Online Appendix

A Discrimination Report Card

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Appendix A Extension to weighted loss

Ranking mistakes may be more costly when the magnitude of the mistake is larger. To capture such concerns, we consider a family of loss functions that weight pairwise concordances and discordances by the p'th power of the difference between the cardinal biases of the two firms.

$$L^p(d,\theta;\lambda) = \binom{n}{2}^{-1} \sum_{i=2}^{n} \sum_{j=1}^{i} \Bigg[\underbrace{1\{\theta_i > \theta_j, d_i < d_j\}(\theta_i - \theta_j)^p + 1\{\theta_i < \theta_j, d_i > d_j\}(\theta_j - \theta_i)^p}_{\text{discordant pairs}} - \lambda\Bigg(\underbrace{1\{\theta_i < \theta_j, d_i < d_j\}(\theta_i - \theta_j)^p + 1\{\theta_i > \theta_j, d_i > d_j\}(\theta_j - \theta_i)^p}_{\text{concordant pairs}} \Bigg)\Bigg].$$

A loss function corresponding to the $(p = 2, \lambda = 1)$ case was previously considered by Sobel (1990). The corresponding family of risk functions take the form

$$\mathcal{R}^p(d;\lambda) = \binom{n}{2}^{-1} \sum_{i=2}^{n} \sum_{j=1}^{i} \mu_{ji}^p d_{ij} + \mu_{ij}^p (1 - e_{ij} - d_{ij}) - \lambda \mu_{ji}^p (1 - e_{ij} - d_{ij}) - \lambda \mu_{ij}^p d_{ij},$$

where $\mu_{ij}^p = \mathbb{E}_B[\max\{(\theta_i - \theta_j), 0\}^p]$. Note that $\lim_{p\to 0} \mu_{ij}^p = \pi_{ij}$. Hence, one can think of our baseline risk function in (5) as a limiting case of $\mathcal{R}^p$ as p approaches zero.

An earlier version of this paper (Kline, Rose and Walters, 2023) reports rankings of both first names and firms for the case where $p = 2$ ("square-weighted loss"). These rankings tended to yield more grades at each value of λ than arise under binary $(p = 0)$ loss. This phenomenon arises because under square weighting finer classifications yield only small mistakes on average, which give rise to correspondingly small expected losses.

When working with p-weighted loss a corresponding weighted version of the conditional discordance rate can be employed:

$$\begin{aligned} DR_{g,g'}^p &= \frac{\sum_{i=2}^{n}\sum_{j=1}^{i-1} 1\{d_i^* = g\} 1\{d_j^* = g'\} \mathbb{E}_B[\max\{(\theta_i - \theta_j), 0\}^p]}{\sum_{i=2}^{n}\sum_{j=1}^{i-1} 1\{d_i^* = g\} 1\{d_j^* = g'\} \mathbb{E}_B[(\theta_i - \theta_j)^p]} \\ &= \frac{\sum_{i=2}^{n}\sum_{j=1}^{i-1} 1\{d_i^* = g\} 1\{d_j^* = g'\} (1 - \mu_{ij}^p)}{\sum_{i=2}^{n}\sum_{j=1}^{i-1} 1\{d_i^* = g\} 1\{d_j^* = g'\} m_{ij}^p}, \end{aligned}$$

where $m_{ij}^p = \mathbb{E}_B[(\theta_i - \theta_j)^p]$. The p-weighted discordance rate nests the corresponding unweighted rate as $DR_{g,g'}^0 = DR_{g,g'}$. For any $p > 0$, $DR_{g,g'}^p$ is guaranteed to lie in the unit interval.

Appendix B Proofs of propositions

This section provides proofs of the propositions discussed in Section 3.6, which are restated here for completeness.

Proposition 1 (λ-Condorcet Criterion)**.** Suppose that firm i satisfies $\pi_{ij} > (1+\lambda)^{-1}\ \forall\ j \neq i$. Then $d_i^* > d_j^*\ \forall\ j \neq i$. Moreover, suppose that firm k satisfies $\pi_{ik} > (1+\lambda)^{-1}$ and $\pi_{kj} > (1+\lambda)^{-1}\ \forall\ j \neq i, j \neq k$, then $d_i^* > d_k^* > d_j^*\ \forall\ j \neq i, j \neq k$.

Proof. First, we establish that no firm can be tied with firm i. Suppose $\exists\ j\ s.t.\ d_j = d_i = d$. Let $\tilde{d} = \inf\{\{d' \in d^*(\lambda)\ s.t.\ d' > d\} \cup \{\infty\}\}$. Then changing firm i's grade to a value in $(d, \tilde{d})$ yields strictly lower loss, because $\sum_{j \neq i\ s.t.\ d_j = d} \pi_{ji} - \lambda\pi_{ij} < 0$, and comparisons between i and all other firms $j\ s.t.\ d_j \neq d$ are unaffected.

