"Soft" Affirmative Action and Minority Recruitment*

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Abstract

We study search, evaluation, and selection of candidates of unknown quality for a position. We examine the effects of "soft" affirmative action policies increasing the relative percentage of minority candidates in the candidate pool. We show that, while meant to encourage minority hiring, such policies may backfire if the evaluation of minority candidates is noisier than that of non-minorities. This may occur even if minorities are at least as qualified and as valuable as non-minorities. The results provide a possible explanation for why certain soft affirmative action policies have proved counterproductive, even in the absence of (implicit) bias.

Keywords: affirmative action, recruitment, sequential evaluations, learning from endogenous consideration sets

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1 Introduction

In 2003, the National Football League established the "Rooney Rule," a policy requiring teams to interview minority candidates for head coaching vacancies.[1] This policy, versions of which have been applied across various industries[2], is an example of "soft" affirmative action (SAA), a term used to refer to policies designed to change the composition of the candidate pool, rather than the criteria used during the hiring process. Contrary to "hard" affirmative action requiring direct consideration of minority status as a part of the hiring decision (e.g., employment quotas), such policies involve taking steps to increase the share of minority candidates considered for a position, but subsequently treating candidates impartially (Schuck, 2002).[3]

This paper studies the effects of SAA on minority recruitment. Indeed, while some SAA policies have proved successful (Heilman, 1980), others, such as the Rooney Rule, have been deemed ineffective, or even counterproductive. One possible explanation is the presence of implicit bias. We show that, even in the absence of bias, SAA policies, while meant to increase the likelihood of hiring minority candidates, may in fact lead to the opposite outcome. This may occur even if qualified minority candidates are at least as valuable as qualified non-minority ones, and minority candidates are ex-ante at least as likely to be qualified.

We consider SAA policies tilting the search technology in favor of minorities, while maintaining the discretion over when to expand the candidate pool based on the sequential evaluation of candidates already under consideration. Our results are driven by the assumption that the evaluation of minority candidates is noisier than that of non-minority ones. This assumption is a central feature in the literature on statistical discrimination[4] building on Phelps' (1972) seminal contribution (e.g., Aigner and Cain, 1977, Borjas and Goldberg, 1979, Lundberg and Straz, 1983, Cornell and Welch, 1996, and more recently Chambers and Echenique, 2018, and Bardhi et al., 2020).[5] The literature has offered various explanations for such differences in evaluation, including: (a) the more limited

[1] See DuBois (2015) for an empirical assessment of the Rooney Rule's impact.

[2] Facebook recently adopted a similar policy (https://money.cnn.com/2018/05/31/technology/facebook-board-diversity/index.html). In 2014, Senate Resolution (511) was introduced (though ultimately not enacted) to encourage companies to voluntarily establish policies to identify and interview qualified minority candidates for managerial openings.

[3] SAA policies are also common in academia (see, e.g., Columbia University's "Guide to Best Practices in Faculty Search and Hiring").

[4] In contrast to taste-based theories of discrimination (Becker, 1957), statistical discrimination theories explain group inequality without assuming prejudice or preference bias.

[5] An important exception is Arrow's (1973) theory of statistical discrimination, which relies on coordination failures rather than differences in the evaluation of particular groups. See Fang and Moro (2011) for an overview of the statistical discrimination literature.

experience that recruiters have in evaluating minorities[6]; (b) differences in "background" between minority candidates and recruiters, which may impede the assessment of intangible qualities which are informal but nevertheless potentially relevant for the position (Arrow, 1972, Cornell and Welch, 1996); and (c) differences in "language" (broadly defined) between recruiters and minority candidates.[7]

The literature on affirmative action has studied its potential unintended effects with regard to incentives for human capital investment, productivity stereotyping, wage differentials, and occupational social status (see, e.g., Fryer and Loury, 2005).[8] In an influential article, Coate and Loury (1993) show that a "patronizing equilibrium" may arise in which minorities' incentives to invest in skills may be reduced when affirmative action is in place. This paper complements this literature by illustrating the possible negative effects of SAA directly on the dimension it is intended for – the enhancement of minority recruitment.

The mechanism we identify by which SAA policies may have an adverse effect on minority recruitment is the following. Such policies, by tilting the search technology in favor of minorities, also alter the desirability of expanding the candidate pool vis-a-vis a more thorough examination of candidates already under consideration. Because minority candidates are assumed to be more difficult to evaluate, they may suffer the most from the change in the relative attractiveness of search. Importantly, this may happen both when SAA increases the relative attractiveness of search, as when it decreases it.

Our results thus suggest that, without taking steps to improve the evaluation of minority candidates, attempts to shift the composition of the candidate pool in favor of minorities may simply amount to "checking a box," or even prove detrimental. Such steps may include creating a sufficiently diverse recruiting committee and ensuring evaluation is based on objective criteria with predetermined weights. In our model, if differences in the evaluation of candidates were entirely eliminated – as in the case of "blind" auditions

[6] Aigner and Cain (1977) suggest that majority-group candidates face "a more homogeneous set of environmental determinants of quality," resulting in a lower variance in qualification, and hence less noisy evaluation. It may be easier to assess a candidate's history if it followed a well-known path, or to interpret a candidate's references when they come from familiar letter writers. Certain tests used in recruitment were initially designed with a specific group in mind; e.g., it has long been argued that the SAT is more informative about the abilities of White students than African-American students (Linn, 1973, Fleming and Garcia, 1998). Further, recruiters often (implicitly) use recent hires with similar backgrounds as benchmarks for evaluating new candidates. If most recent hires were majority-group candidates, such benchmarking may be less effective for evaluating minority candidates.

[7] Lang (1986) proposes that noisier evaluation of minorities results from differences in "language" impeding communication. Recent research also suggests women tend to use language quite different from men in job interviews (Leaper and Robnett, 2011).

