, h \in g_1) > E_h(q_j/j \in g_2, h \in g_1)$$

where $P_h(k \in g_l/k \notin g_l)$ represents the likelihood that candidate k is assigned to the wrong group by evaluator h.

[7] The extreme case where signals provide perfect information about candidates' group belonging corresponds to a setup where individuals from different groups cannot deliver similar signals. In such context, evaluations would be in practice non blind.

Proof. Without loss of generality let us consider the case where the evaluator h is a typical group g_1 member such that $x_{h1} > x_{h2}$.

$$E_h\left(q_i/i \in g_1\right) - E_h\left(q_j/j \in g_2\right) =$$

$$= \sum_{d=1,2}\left[\gamma_d^h p_d^{(g_1)} + \left(1-\gamma_d^h\right) E_h\left(p_{id}/i \in g_1\right)\right] - \sum_{d=1,2}\left[\gamma_d^h p_d^{(g_2)} + \left(1-\gamma_d^h\right) E_h\left(p_{jd}/j \in g_2\right)\right] =$$

$$= \sum_{d=1,2}\left[\gamma_d^h p_d^{(g_1)} + \left(1-\gamma_d^h\right)\left[P_h(i \in g_1/i \in g_1)\right] * \left(p_d^{(g_1)} - p_d^{(g_2)}\right) + p_d^{(g_2)}\right] -$$

$$- \sum_{d=1,2}\left[\gamma_d^h p_d^{(g_2)} + \left(1-\gamma_d^h\right)\left[P_h\left(j \in g_1/j \in g_2\right)\right] * \left(p_d^{(g_1)} - p_d^{(g_2)}\right) + p_d^{(g_2)}\right] = \{\text{by } (4)\} =$$

$$= \left[\left(\gamma_1^h - \gamma_2^h\right) * (p_1 - p_2)\right] * \left[P_h(i \in g_2/i \in g_1) + P_h\left(j \in g_1/j \in g_2\right)\right]$$

which is positive since $\gamma_1^h > \gamma_2^h$, $p_1 > p_2$ and $P_h\left(k \in g_l/k \notin g_l\right) > 0,\ k = i, j$

■

3 Conclusion

In this paper we build on the standard model of statistical discrimination where an employer must select a candidate in a context of imperfect information. Our main departure from the traditional framework is to allow for the existence of multiple dimensions of ability and to make the accuracy of the evaluation at each dimension depend on the evaluators' knowledge of this dimension. The model yields two main results. First, it rationalizes the existence of a similar-to-me-in-skills effect which favors candidates who excel in the same dimensions as the evaluator. Second, the model casts doubts on the capability of blind evaluations to eradicate discrimination. If groups of individuals differ in their distribution of ability across dimension, an in-group bias may arise unless evaluators are well informed about the extent of these differences and, moreover, they can observe candidates' group belonging. Several reasons may prevent evaluators from taking into account the group belonging of candidates. Evaluators may not be aware of the existence of differences in quality profiles across groups. This may happen when groups have little interaction, perhaps because the size of the minority is relatively small,[8] or in the presence of a number of cognitive biases such as observational selection bias, availability bias or anchoring that can generate a divergence between individuals' perception of other groups' quality at each dimension and their true quality distribution. As well, even if evaluators are well informed about these differences, they may be restricted not to use this information. This is the case, for instance, in many firms and institutions where candidates' identity is kept anonymous (as in Blank [6] or Goldin and Rouse [15]). Paradoxically, in the framework considered here, these policies may aggravate discrimination.

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