Screening for Talent: tests and affirmative action in the skilling pipeline

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Motivation

Allocating jobs to skilled workers is the bedrock of a productive economy. Since a large number of breadwinners are thus employed, job allocation is the primary determinant of the standard of living for most households. On a macro level, it is well documented that periods of development are associated with change in the structure of employment to higher skilled jobs (Buera, Kaboski and Shin (2011)). On a micro-level, access to higher income provided by these jobs is associated with long term improvement of life outcomes (Chetty et al. (2016)). Owing to its profound welfare implications, any distortions to job allocations deserve close attention.

Large gaps in access to these 'good jobs' between forward and marginalised communities might be indicative of such distortions. These have been documented in a variety of contexts- Chetty et al. (2019) finds evidence of racial disparity in job opportunities in the US, while similar patterns have been documented on caste lines in India (Madheswaran and Attewell (2007)). Diving deeper into these patterns reveals an observation- if we look across job ladders marked by many levels of training or experience, the higher rungs have fewer and fewer people from underprivileged backgrounds. Despite large social programs to foster opportunity in recent years, any single employer at the end of this pipeline finds a small pool of underprivileged candidates to hire from. This phenomenon is anecdotally called the 'pipeline problem'.

In a world where inherent ability has no differences across populations- so the hispanic community in the US has equally talented individuals as the white community- an efficient allocation would roughly have proportional representation for both these communities. What explains this shrinkage in the pipelines? Possible reasons of this could be differences in ability, differences in preferences, disparate access to credit, disparate costs associated with training, bad equilibria, or incomplete information. We will zoom in on the last channel and focus on incomplete information in this project- **how might imperfect screening of talent shape this skill pipeline, and what are effective policy instruments to counter it?**

In this project, we want to take seriously the fact that communities could differ by privilege (which is a confounder in our setup), screening is imperfect and training is multi-staged and costly. In this world, we get patterns of reduced participation across different stages simply because privilege is obfuscating. We start by demonstrating a simple fact- in a world where the only good to screen for is talent, policies that differ by group identify- "affirmative action" move us closer to more efficient outcomes. Specifically, we show that a one-shot affirmative action policy in the final stages of screening generates the first best outcome when the groups are homogeneous in privilege. With more general distributions, first best is out of reach but one-shot affirmative action does restore the second best which can be achieved with this test technology. Not all second bests are equally satisfactory, and we note that if tests substitutes talent and privilege disparately across these groups, we get terrible selection. In the future, we want to incorporate investment by agents into this setup.

Background and related literature

This project is related to the classical literature on discrimination, beginning with Becker's model of taste based discrimination. Phelps (1972) talks about statistical discrimination in presence of exogenous differences in group characteristics or signals. Arrow (2015) explains endogenous reasons for statistical discrimination. Wages are endogenized in a similar model through an extension where individuals make investments on human capital Coate and Loury (1993). Fryer and Loury (2013) explores policy tools in economies where it is not possible to contract on group identity and characterise what the second best would look like. Fang and Moro (2011) have a good review of various models of statistical discrimination and affirmative action.

Dynamic models of affirmative action have been explored to some extent in the literature. Athey, Avery and Zemsky (2000) obtain disparate group outcomes because of positive effects of in-group mentoring in organisations. Fryer (2007) and Bohren, Imas and Rosenberg (2019) have very interesting models about how belief flipping may arise in a dynamic model. Our model has multi-staged screening, and therefore is closely linked to this literature of dynamic affirmative action.

There is a large literature on testing for statistical discrimination (Knowles, Persico and Todd (2001) Anwar and Fang (2006) Arnold, Dobbie and Hull (2020)). Empirical work on affirmative action is relatively more limited in comparison, since there are fewer contexts where there are quantifiable affirmative action programs. Some very relevant papers in this context for us are Bertrand, Hanna and Mullainathan (2010), Miller (2017).

Finally, the papers perhaps most related to this project are Krishna and Tarasov (2016) on tournaments and Kannan, Roth and Ziani (2019) about selection in a multi-step setting. Krishna and Tarasov (2016) explore tournaments as selection mechanisms in a static setting where agents deploy endogenous effort. The central tradeoff in their setting is that quotas achieve better selection but could induce suboptimally larger amounts of effort by individuals. Kannan, Roth and Ziani (2019), on the other hand, try to think about downstream effects of affirmative action in a two-staged model. In this project, own main contribution is to have a unified setup which models multi-stage screening procedures in a world with differential privilege. Ultimately, the goal is to make predictions about who these tests select for and when can affirmative action be an effective policy tool.