[8] The literature on the economics of affirmative action includes Welch (1976), Lundberg and Straz (1983), Chung (2000), Moro and Norman (2003), and Fryer and Loury (2013), and is too broad to be succinctly discussed here. For evidence on the effectiveness of affirmative action, see Holzer and Neumark (2000).

– SAA would be guaranteed to increase the probability of hiring a minority candidate. If differences in candidates' evaluation cannot be sufficiently reduced, "hard" affirmative action may be necessary to foster minority recruitment.

2 Model

The recruitment problem described below applies to a variety of environments. For concreteness, we focus on a university committee recruiting faculty, or students, for an available position. The recruitment of a candidate is subject to university approval standards. There are two categories of candidates, A and B (race/gender/field of study). Candidates' qualifications $\theta \in \{L, H\}$ are unknown and independent ex-ante. Let $p_0^j = \Pr(\theta^j = H)$ denote the prior that a category-j candidate is qualified. The value of hiring a qualified category-j candidate is $v^j > 0$, whereas the value of hiring any non-qualified candidate is zero. That is, the school wishes to hire only qualified candidates, but candidates of one category may be preferred.

Candidates can be recruited only if they are in the school's candidate pool. We assume that at the outset there are only two candidates in the pool, one from each category.[9] At each period $t = 0, 1, ...$, the committee either chooses a candidate to evaluate among those in the pool, or decides to expand the pool by searching for additional candidates. The evaluation of a candidate generates new information, formally captured by a signal about the candidate's qualification. The evaluation of a qualified category-j candidate yields a signal realization $s = 1$ with probability $q_H^j \equiv \Pr(s = 1|\theta^j = H)$, whereas the evaluation of a non-qualified category-j candidate yields a signal realization $s = 0$ with probability $q_L^j \equiv \Pr(s = 0|\theta^j = L)$, with $q_H^j \geq 1 - q_L^j$. Conditional on a candidate's type, the signals are iid draws from the above Bernoulli distribution.

Given a history $\sigma = (s_1, s_2, ...)$ of signal realizations, the posterior probability that a category-j candidate is qualified will be denoted by $p^j(\sigma)$. The null history is denoted by $\sigma = \emptyset$. Each time the committee searches for new candidates, it identifies a category-j candidate with probability μ^j, and no candidate with probability $1 - \mu^A - \mu^B$. Beyond the opportunity cost of not being able to evaluate one of the candidates in the pool while searching, search entails no direct cost. Likewise, the only cost of evaluating a candidate in the pool is the cost of postponing search and the evaluation of other candidates.[10]

[9] This assumption simplifies some of the derivations, but is not essential for the results.

[10] Most of the assumptions introduced above can be relaxed. For example, the results extend to more general search technologies yielding a random number of candidates from each category. Likewise, the assumption that the cost of each action is the time cost of postponing other actions can easily be amended by introducing additional costs. Finally, that signal realizations take only two values is also not essential.

The entire recruiting process ends when the committee finds a candidate "above the bar," i.e., whose (category-adjusted) expected quality is large enough. Formally, for any $j = A, B$, there exists a threshold $\bar{P}^j \in (0, 1]$ such that each category-j candidate is given the slot at history σ if and only if $p^j(\sigma) \geq \bar{P}^j$. The threshold $\bar{P}^j$ can be thought of as reflecting standards imposed by the university, which may, but need not, coincide with the preferences of the recruiting committee. To avoid trivialities, assume $p_0^j < \bar{P}^j$, so that each candidate must be evaluated at least once to be recruited.[11]

A *recruitment rule* specifies in each period either a candidate to evaluate among those in the pool, or search for a new candidate. A recruitment rule is *optimal* if it maximizes the expected discounted payoff $\mathbb{E}\left(\delta^T \tilde{v}_T\right)$ over all feasible recruitment rules, where $\delta \in (0, 1)$ is the discount factor, T the (stochastic) time at which a selection is made, and $\tilde{v}_T$ the value of the selected candidate.

Maintained assumptions. Throughout, we assume the following:

(i) The evaluation of A-candidates is Blackwell less informative than that of B-candidates: $q_k^A \leq q_k^B$, $k = H, L$, with at least one inequality strict;

(ii) A-candidates are more valuable to the organization: $v^A \geq v^B$;

(iii) A-candidates are more likely to be qualified: $p_0^A \geq p_0^B$;

(iv) A-candidates have a lower acceptance threshold: $\bar{P}^A \geq \bar{P}^B$.

Condition (i) means A is the minority category. Conditions (ii)-(iv) guarantee that the potentially negative effects of SAA on the recruitment of minority candidates are not driven by any bias in the evaluation process favoring non-minority candidates: A-candidates are *strictly better* than B-candidates in all dimensions but the effectiveness of their evaluation.

3 Myopic Recruitment Rule

We start by assuming the recruitment process is conducted under a myopic rule. Given a history of signal realizations σ, denote by $\lambda^j(\sigma)$ the probability that a category-j candidate with history σ is recruited after a single additional evaluation ($\lambda^j(\sigma) = \Pr(s : p^j(\sigma, s) \geq \bar{P}^j | j, \sigma)$). The myopic value the committee attaches to an additional evaluation of a category-j candidate with history σ is equal to $u^j(\sigma) = \lambda^j(\sigma) v^j$. Likewise, the myopic value it attaches to an additional search is equal to the expected value

What matters is that signals about minority candidates are noisier, as shown below.

[11] That the selection of a candidate is governed by a threshold rule guarantees that the optimal evaluation and search policy is indexable. Allowing for arbitrary selection rules would (in most cases) preclude a tractable representation of the optimal policy.

