Adaptive Correspondence Experiments†

By Hadar Avivi, Patrick Kline, Evan Rose, and Christopher Walters*

A large social science literature uses correspondence experiments to measure discrimination (Bertrand and Duflo 2017, Baert 2018). Kline and Walters (forthcoming) argue that experiments sending multiple applications to each job can be used to reliably detect discrimination by particular employers. A practical impediment to such exercises is that employer callback rates are often very low, leading a large fraction of applications to be wasted on unresponsive jobs. Sending many applications to a particular job may also compromise the callback evidence by alerting an employer to the experiment.

This paper considers the potential for dynamic correspondence experiments to reduce the costs of detecting discrimination by particular employers. We consider an experimental design in which the researcher adapts the number and characteristics of applications sent to each job in response to prior callback outcomes. Our analysis is inspired by proposals in the medical sciences to personalize treatments based on time-varying health information (Chakraborty and Murphy 2014) as well as econometric procedures that update estimators, decision rules, and experimental designs in response to new data (Kasy and Sautmann 2021, Tabord-Meehan 2020). In the discrimination context, adaptive experimentation provides a potential tool for regulatory agencies such as the Equal Employment Opportunity Commission (EEOC), which is charged with preventing and remedying discrimination by individual employers in the labor market.

We begin by building a statistical model of job callback decisions, which we fit to data from a recent correspondence study by Nunley et al. (2015) (henceforth, NPRS), who submitted four applications with racially distinctive names to each of 2,305 entry-level jobs for new college graduates in the United States. One can imagine such training data coming from a pilot study commissioned by the EEOC. We then ask how an auditor who has learned the distribution of discrimination from this pilot might send applications to new vacancies to find discriminatory jobs at minimum cost.

Simulating the performance of the optimal auditing strategy, we find that adaptive experiments can cut the number of applications needed to detect a fixed number of discriminators by more than half without increasing the prevalence of type 1 errors. This feat is accomplished primarily by giving up early on jobs with very low callback rates and those that demonstrate a willingness to call Black applicants. These results reinforce the conclusion of Kline and Walters (forthcoming) that correspondence experiments can potentially be used by regulatory agencies to target investigations more efficiently.

I. A Model of Callbacks

Following Kline and Walters (forthcoming), we model callbacks at each job as independent Bernoulli trials. A fictitious applicant of race \( r \in \{w, b\} \) (white or Black) possessing observable characteristics \( x \) has a callback probability \( p_r(x) \) of being called back by job \( j \). We assume that

\[
p_r(x) = \Lambda(\alpha_j - \beta_j x_r + x'\gamma),
\]

where \( \Lambda(z) \equiv \left[1 + \exp(-z)\right]^{-1} \) is the logit link function. The parameter \( \alpha_j \) governs the white callback rate, \( \beta_j \) governs the callback penalty for a Black name, and \( x'\gamma \) is an application quality index. We treat the parameters \( (\alpha_j, \beta_j) \) as random draws from a bivariate distribution. Kline and Walters (forthcoming)
were unable to reject the hypothesis that white names are never discriminated against in the NPRS experiment. We therefore assume that \( \beta_j = \max\{0, \beta_j\} \), which censors discrimination from below at zero. The model is completed by the following distributional assumption:

\[
(\alpha_j / \beta_j) \sim \mathcal{N}\left(\alpha_0, \frac{\sigma_0^2}{\beta_j^2}, \rho\right),
\]

which allows for continuous heterogeneity in overall callback rates and discrimination severity as well as a positive mass of jobs that do not discriminate at all.

Maximum likelihood estimates of this model are presented in Table 1. We cannot reject that \( \rho = 0 \) and therefore impose this restriction in what follows. Using the estimates in column 1, the share of jobs with white callback probabilities lower than 1 percentage point is \( \Phi\left(\frac{4.922 - \ln(99)}{4.968}\right) \approx 0.53 \), suggesting that a majority of the jobs in this study are essentially unresponsive to applications of either race. The share of jobs with \( \beta_j = 0 \) is \( \Phi(5.035/6.347) \approx 0.79 \). Hence, discrimination is confined to a small minority of jobs. However, the average severity of discrimination among this minority is intense, as \( E\left[\beta_j \mid \beta_j > 0\right] = \beta_0 + \sigma_\beta \frac{\phi(\beta_0/\sigma_\beta)}{\Phi(\beta_0/\sigma_\beta)} \approx 3.6 \), which implies that the odds of being called back by a discriminating job are roughly 36 times higher for whites than equivalent Blacks. This finding of rare but intense discrimination accords closely with the nonparametric analysis of the NPRS data in Kline and Walters (forthcoming) and suggests that it may be possible to ascertain whether or not a responsive job is discriminating with very few applications.