Model

We have two kinds of economic actors here- individual agents and training firms. There is a mass M of individuals who can be trained. There are finite steps of training that agents can undergo, and these are serviced by training firms T_k.

We model agents in our economy to have two characteristics- talent t_i and privilege p_i. Throughout this setup, talent will be a catch all term for a net "good" that we ultimately want to select for. Privilege, on the other hand, is a confounder. We will expand on this when we talk about screening.

Agents belong to one of two groups: Advantaged or Disadvantaged. $g \in \{A, D\}$. As the name suggests, agents in the advantaged group represent a better off social class. We make some assumptions about characteristics within the group identity.

Assumption 1: Distribution of talent is identical across the two groups- $F_A(t) = F_D(t) \quad \forall t.$

We think of this assumption as an ideal benchmark, since our focus is on how the other features of this setting- imperfect tests and obfuscation- create less than ideal outcomes.

Assumption 2: (t_i, p_i) *are independent.*

This assumption may seem dogmatic but is relatively toothless in our setting. Since we explicitly focus on seeking t_i through screening procedures, any characteristic of p_i which is informative about t_i can be loaded into t_i and the residual p_i can be relabelled as the new p_i. Notice, we do end up assuming that this residual's moments are invariant across t_i. This is a simplifying assumption for sure- we don't focus on test precision varying with different levels of talent in this project.

Assumption 3: Group A dominates D in privilege in a FOSD sense. $F_A(p_i) < F_D(p_i) \quad \forall p_i.$

In the simplest case we can model privilege as being homogenous within a group and $p_A > p_D$.

We have screening procedures in our setup, which we call 'tests'. Agents' performance in tests is informative of their talent p_i, but they are confounded by privilege p_i. Let us call the signal realisation for a given test k, S_k.

Assumption 4: Signals are increasing in t_i, p_i- $S_{p_i}(p_i, t_i) > 0; S_{t_i}(p_i, t_i) > 0 \quad \forall (p_i, t_i).$

These screening procedures can be employed by training facilities. Training facilities are modelled as profit maximising entities. We abstract away from modelling the market structure of these training firms, and assume that each stage of the market is perfectly competitive. These firms derive revenue from placing individuals in productive activities post training. They have a constant marginal cost of training. We assume that these revenues and costs reflect social marginal utility and social marginal cost of training respectively, which is where the perfect competition comes in.

Assumption 5: Training firms are profit maximising. $\pi_k = \mathbf{E}_m[r_k(t_i)] - c_i\mu(m); \quad r_k(t_i) = e_k(t_i) + s_{k+1}(t_i)$.

This breakdown of $r_k(t_i)$ corresponds to the social surplus generated by training this agent. $e_k(t_i)$ is the component of externality generated by training individual (in our running example, say the person drops out of this career pipeline and does something with the skillset they already have). On the other hand, $s_{k+1}(t_i)$ is the value of training to individuals who are selected to continue to the next stage of the pipeline. We assume both of these are increasing in t_i for this setup.

Finally, to fix ideas we will pose a concrete case of this setup as an example for the reader. The academic pipeline can be modelled as above, with tests being screening devices of any sort. Skilling here is clearly multi-staged, as students proceed from high school to college to PhD programs and onwards to become academics.

Preliminary results

The objective will be to maximise the talent selected in the people screened into the final task. Denoting by $\{m\}$ the set of people selected, the objective is:

$$max \qquad \int_{\{m\}} \sum_k s_k(t(i))$$

$$st \quad \mu(m) = k$$

Obviously, this could be achieved by an oracle who would select for all people above a certain threshhold of talent t^* in both populations A, D.

We start with stating some results that come from this setup, some of which are immediate. We first start with homogenous privilege within group- p_A, p_D.

Lemma 0 *In a one-stage screening (so no intermediate training), screening with identical test scores leads to inefficient outcomes. Quota-based affirmative action restores first best.*

Proof: This is straightforward. For the group blind test selection procedure, let t^* be the test score used to screen. Denote the marginal selected person from each group as A^* and D^* respectively. The test score to select is the same, it must be that

$$t^* = S_1(p_A, t_A^*) = S_1(p_A, t_A^*)$$

But note from assumption 4 and the fact that $p_A > p_D$, it must be the case that $t_A^* < t_D^*$. By assumption 1, first best should have equally talented people selected on the margin. Thus, this is sub-optimal.

Once we have quotas based on population weights, given that privilege is homogeneous within a group, test scores rank people by their talent t_i^g, $g = \{A, D\}$. Given that the distributions of talents are identical across the groups, population weighted quotas select the marginal agent with identical talents $t_A^* = t_D^*$. $\square$

We extend this result to a multi-stage setting.