$u^S = \delta\left(\mu^A u^A(\emptyset) + \mu^B u^B(\emptyset)\right)$ of bringing a "blank-slate" candidate to the pool. Under a myopic rule, in each period, the committee selects the alternative (evaluation of a candidate from the pool, or search) with the highest myopic value. To avoid trivialities, assume $u^A(\emptyset), u^B(\emptyset) > u^S$, so that, once added to the pool, each candidate has a greater myopic value than search.

Given $v \equiv (v^A, v^B)$, $p_0 \equiv (p_0^A, p_0^B)$, $\mu \equiv (\mu^A, \mu^B)$, $q \equiv (q_L^A, q_H^A, q_L^B, q_H^B)$, and $\bar{P} \equiv (\bar{P}^A, \bar{P}^B)$, denote by $\gamma^j(v, p_0, \mu, q, \bar{P})$ the ex-ante probability a category-j candidate is selected under a myopic rule.

Our first result pertains to SAA policies promoting the expansion of the candidate pool. Formally, such policies can be captured by an increase in μ^A and μ^B (with μ^A increasing more than μ^B). To ease the exposition, and without any important implication for the results, we assume that, prior to the introduction of the policy, $\mu = (0, 0)$.

To further simplify the derivations, suppose that

$$q_H^A \in (0,1) \quad \text{and} \quad q_L^A = q_H^B = q_L^B = 1. \tag{1}$$

That is, the evaluation of B-candidates is perfectly revealing, whereas the evaluation of A-candidates takes the typical "no-news-bad-news" form. Under this technology, $\lambda^B(\emptyset) = p_0^B$, $\lambda^A(\emptyset) = q_H^A p_0^A$ and $\lambda^A(0) = q_H^A p^A(0)$, with

$$p^A(0) = \frac{(1 - q_H^A)p_0^A}{(1 - q_H^A)p_0^A + 1 - p_0^A}.$$

Status-quo ($\mu = (0,0)$). Assume the A-candidate is evaluated first:

$$\underbrace{p_0^A q_H^A v^A}_{u^A(\emptyset)} > \underbrace{p_0^B v^B}_{u^B(\emptyset)}. \tag{2}$$

Then $\gamma^A(v, p_0, (0,0), q, \overline{P}) = p_0^A\left(1 - p_0^B + p_0^B q_H^A\right)$. That is, the minority candidate is selected if and only if she is qualified and either (a) the non-minority candidate is unqualified, or (b) she is qualified and the initial evaluation of the minority candidate yields a positive result.

Search under SAA ($\mu = (\mu^A, \mu^B)$ with $\mu^A \geq \mu^B = 1 - \mu^A$). Further assume

$$p_0^B v^B > \underbrace{\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B v^B\right)}_{u^S}. \tag{3}$$

and

$$\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B v^B\right) > \underbrace{\frac{(1-q_H^A)p_0^A q_H^A v^A}{(1-q_H^A)p_0^A + 1 - p_0^A}}_{u^A(0)}. \tag{4}$$

Jointly, (1)-(4) imply that evaluation of any "blank-slate" candidate is preferred to search, whereas search is preferred to a second evaluation of an A-candidate whose initial evaluation yielded a negative result.

Let

$$\gamma_S^A = \mu^A\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\gamma_S^A\right) + \mu^B(1-p_0^B)\gamma_S^A$$

denote the probability an A-candidate is selected after search is carried-out.[12] Rearranging and using $\mu^A + \mu^B = 1$, we have that

$$\gamma_S^A = \frac{\mu^A\lambda^A(\emptyset)}{\mu^A\lambda^A(\emptyset) + \mu^B p_0^B}.$$

Hence, the ex-ante probability of selecting a minority candidate under SAA is

$$\gamma^A(v, p_0, \mu, q, \overline{P}) = \lambda^A(\emptyset) + (1-\lambda^A(\emptyset))(1-p_0^B)\left(\frac{\mu^A\lambda^A(\emptyset)}{\mu^A\lambda^A(\emptyset) + \mu^B p_0^B}\right).$$

Comparison. Under (1)-(4), for any $\mu = (\mu^A, \mu^B)$ with $\mu^A + \mu^B = 1$, $\gamma^A(v, p_0, \mu, q, \overline{P}) < \gamma^A(v, p_0, (0,0), q, \overline{P})$ if and only if

$$\frac{q_H^A}{1-q_H^A} < \frac{\mu^B p_0^B}{\mu^A(1-p_0^A)}. \tag{5}$$

The left-hand side of (5) is a measure of the effectiveness of the evaluation of minority candidates, whereas the right-hand side is the ratio between the probability that search brings a qualified non-minority candidate and an unqualified minority one.

Proposition 1. *Suppose Conditions (1)-(5) hold.*[13] *SAA policies promoting the expansion of the candidate pool reduce the ex-ante probability that minority candidates are selected:* $\gamma^A(v, p_0, \mu, q, \bar{P}) < \gamma^A(v, p_0, (0,0), q, \bar{P})$, *for any* $\mu = (\mu^A, \mu^B)$ *with* $\mu^A \geq \mu^B = 1 - \mu^A$.

[12] Note that, once search is launched, candidates already in the pool are never evaluated again.

[13] These conditions, together with the maintained assumptions (i)-(iv), hold for a non-empty open set of parameters. For example, they hold when $\delta = 0.9$, $p_0^A = 0.8$, $p_0^B = 0.7$, $v^A = 1.5$, $v^B = 1$, $q_H^A = 0.6$, and $\mu^A = 2/3 = 1 - \mu^B$.

Proof. The result follows from the arguments preceding the proposition. □

When $\mu^A > \mu^B$, under such SAA policies, the expected number of minority candidates considered for a position, and their share relative to non-minority candidates, increase. However, such policies also reduce the length of the evaluation of candidates whose early evaluation yields negative results. As minority candidates are more difficult to evaluate, they suffer more from the truncation in the evaluation process, which may lead to a reduction in the ex-ante probability of selecting a minority candidate.