### II. The Auditor’s Problem

Consider now a hypothetical auditor who knows the parameters of Table 1 and can draw additional jobs from the same distribution. Her goal is to find as many discriminating jobs as possible by sending fictitious applications. The auditor may send up to eight applications to each job and is free to choose the race and quality \( q \) of each application. To simplify the problem, we coarsen applicant quality to two levels (labeled “high” and “low”) that correspond to setting the covariate index \( x^\gamma \) to one standard deviation above or below its estimated mean. If the auditor believes that a job is discriminating, she can initiate an investigation. Once an investigation is initiated, the job’s true type is revealed and the auditor receives a payoff

\[
\text{payoff} = \frac{1}{2} \sum_{q \in \{h,l\}} \left[p_{\text{hu}}(q) - p_{\text{lb}}(q)\right] - \kappa,
\]

where \( \kappa \) is the cost of conducting an investigation. Choosing not to investigate yields a payoff of zero. Hence, an auditor with \( \kappa = 0.01 \) is indifferent about investigating a job that contacts Black applicants a percentage point less often than comparable white applicants. The linear formulation in (2) implies that the auditor cares about the expected number of callbacks lost to racial discrimination, which reflects both discrimination severity and the baseline callback rate for white applicants. Severity is unknown and must be assessed by sending job applications.

Rather than send eight applications to each job, the auditor solves a sequential problem: in each period, she may send an application with a race and quality of her choosing, launch an investigation, or give up. The auditing history \( H_n \) encodes the assigned race and observable

| Table 1—Mixed Logit Censored Normal Results, Nunley et al. (2015) Data |
|---|---|---|
| | (1) | (2) |
| \( \alpha_0 \) | -4.922 | -4.918 |
| (0.234) & (0.234) & |
| \( \sigma_0 \) | 4.968 | 4.963 |
| (0.240) & (0.240) & |
| \( \beta_0 \) | -5.035 | -5.022 |
| (0.176) & (0.329) & |
| \( \sigma_0 \) | 6.347 | 6.521 |
| (0.148) & (0.154) & |
| \( \rho \) | -0.013 | 0.017 |
| (0.017) & (0.017) & |
| Likelihood | -2,788.3 | -2,788.3 |
| Number of jobs | 2,305 | 2,305 |

Notes: This table presents simulated maximum likelihood estimates of the mixed logit censored normal model in the Nunley et al. (2015) data. Models also include demeaned resume covariates: gender, industry, high socioeconomic status indicator, work history gaps, business degree, internship experience, and grade point average. Robust standard errors in parentheses.
characteristics of the \( n \) prior applications sent to
a given job along with whether each application
was called back. The auditor’s value function
can be written

\[
V(H_n) = \begin{cases}
  \max_{r,q} \left\{ \max_{H_{n+1}} v_{rq}(H_n), v_i(H_n), 0 \right\}, & \text{if } n < 8; \\
  \max_{H_{n+1}} v_i(H_n), 0 & \text{if } n = 8,
\end{cases}
\]

where \( v_{rq}(H_n) = -c + E[V(H_{n+1})|H_n] \) is the
expected value of sending an application of race
\( r \) and quality \( q \) net of the cost \( c \) of sending
a new application. The value of giving up on a job
equals zero, while the auditor’s expected payoff
from investigating is \( v_i(H_n) = E[S_j|H_n] - \kappa. \)
All expectations are evaluated via Bayes’ rule
starting from a prior distribution based on the
parameters in column 1 of Table 1. As Kline
and Walters (forthcoming) emphasize, the use
of Bayes’ rule allows the auditor to borrow
strength from the experience of the pilot study,
which can generate informative conclusions
about a particular job even when very few
applications have been sent.

III. Optimal Auditing Policy

The solution to the sequential problem was
computed numerically by backward induction.
Figure 1 shows the decision problem that
arises after 3 applications when setting \( \kappa = 0.13 \)
and \( c = 10^{-4} \). Seven distinct values of \( H_3 \) arise
under optimal auditing, which we have ordered
by the auditor’s posterior expectation of dis-

\[
H_3  \quad \text{Job histories}
\]

The configuration in Figure 1. Because the posterior
probability that the job is discriminating is only
about 18.8 percent in this scenario, the auditor
decides to send another high-quality Black
application to obtain greater certainty regarding
the severity of any discrimination present.

Receiving one callback for a high-quality
Black application produces the third most suspi-
cious configuration in Figure 1. While the call-
back to the Black application makes it unlikely
that this job is discriminating, the evidence
could also be rationalized by a very high base-
line white callback probability \( \omega_j \gg 0 \) in con-
junction with nontrivial discrimination severity
\( S_j > \kappa. \) To assess this possibility, the auditor
opts to send a low-quality white application.
Similar logic applies to the auditor’s choices for
additional histories, the full set of which appear
in Figure A1 in the online Appendix.