As in assumption (5), we have that each stage of training gives a revenue of $r_k(t_i) = e_k(t_i) + s_{k+1}(t_i)$ for training individuals with talent t_i. The marginal cost of training in each stage is c_k.

The social optimal here will correspond to an allocation where agents with t_i undergo upto k stages of training when

$$\sum_{i=1}^{k} c_i \leq \sum_{i=1}^{k} r_k(t_i) < \sum_{i=1}^{k+1} c_i$$

Using group determined cutoffs (or equivalent quotas) in the final stage of screening will generate first best again.

Lemma 1 *In multi-stage screening, group-blind test screening leads to inefficient outcomes. Affirmative action in the final stage of screening leads to a first best equilibrium.*

Proof argument: The argument for why group-blind screening leads to inefficient outcomes is exactly as above.

We can show that the social optimal allocation stated above can be implemented using quotas in the final stage. We claim that the for each stage of test S_{k+1} faced by a training firm T_k's trainees, if the upstream test S_{k+1} is used along with population weighted quotas to select trainees, T_k will find it optimal to select from the pool of test takers S_k as if they had an internal quota themselves.

By assumption (5) and the setup above, the return from training an individual (i, g) is $r_k(t_i)$. From the point of view of trainer T_k, since r_k is increasing in t_i and marginal costs are independent of the individuals they train, maximising $r_k(t_i)$ is equivalent to maximising $\int(t_i)$ that they input. This means that, if the mass of individuals that applied to T_k (took the test S_k) contains the group of people M_k^{A*}, M_k^{D*}, it will select for them.

Finally, we can proceed by induction to show that by the argument above, the lowest indexed training firm S_l which is not using population based quotas will find it strictly beneficial to switch to population quotas. □

The intuition for last stage quotas being powerful instruments can be understood as a 'demand shock'. Creating quotas in the last stage is able to transmit the societal taste for having more talented individuals allocated to the jobs throughout the training pipeline.

Note that the argument above also spells out that this result is robust in interesting ways. One is that whatever be the distribution of people generated by the earlier stages of screening, as long as the stage $k + 1$ has quotas, trainer T_k will find it optimal to select for the best possible pool they can. The second is that if our sole objective is 'social justice', ie, to make the final outcomes equitable for the two groups, quotas are robust to externalities scaling against talented people. This is because, for the quotas to work, all we need is that $r_k(t_i)$ is increasing in t_i, which can hold even if $e_k(t_i)$ are decreasing.

One fragility of this result is that if the externalities reflect any group-specific distortions in *levels*, we will not get the first best. We will motivate this with our running example, suppose there the stage of screening is to undergrad training. Colleges admit undergraduates who can continue to PhD programs if they are successfully screened in the next stage, or get jobs and generate social surplus $e_k^g(t_i)$. If $e_k^A(t_i) = W^A > W^D = e_k^D(t_i)$, say that advantaged group individuals are better paid in their jobs because of access to an extensive network, the college will distort away from the optimal quotas for academic screening to let in more advantaged kids into their undergrad program.

Case of heterogenous p_i within groups

When groups are not homogeneous in privilege, even a social planner cannot play oracle to select for highest talent. Thus, the first best is not possible to achieve. We conjecture that a second best outcome- one that maximises the talent pool given the screening technology, can still be achieved.

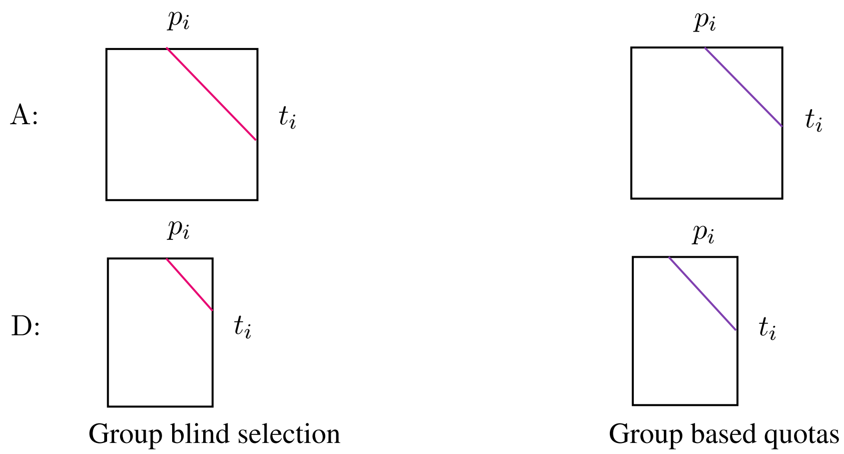
We work with a specific signal structure to give some intuition for who is selected here.