Note that the probability of selecting A-candidates is reduced not only relative to the probability of selecting B-candidates, but overall; that is, promoting the expansion of the candidate pool may reduce the ex-ante probability of recruiting minority candidates, despite increasing the overall probability of filling the slot.

Next, consider SAA policies tilting the search technology in favor of minorities at the expense of non-minorities (formally captured by an increase of $\zeta > 0$ in μ^A with an equal reduction in μ^B). Let

$$q_L^A = q_L^B = 1 \quad \text{and} \quad 1 > q_H^B > q_H^A > 0. \tag{6}$$

Under (6), the evaluation of either type of candidate takes the familiar "no-news-bad-news" form. Consequently, $\lambda^j(\emptyset) = p_0^j q_H^j$, $p^j(0) = (1 - q_H^j)p_0^j/(1 - q_H^j p_0^j)$, and $\lambda^j(0) = q_H^j p^j(0)$.

Status-quo ($\mu = (\mu^A, \mu^B)$ *with* $\mu^A = 1 - \mu^B < 1$). Suppose that

$$\overbrace{\lambda^B(\emptyset)v^B}^{u^B(\emptyset)} > \overbrace{\lambda^A(\emptyset)v^A}^{u^A(\emptyset)} > \overbrace{\delta\left(\mu^A\lambda^A(\emptyset)v^A + \mu^B\lambda^B(\emptyset)v^B\right)}^{u^S} \tag{7}$$

$$> \underbrace{\frac{(1-q_H^A)\lambda^A(\emptyset)v^A}{1-q_H^A p_0^A}}_{u^A(0)}, \underbrace{\frac{(1-q_H^B)\lambda^B(\emptyset)v^B}{1-q_H^B p_0^B}}_{u^B(0)}. \tag{8}$$

Conditions (6)-(8) imply the evaluation of any blank-slate candidate is preferred to search, whereas the latter is preferred to the evaluation of any candidate whose first evaluation yields a negative result. The probability of selecting an A-candidate after search is launched is then equal to

$$\gamma_S^A(0) = \mu^A\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\gamma_S^A(0)\right) + \mu^B\left(1-\lambda^B(\emptyset)\right)\gamma_S^A(0),$$

or

$$\gamma_S^A(0) = \frac{\mu^A \lambda^A(\emptyset)}{\mu^A \lambda^A(\emptyset) + \mu^B \lambda^B(\emptyset)}.$$

The ex-ante probability of selecting an A-candidate under the status-quo search protocol is then equal to

$$\gamma^A\left(v, p_0, (\mu^A, \mu^B), q, \overline{P}\right) = (1-\lambda^B(\emptyset))\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\left(\frac{\mu^A \lambda^A(\emptyset)}{\mu^A \lambda^A(\emptyset) + \mu^B \lambda^B(\emptyset)}\right)\right).$$

Search under SAA ($\mu = (\mu^A + \zeta, \mu^B - \zeta)$, with $\zeta > 0$). Assume that

$$\frac{(1-q_H^B)\lambda^B(\emptyset)v^B}{1-q_H^B p_0^B} > \delta\left((\mu^A+\zeta)\lambda^A(\emptyset)v^A + (\mu^B-\zeta)\lambda^B(\emptyset)v^B\right) > \frac{(1-q_H^A)\lambda^A(\emptyset)v^A}{1-q_H^A p_0^A}. \quad (9)$$

Condition (9) implies that, after a single negative evaluation, search is preferred to a second evaluation if the candidate is an A-candidate, whereas the opposite is true for B-candidates. Denote by $\gamma_S^A(\zeta)$ the probability of selecting an A-candidate after search is launched, under the search protocol promoted by SAA. Conditions (6)-(9) imply that

$$\gamma_S^A(\zeta) \le (\mu^A+\zeta)\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\gamma_S^A(\zeta)\right) + (\mu^B-\zeta)(1-\lambda^B(\emptyset))(1-\lambda^B(0))\gamma_S^A(\zeta),$$

where the inequality follows from the fact that a B-candidate may be evaluated more than twice before search is launched. Rewriting this inequality, we have that

$$\gamma_S^A(\zeta) \le \frac{(\mu^A+\zeta)\lambda^A(\emptyset)}{(\mu^A+\zeta)\lambda^A(\emptyset) + (\mu^B-\zeta)\left(\lambda^B(\emptyset) + \lambda^B(0)\left(1-\lambda^B(\emptyset)\right)\right)}.$$

Therefore, the ex-ante probability of selecting an A-candidate under the search protocol promoted by SAA satisfies

$$\begin{aligned}
&\gamma^A\left(v, p_0, (\mu^A+\zeta, \mu^B-\zeta), q, \overline{P}\right)\\
&\quad \le (1-\lambda^B(\emptyset))\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))(1-\lambda^B(0))\gamma_S^A(\zeta)\right)\\
&\quad = (1-\lambda^B(\emptyset))\lambda^A(\emptyset)\left(1 + \frac{(1-\lambda^B(0))(1-\lambda^A(\emptyset))(\mu^A+\zeta)}{(\mu^A+\zeta)\lambda^A(\emptyset) + (\mu^B-\zeta)\left(\lambda^B(\emptyset) + \lambda^B(0)\left(1-\lambda^B(\emptyset)\right)\right)}\right).
\end{aligned}$$

Comparison. Given the arguments above, we have that $\gamma^A\left(v, p_0, (\mu^A+\zeta, \mu^B-\zeta), q, \overline{P}\right) <$

$\gamma^A\left(v, p_0, (\mu^A, \mu^B), q, \overline{P}\right)$ if

$$\frac{\mu^A}{\mu^A\lambda^A(\emptyset)+\mu^B\lambda^B(\emptyset)} > \frac{(1-\lambda^B(0))(\mu^A+\zeta)}{(\mu^A+\zeta)\lambda^A(\emptyset)+(\mu^B-\zeta)\left(\lambda^B(\emptyset)+\lambda^B(0)\left(1-\lambda^B(\emptyset)\right)\right)}. \tag{10}$$

Proposition 2. *Suppose Conditions (6)-(10) hold.*[14] *SAA policies tilting the search technology in favor of minorities reduce the ex-ante probability of selecting a minority candidate:* $\gamma^A\left(v, p_0, (\mu^A+\zeta, \mu^B-\zeta), q, \overline{P}\right) < \gamma^A\left(v, p_0, (\mu^A, \mu^B), q, \overline{P}\right)$, *for any* $\zeta > 0$.