Once eight applications have been sent,
the auditor can no longer send additional
applications, and the decision problem simplifies to a binary choice: either launch an investigation or give up. Figure 2 shows the auditor’s posterior expectation $E[S_j|H_0]$ of the job’s discrimination severity given its callback history $H_0$. The relevant values of $H_0$ have been depicted by the 23 distinct callback configurations that might arise under optimal auditing. Expected discrimination severity is maximized when three high-quality white applications and five high-quality Black applications have been sent and all three white applications but only one Black application have been called back.¹ A horizontal line gives the investigation cost $\kappa$. When the expected benefit exceeds $\kappa$, an investigation is launched. Otherwise, the auditor gives up.

¹ All histories with zero Black callbacks lead the auditor to investigate or give up before $n = 8$.

### IV. The Gains from Sequential Auditing

To evaluate the performance of various auditing strategies, we borrow concepts from the medical literature on diagnostic testing. The sensitivity of an auditing strategy is the probability that an investigation is launched when a job is engaged in discrimination (i.e., when $\beta_j > 0$). The specificity of an auditing strategy is the probability that an investigation is not launched when a job is not discriminating (i.e., when $\beta_j = 0$).

Figure 3 plots the average number of applications per job associated with a given auditing strategy against its sensitivity when jobs are drawn randomly from the data-generating process described in column 1 of Table 1. To enumerate auditing strategies, the parameters $(\kappa, c)$ have been varied over a range that results in the probability of investigation falling in the interval $[0.055, 0.06]$; each dot, therefore, corresponds

![Figure 2. The Auditor’s Value after Sending Eight Applications ($\kappa = 0.13, c = 10^{-4}$)](image-url)
to a different strategy that results in roughly the same expected number of investigations.

To illustrate the gains from sequential optimization, we include strategies where the auditor’s discretion is constrained by requiring her to send a fixed number of mixed-race application pairs (of random quality) before behaving optimally. Hence, the case where four pairs must be sent corresponds to a static auditing strategy, where the auditor must either decide to investigate each job or give up. As the auditor is given more discretion, the number of applications sent to each job falls. For example, when the auditor is allowed to optimize after sending 3 pairs, it is possible to maintain a sensitivity of 14 percent by sending an average of only 6.3 applications to each job. A fully unconstrained (0 pairs) auditor can achieve a sensitivity of 14.5 percent while sending fewer than 3 applications per job. In sum, by giving up on unresponsive jobs and jobs that call back some Black applicants in early trials, the dynamic auditor is able to correctly identify more discriminators than the static auditor with fewer than half as many applications.

Figure 3 held the probability of investigation fixed, which can be thought of as approximating a setting where the auditor faces an ex ante budget constraint on the expected number of investigations to be conducted. Figure 4 depicts an analogous exercise fixing the sensitivity of the auditing strategy in the interval [0.14, 0.145] but allowing the marginal probability of an investigation to vary. This scenario can be thought of as one where the auditor plans to continue to experiment until a desired number of discriminators are investigated. Because investigations of nondiscriminating jobs constitute type I errors, points in the southeast quadrant of Figure 4 are preferable. Evidently, an unconstrained auditor (zero pairs) can achieve the same sensitivity as a static auditor (four pairs) while incurring fewer false positives and utilizing less than half as many applications.

Figure 5 provides a histogram of discrimination severity for investigated and noninvestigated jobs for an auditor with cost parameters of $\kappa = 0.13$ and $c = 10^{-4}$. The unconstrained auditor investigates only 3.5 percent of the jobs, but the jobs she investigates tend to be heavy discriminators. Roughly 30 percent of investigated jobs are not engaged in any discrimination, far below the 79 percent
prevalence of nondiscrimination in the overall population. Given her low investigation rate, the auditor’s type I error rate evaluates to only
\[ \left( \frac{0.3 \times 0.035}{0.79} \right) \times 100 = 1.3\%. \]
Discrimination tends to be much less severe among jobs that the auditor chooses not to investigate: 80% of the jobs not investigated are not engaged in discrimination at all, 15% engage in negligible discrimination with
\[ S_j \in (0, 0.03], \]
and the remainder exhibit only mild racial gaps in callback rates.

V. Conclusion

Correspondence experiments are a widespread tool used throughout the social sciences to detect discrimination in many contexts. While such experiments typically send a predetermined number of applications to each job, substantial cost reductions can, in principle, be achieved by giving up on unresponsive jobs. Our analysis suggests that adaptive correspondence experiments can yield substantial reductions in the number of applications per job needed to achieve a desired level of sensitivity and specificity of investigative decisions.

Our analysis was predicated on the existence of a pilot study from which the distribution of unit heterogeneity could be learned in a first step. While dividing the problem into separate “exploration” and “exploitation” steps simplified our analysis considerably, in practice it may be desirable to combine these steps to reduce the costs of making an initial determination of market-wide discrimination. Likewise, updating estimates of the job heterogeneity distribution may be important for enforcement if one is worried that the parameters of the callback process are drifting over the course of a study, perhaps because of the enforcement activities themselves. An interesting topic for future research is the potential for reinforcement learning techniques (e.g., Kasy and Sautmann 2021) to balance the exploration and exploitation goals of correspondence experiment design without relying on parametric assumptions regarding the job callback process.

REFERENCES