Example 1: $S_k(t_i, p_i) = t_i + p_i + \epsilon_i$. Talent is uniformly distributed across groups $t_i \in \mathcal{U}[0, 1]$. Privilege is very disparate across groups $p_i^A \in \mathcal{U}[0, 1], p_i^D \in \mathcal{U}[0, 0.5]$

We will draw iso-test score curves that tell us who are screened in tests of this sort.

In the figure that follows, higher test scores screen for people on the upper right corner. With affirmative action (right two panels), we are able to increase the mass of individuals with higher talent. A similar argument to the one for homogenous privilege should work here to give optimal outcomes with one-shot affirmative action.

Figure 1: Selection with and without affirmative action

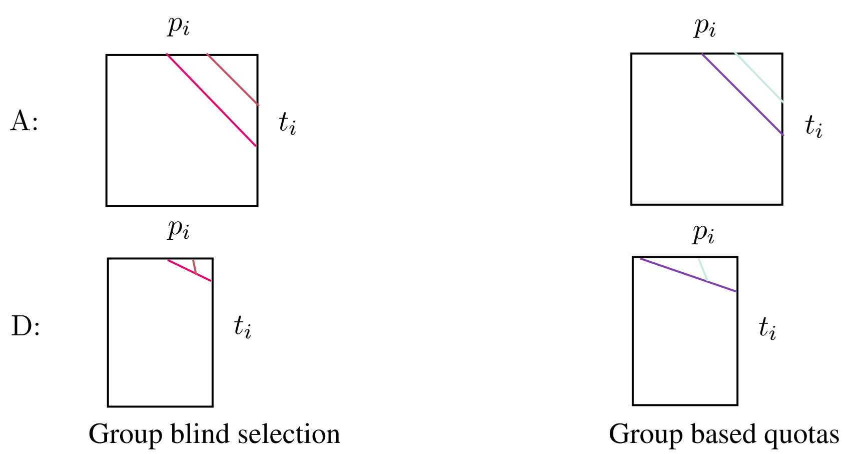


Now we change the structure of tests in a particular way to make a point. We have two successive tests, which substitute between talent and privilege the same way for the advantaged group. However, for the disadvantaged group, the tests favour talent in one stage of the process and privilege in another stage of the process. An infeasible 'time-average' of these two tests gives identical scores to individuals. We note that this tweak drastically changes who we can select for.

Example 2: . $S_k^A(t_i, p_i) = t_i + p_i + \epsilon_i$.
$S_1^D(t_i, p_i) = 0.5t_i + p_i + \epsilon_i$. $S_2^D(t_i, p_i) = 1.5t_i + p_i + \epsilon_i$
Talent is uniformly distributed across groups $t_i \in \mathcal{U}[0, 1]$. Privilege is disparate across groups $p_i^A \in \mathcal{U}[0, 1], p_i^D \in \mathcal{U}[0, 0.5]$

We conjecture the following outcome in equilibrium.

Figure 2: 2-stage selection with disparate tests



Notice that the disparate test technology cripples our ability to screen for talent in the group D. Affirmative action here improves upon outcomes, but not dramatically so. The intuition for this is that given one of the tests gives out a population which has a low proportion of talent to privilege, it is socially undesirable to select anyone but the best performers.

We think this arcane seeming example might map to interesting analogues in the world. Taking the academic pipeline example- assume that advanced mathematics has a particularly convex learning curve for individuals who study in worse off high schools. If this is the case, then early stages of testing will deliver poorer results to these students than their better schooled peers. Optimal affirmative action in this case would be unable to move their outcomes much. In this setup, an improvement of the test technology S_1^D is extremely valuable.

Future directions

We have attempted to formulate a clean and unified setup to model the joint effects of testing technology, obfuscation and multi-staged nature of the 'skill-pipeline'. We show that there in this simple setup, last stage affirmative action policies are efficiency improving. Nevertheless, the example (2) in the previous section makes the point that despite this characterisation, it might be useful to determine who is selected through these tests.

For next steps, we want to incorporate investments by individuals in our setup. The idea will be similar to Coate and Loury (1993) where individuals can invest in that trainers can form expectations about investments made by individuals on the basis of their observables. We expect this to attenuate the dynamic robustness of one-shot affirmative action- trainers at later stages will not set high quotas only based on downstream demand, since they must take into account upstream actions taken by the agents themselves.

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