Proof. The result follows from the arguments preceding the proposition. □

Under such SAA policies, A-candidates are more likely to be included in the candidate pool at the expense of B-candidates. However, because A-candidates are more difficult to evaluate, such policies, contrary to those examined above, reduce the overall attractiveness of search relative to a lengthier evaluation of existing candidates. The committee may therefore substitute search primarily with the evaluation of B-candidates, as they are easier to evaluate. When strong enough, the latter effect may trigger a reduction in the ex-ante probability that minority candidates are selected.

4 Optimal (forward-looking) Rule

We now show that the effects identified above are not a mere consequence of the committee following a myopic rule.

4.1 Preliminaries

We first establish that the optimal rule is an index rule. That is, each candidate is assigned an index V^j that depends only on the candidate's category, j, and the candidate's history of signal realizations, σ. The indices take the form

$$V^j(\sigma) \equiv \sup_{\tau^j>0} \frac{\mathbb{E}\left[\delta^{\phi^j}\left(1-\delta^{\tau^j-\phi^j}\right)\mathbf{1}_{\{\phi^j<\tau^j\}}\tilde{v}^j|j,\sigma\right]}{1-\mathbb{E}\left[\delta^{\tau^j}|j,\sigma\right]}, \tag{11}$$

where τ^j is a (stochastic) stopping-time, ϕ^j is the (stochastic) time at which $p^j(\sigma)$ exceeds the acceptance threshold $\bar{P}^j$ for the first time, and $\tilde{v}^j \in \{0, v^j\}$ denotes the candidate's

[14] Conditions (6)-(10), along with the maintained assumptions (i)-(iv), hold for a non-empty open set of parameters. For example, they hold when $\delta = 0.9$, $p_0^A = 0.8$, $p_0^B = 0.64$, $v^A = 1.5$, $v^B = 1$, $q_H^A = 0.2$, $q_H^B = 0.75$, $\mu^A = 0.9 = 1 - \mu^B$, and $\zeta = 0.04$.

value to the organization.[15]

The indices defined by (11) are forward-looking, and have an intuitive interpretation. They represent the maximal average expected discounted payoff (averaging over discounted time) from the sequential evaluation of the candidates, ignoring the existence of the other candidates.

Next, let

$$V^S \equiv \sup_{\tau^A,\tau^B>0} \frac{\delta \sum_{j\in\{A,B\}} \mu^j \mathbb{E}\left[\delta^{\phi^j}\left(1-\delta^{\tau^j-\phi^j}\right)\mathbf{1}_{\{\phi^j<\tau^j\}}\tilde{v}^j|j,\emptyset\right]}{1-\sum_{j\in\{A,B\}} \mu^j \mathbb{E}\left[\delta^{\tau^j}|j,\emptyset\right]} \tag{12}$$

be the index of search, where τ^j, ϕ^j and $\tilde{v}^j$ are as defined above. This index represents the maximal average expected discounted payoff from the sequential evaluation of the first candidate that arrives as the result of search.

Under the optimal rule described below, the value the committee assigns to the additional evaluation of any candidate in the pool takes into account the effects of this evaluation on the desirability of all further evaluations. Likewise, the value the committee assigns to search accounts for the fact that the new candidates may be evaluated multiple times. Note that V^S is directly linked to the indices of the candidates expected to be identified by search. Specifically, the optimal stopping-time in (12) is the first time at which the index of any candidate that arrives as a result of search drops below V^S.

Lemma 1. *The optimal recruitment rule consists in evaluating in each period one of the candidates in the pool with the highest index, as defined in (11), provided this index is greater than V^S, and searching for new candidates otherwise.*

Proof. Consider the following fictitious environment in which, contrary to the problem under consideration, the recruitment of a candidate is reversible. Let the flow payoff from the evaluation of each candidate for whom $p^j(\sigma) < \bar{P}^j$ be equal to zero (recall that these are candidates who, given the University's rules, are not acceptable yet for the position). Let the flow payoff from hiring a candidate for whom $p^j(\sigma) \geq \bar{P}^j$ be equal to $p^j(\sigma^{\phi^j})v^j(1-\delta)$, where ϕ^j is the first time at which the candidate is found acceptable, and where σ^{ϕ^j} is the history of signal realizations at that time. In accordance with the primitive environment, assume that, after the ϕ^j-th evaluation, no further information is gathered about the candidate's qualification. Contrary to the primitive environment, however, assume that, at any point in time, the committee can reverse its decision. That is, once an acceptable

[15] The stopping decision is measurable with respect to the filtration induced by the process governing the arrival of information about the candidate's qualification. Because no new information arrives after ϕ^j, any stopping occurring after ϕ^j must be based on the information σ^{ϕ^j} available in period ϕ^j.

candidate is found (i.e., for whom $p^j(\sigma) \geq \bar{P}^j$), the committee is not obliged to hire that candidate indefinitely, and the temporary recruitment of such a candidate (which yields a flow payoff $p^j(\sigma^{\phi^j})v^j(1-\delta)$) does not preclude subsequent evaluation and recruitment of other candidates.

The committee's problem in this fictitious environment is a multi-armed bandit problem with an endogenous set of arms, satisfying all the conditions in Fershtman and Pavan (2020) (see also the literature on branching bandits, e.g., Weiss, 1988, and Weber, 1992). Fershtman and Pavan (2020) show that the optimal rule for such problems is an index rule, with a special index for search. The latter index is the maximal expected average discounted payoff from searching for new arms and pulling any of the new arms that arrive as the result of search, where the maximization is over both a stopping-time and a rule that chooses among search and the pull of the new arms that arrive as the result of search. In the fictitious environment described above, the index of search is equal to

$$V^S = \sup_{\tau,\pi} \frac{\delta \mathbb{E}^{\pi,\tau}\left[\sum_{s=1}^{\tau-1} \delta^s r_s^\pi\right]}{1-\mathbb{E}^{\pi,\tau}\left[\delta^\tau\right]}, \tag{13}$$

where τ is a stopping-time, π is a rule governing the alternation between the evaluation of one of the new candidates brought in by search and further search, and r_s^π is the flow payoff under the rule π. The latter flow payoff is equal to zero when π selects search or one of the candidates that are not acceptable yet (i.e., for whom $p^j(\sigma) < \bar{P}^j$) and is equal to $p^j(\sigma^{\phi^j})v^j(1-\delta)$ when π selects an acceptable candidate (i.e., one for whom $p^j(\sigma) \geq \bar{P}^j$).[16] Importantly, note that the index of search is independent of any information regarding the candidates already in the pool. Fershtman and Pavan (2020) also show that the optimal rule π in (13) is in fact the same index rule characterizing the solution to the entire decision problem, and that the optimal stopping-time τ in (13) is the first time at which the search index and the index of all newly arrived arms fall below the index of search when the latter was launched. In the context of the fictitious environment described above, because the search technology is stationary, τ coincides with the first time at which the index of the *first* candidate identified through search falls below the index of search. Given these features, (13) can be rewritten as

$$V^S = \sup_{\tau^A,\tau^B>0} \frac{\delta \sum_{j\in\{A,B\}} \mu^j \mathbb{E}\left[\sum_{s=\phi^j}^{\tau^j-1} \delta^s p^j(\sigma^{\phi^j})v^j(1-\delta)|j,\emptyset\right]}{1-\sum_{j\in\{A,B\}} \mu^j \mathbb{E}\left[\delta^{\tau^j}|j,\emptyset\right]},$$

[16] Recall that, after the ϕ^j-th evaluation, there is no further information that can be gathered about the candidate.

which coincides with the formula in (12). Fershtman and Pavan (2020) also show that, in multi-armed bandit problems with an endogenous set of arms, the index of any arm other than search coincides with the standard Gittins index (Gittins and Jones, 1974). In the fictitious problem, the arms are candidates and the Gittins index of each candidate is

$$V^j(\sigma) = \sup_{\tau^j>0} \frac{\mathbb{E}\left[\sum_{s=\phi^j}^{\tau^j-1} \delta^s v^j p^j(\sigma^{\phi^j})(1-\delta)|j,\sigma\right]}{1-\mathbb{E}\left[\delta^{\tau^j}|j,\sigma\right]},$$

which coincides with the formula in (11). Hence, the optimal rule in the fictitious environment consists in selecting in each period the candidate in the pool for whom $V^j(\sigma)$ is the highest, provided that such index is greater than V^S, and in expanding the pool by searching for new candidates if V^S is greater than the index of any candidate in the pool.

Now consider the primitive problem where recruitment is irreversible. In general, index policies are not optimal in the presence of irreversible decisions. However, this is not the case for the specific problem under consideration. To see this, observe that in the fictitious environment, once an arm is pulled for which $p^j(\sigma) \geq \bar{P}^j$, its index $V^j(\sigma) = p^j(\sigma^{\phi^j})v^j(1-\delta)$ remains the same at all subsequent periods. Because the indices of the other arms and of search also remain the same, under the optimal rule in the fictitious environment, once the evaluation of a candidate yields a posterior $p^j(\sigma)$ exceeding the acceptance threshold $\bar{P}^j$, that candidate is selected in each subsequent period. Because the fictitious environment is a relaxation of the primitive one, it follows that the optimal rule in the primitive environment coincides with the one in the fictitious environment. □

4.2 Soft affirmative action

We now show that the possible negative effects of SAA policies on the recruitment of minorities may also arise under optimal (forward-looking) policies.

Consider first SAA policies akin to those in Proposition 1. Let $\Gamma^j(v, p_0, \mu, q, \overline{P})$ denote the ex-ante probability of selecting a category-j candidate *under the optimal rule*. Consider the same "no-news-bad-news" evaluation technology as in (1). Using the results in the previous subsection, the index of a blank-slate j-candidate is equal to

$$V^j(\emptyset) = \frac{\lambda^j(\emptyset)v^j}{1-\delta(1-\lambda^j(\emptyset))}. \tag{14}$$

This is because, under the assumed evaluation technology, the optimal stopping-time τ^j in the definition of the index in (11) specifies stopping immediately ($\tau^j = 1$) following a negative signal $s = 0$, and never stopping ($\tau^j = \infty$) following a positive signal $s = 1$,

$j = A, B$. Also recall that, under the assumed evaluation technology, $\lambda^B(\emptyset) = p_0^B$ and $\lambda^A(\emptyset) = p_0^A q_H^A$. Hence, $V^B(0) = 0$ and $V^A(1) = V^B(1) = v^j$. It is also easy to see that, after a single negative evaluation, the index of any A-candidate is equal to

$$V^A(0) = \frac{\lambda^A(0) v^A}{1 - \delta(1 - \lambda^A(0))}. \tag{15}$$

Status-quo ($\mu = (0,0)$). In this case, the search index equals $V^S = 0$, as search does not bring candidates. Assume the B-candidate is evaluated first:

$$\underbrace{\frac{p_0^B v^B}{1 - \delta(1 - p_0^B)}}_{V^B(\emptyset)} \geq \underbrace{\frac{p_0^A q_H^A v^A}{1 - \delta(1 - p_0^A q_H^A)}}_{V^A(\emptyset)}. \tag{16}$$

It follows that, under Conditions (1) and (16), $\Gamma^A(v, p_0, (0,0), q, \overline{P}) = (1 - p_0^B) p_0^A$.

Search under SSA ($\mu = (\mu^A, \mu^B)$ with $\mu^A \geq \mu^B = 1 - \mu^A$). From Lemma 1, the optimal stopping-time τ in the definition of the search index (12) is the first time at which the index of the candidate identified through search drops below V^S. Now suppose that

$$V^A(\emptyset), V^B(\emptyset) > \frac{\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B v^B\right)}{1 - \delta^2 + \delta^2\left(\mu^A p_0^A q_H^A + \mu^B p_0^B\right)} > V^A(0), \tag{17}$$

with $V^j(\emptyset)$, $j = A, B$, and $V^A(0)$ as in (14) and (15), respectively. We argue that the search index is then equal to

$$V^S = \frac{\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B v^B\right)}{1 - \delta^2 + \delta^2\left(\mu^A p_0^A q_H^A + \mu^B p_0^B\right)}. \tag{18}$$

To see this, recall that the optimal stopping-times τ^j in (12) are the first times at which the index of the arriving candidate drops weakly below V^S. Condition (17), along with the fact that $V^B(0) = 0$, guarantee that τ^j coincides with the first time at which an evaluation yields a negative signal realization $s = 0$, and is otherwise equal to $\tau^j = +\infty$. That the search index is equal to (18) then follows from these properties along with the definition of the search index in (12).

Given Lemma 1 and the stationarity of the search index, if search is preferred to the evaluation of a candidate at some history, this continues to hold at all future periods. Let Γ_S^A denote the probability of selecting an A-candidate once search is launched. Given the above conditions,

$$\Gamma_S^A = \mu^A \left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\Gamma_S^A\right) + \mu^B \left(1-p_0^B\right)\Gamma_S^A,$$

or

$$\Gamma_S^A = \frac{\mu^A\lambda^A(\emptyset)}{\mu^A\lambda^A(\emptyset)+\mu^B p_0^B}.$$

Therefore, under Conditions (1), (16), and (17), for any $\mu = (\mu^A, \mu^B)$ with $\mu^A + \mu^B = 1$, the ex-ante probability of selecting an A-candidate under SAA is equal to

$$\Gamma^A(v, p_0, \mu, q, \overline{P}) = (1-p_0^B)\left(\lambda^A(\emptyset) + (1-\lambda^A(\emptyset))\left(\frac{\mu^A\lambda^A(\emptyset)}{\mu^A\lambda^A(\emptyset)+\mu^B p_0^B}\right)\right).$$

Comparison. Under Conditions (1), (16)-(17), for any $\mu = (\mu^A, \mu^B)$ with $\mu^A + \mu^B = 1$, $\Gamma^A(v, p_0, \mu, q, \overline{P}) < \Gamma^A(v, p_0, (0,0), q, \overline{P})$ if and only if (5) holds. Hence,

Proposition 3. *Suppose Conditions (1), (5), (16), and (17) hold.*[17] *SAA policies promoting the expansion of the candidate pool reduce the ex-ante probability that minority candidates are selected:* $\Gamma^A(v, p_0, \mu, q, \overline{P}) < \Gamma^A(v, p_0, (0,0), q, \overline{P})$*, for any* $\mu = (\mu^A, \mu^B)$ *with* $\mu^A \geq \mu^B = 1 - \mu^A$.

Proof. The result follows from the arguments preceding the proposition. □

The intuition is similar to the one for the myopic rule. Qualified minority candidates whose initial evaluation yields negative results due to noise in the evaluation process may not have the opportunity to prove themselves when search is an attractive alternative to further evaluation. When this is the case, SAA policies promoting improvements in the search technology may reduce the ex-ante probability that a position is given to a minority candidate. Importantly, this may occur even if such improvements bring more minority candidates to the pool than non-minority ones (that is, even if $\mu^A > \mu^B$).

Next, consider SAA policies tilting the search technology in favor of minorities at the expense of non-minorities (formally, an increase in μ^A along with a reduction in μ^B). Consider the same evaluation technology as in (6). Arguments identical to those for SAA policies promoting improvements in the search technology imply that $V^j(\emptyset) =$

[17] These conditions, along with the maintained assumptions (i)-(iv), hold for a non-empty open set of parameters. For example, they hold when $\delta = 0.9$, $p_0^A = 0.75$, $p_0^B = 0.7$, $v^A = 1.2$, $v^B = 1$, $q_H^A = 0.19$, and $\mu^A = 0.52 = 1 - \mu^B$.

$\lambda^j(\emptyset)v^j/\left(1-\delta(1-\lambda^j(\emptyset))\right)$ and $V^j(0) = \lambda^j(0)v^j/\left(1-\delta(1-\lambda^j(0))\right)$, with $\lambda^j(\emptyset) = p_0^j q_H^j$ and

$$\lambda^j(0) = p^j(0)q_H^j = \frac{(1-q_H^j)p_0^j q_H^j}{1-q_H^j p_0^j},$$

$j = A, B$. Assume the B-candidate is evaluated first:

$$\underbrace{\frac{p_0^B q_H^B v^B}{1-\delta(1-p_0^B q_H^B)}}_{V^B(\emptyset)} > \underbrace{\frac{p_0^A q_H^A v^A}{1-\delta(1-p_0^A q_H^A)}}_{V^A(\emptyset)}. \tag{19}$$

Status-quo ($\mu = (\mu^A, \mu^B)$ *with* $\mu^A = 1-\mu^B < 1$). As in the case of SAA policies promoting improvements in the search technology, assume

$$V^A(\emptyset), V^B(\emptyset) > \frac{\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B q_H^B v^B\right)}{1-\delta^2+\delta^2\left(\mu^A p_0^A q_H^A + \mu^B p_0^B q_H^B\right)} > V^A(0), V^B(0), \tag{20}$$

and observe that this condition implies that the optimal stopping-time in the formula for V^S is the first time at which an evaluation yields a negative realization $s = 0$, which in turn implies the search index is equal to

$$V^S = \frac{\delta\left(\mu^A p_0^A q_H^A v^A + \mu^B p_0^B q_H^B v^B\right)}{1-\delta^2+\delta^2\left(\mu^A p_0^A q_H^A + \mu^B p_0^B q_H^B\right)}.$$

Search under SAA ($\mu = (\mu^A+\zeta, \mu^B-\zeta)$, $\zeta > 0$). Now assume

$$V^A(\emptyset), V^B(0) > \frac{\delta(\mu^A+\zeta)\lambda^A(\emptyset)v^A + \delta(\mu^B-\zeta)v^B\left(\lambda^B(\emptyset)+\delta(1-\lambda^B(\emptyset))\lambda^B(0)\right)}{1-\delta^2\left((\mu^A+\zeta)\left(1-\lambda^A(\emptyset)\right)+(\mu^B-\zeta)(1-\lambda^B(\emptyset))(1-\lambda^B(0))\delta\right)} \tag{21}$$

$$> V^A(0), V^B(0,0), \tag{22}$$

where $V^A(\emptyset)$ and $V^B(0)$ are as defined above and where

$$V^B(0,0) = \frac{\lambda^B(0,0)v^B}{1-\delta(1-\lambda^B(0,0))},$$

with $\lambda^B(0,0) = p^B(0,0)q_H^B$ and

$$p^B(0,0) = \frac{(1-q_H^B)p^B(0)}{1-q_H^B p^B(0)}.$$

Conditions (21)-(22) imply that it takes one negative signal realization $s = 0$ for the index of an A-candidate to drop below

$$\frac{\delta(\mu^A + \zeta)\lambda^A(\emptyset)v^A + \delta(\mu^B - \zeta)v^B\left(\lambda^B(\emptyset) + \delta(1-\lambda^B(\emptyset))\lambda^B(0)\right)}{1 - \delta^2\left((\mu^A+\zeta)\left(1-\lambda^A(\emptyset)\right) + (\mu^B-\zeta)(1-\lambda^B(\emptyset))(1-\lambda^B(0))\delta\right)} \tag{23}$$

and two negative signal realizations $s = 0$ for the index of a B-candidate to drop below the value in (23). These properties in turn imply the search index is equal to the value in (23).[18]

Comparison. Now observe that when (10) holds in addition to the conditions assumed above,

$$\Gamma^A\left(v, p_0, (\mu^A, \mu^B), q, \overline{P}\right) > \Gamma^A\left(v, p_0, (\mu^A+\zeta, \mu^B-\zeta), q, \overline{P}\right).$$

Proposition 4. *Suppose Conditions (6), (10), and (19)-(22) hold.*[19] *SAA policies tilting the search technology in favor of minorities reduce the ex-ante probability of selecting a minority candidate:* $\Gamma^A\left(v, p_0, (\mu^A+\zeta, \mu^B-\zeta), q, \overline{U}\right) < \Gamma^A\left(v, p_0, (\mu^A, \mu^B), q, \overline{U}\right)$, *for any* $\zeta > 0$.

Proof. The result follows from the arguments preceding the proposition. □

The mechanism behind this result is similar to the one under the myopic rule. Such policies reduce the overall attractiveness of search relative to a more careful evaluation of the candidates already in the pool. Because minority candidates are more difficult to evaluate, the committee may then respond to such policies by substituting search with the evaluation of non-minority candidates at the expense of minority ones. When this effect is strong enough, such policies may thus have the unintended effect of reducing the ex-ante probability of selecting a minority candidate.

5 Discussion

The Rooney rule was adopted in 2003. Yet in 2020, there are only three African-American head coaches, the same number as in 2003, prompting criticism viewing the rule as merely a means of "checking a box".[20] Similar hesitations about the effectiveness of other SAA

[18] The arguments are similar to those for the SAA policies promoting improvements in search technology.

[19] These conditions, along with the maintained assumptions (i)-(iv), hold for a non-empty open set of parameters. For example, they hold when $\delta = 0.9$, $p_0^A = 0.69$, $p_0^B = 0.68$, $v^A = 1.01$, $v^B = 1$, $q_H^A = 0.4$, $q_H^B = 0.8$, $\mu^A = 0.15 = 1 - \mu^B$, and $\zeta = 0.01$.

[20] See the *Washington Post*, Jan 5, 2020: "The dearth of black coaches in the NFL is a problem that somehow still hasn't been fixed".

policies have recently been raised in contexts ranging from academic recruitment to CEO hiring.

Why are many SAA policies unsuccessful? This paper suggests a possible explanation based on differences in the effectiveness of evaluating minority and non-minority candidates, which does not presume any bias in decision making. SAA policies promoting the expansion of the candidate pool or tilting the search technology in favor of minorities (while retaining discretion over when to expand the pool) do increase the percentage of minority candidates considered for a position, but also alter the desirability of searching for new candidates relative to evaluating those already under consideration. The purpose of this article is to show that such policies may lead to a reduction in the probability a position is assigned to a minority candidate. Unless accompanied by steps to reduce difficulties in the evaluation of minorities, such SAA policies thus do not guarantee their desired effects; they may indeed amount to "checking a box," or even prove counterproductive. In such circumstances, "hard" affirmative action may be necessary to enhance minority recruitment.

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