Now suppose $\exists\ d \in d^*(\lambda)\ s.t.\ d > d_i$. Let $d' = \inf\{d \in d^*(\lambda)\ s.t.\ d > d_i\}$. Then $\forall j\ s.t.\ d_j = d'$, the risk of re-assigning $d_i = d' + \epsilon < \inf\{\{d \in d^*(\lambda)\ s.t.\ d > d'\} \cup \{\infty\}\}$ is strictly lower because $\sum_{j \neq i\ s.t.\ d_j = d'} \pi_{ji} - \lambda\pi_{ij} < 0 < \sum_{j \neq i\ s.t.\ d_j = d'} \pi_{ij} - \lambda\pi_{ji}$, and comparisons between i and all other firms $j\ s.t.\ d_j \neq d'$ are unaffected. Since the same argument applies to firm k removing firm i from set of firms under consideration, the proof of the second part of the claim is identical. □

Proposition 2 (λ-Smith criterion)**.** Let $\mathcal{S}$ denote a collection of firms exhibiting the following dominance property: $\pi_{ij} > (1+\lambda)^{-1}\ \forall i \in \mathcal{S}, j \notin \mathcal{S}$. Then the top graded firms must be a member of $\mathcal{S}$.

Proof. First, note that if $\mathcal{S}$ is a singleton, then Proposition 1 applies directly. Otherwise, let $\tilde{d} = \sup\{d_i\ s.t.\ i \in \mathcal{S}\}$ and let $\bar{\mathcal{S}}$ denote the set $\{i \in \mathcal{S}\ s.t.\ d_i = \tilde{d}\}$. Suppose $\exists\ j \notin \mathcal{S}\ s.t.\ d_j > \tilde{d}$. Let $d' = \inf\{d \in d^*(\lambda)\ s.t.\ d > \tilde{d}\}$ and $\underline{\mathcal{S}}$ denote the set $\{j \notin \mathcal{S}\ s.t.\ d_j = d'\}$. Then swapping grades such that all firms in $\bar{\mathcal{S}}$ receive grade d' and all firms in $\underline{\mathcal{S}}$ receive grade $\tilde{d}$ must decrease risk, because $\sum_{i \in \bar{\mathcal{S}}} \sum_{j \in \underline{\mathcal{S}}} \pi_{ji} - \lambda\pi_{ij} < 0 < \sum_{i \in \bar{\mathcal{S}}} \sum_{j \in \underline{\mathcal{S}}} \pi_{ij} - \lambda\pi_{ji}$, comparisons between all firms within $\bar{\mathcal{S}}$ and $\underline{\mathcal{S}}$ are unaffected, and comparisons between all firms $k \notin \{\bar{\mathcal{S}} \cup \underline{\mathcal{S}}\}$ are unaffected. Thus no firm $j \notin \mathcal{S}$ may be ranked above the top graded member of $\mathcal{S}$. □

Proposition 3 (Unordered λ-Smith candidates are tied)**.** Let $\mathcal{S}$ denote a collection of firms exhibiting the following dominance property: $\pi_{ij} > (1+\lambda)^{-1}\ \forall i \in \mathcal{S}, j \notin \mathcal{S}$. Moreover, suppose $\pi_{ij} < (1+\lambda)^{-1}\ \forall (i,j) \in \mathcal{S}$. Then all firms in $\mathcal{S}$ receive the highest grade.

Proof. First, we show that all firms $j \notin \mathcal{S}$ must be ranked below every member of $\mathcal{S}$. Suppose not. Let $d' = \inf\{d_j\ s.t.\ j \notin \mathcal{S}, \exists\ i \in \mathcal{S}\ s.t.\ d_j > d_i\}$, $\underline{\mathcal{S}} = \{j \notin \mathcal{S}\ s.t.\ d_j = d'\}$, $\tilde{d} = \sup\{d_i\ s.t.\ i \in \mathcal{S}, d_i < d'\}$, $\bar{\mathcal{S}} = \{i \in \mathcal{S}\ s.t.\ d_i = \tilde{d}\}$. Then setting grades so that all firms in $\underline{\mathcal{S}}$ receive a grade $m \in (d', \tilde{d})$ and all firms in $\bar{\mathcal{S}}$ receive grade d' must decrease risk because $\sum_{i \in \bar{\mathcal{S}}} \sum_{j \in \underline{\mathcal{S}}} \pi_{ji} - \lambda\pi_{ij} < 0 < \sum_{i \in \bar{\mathcal{S}}} \sum_{j \in \underline{\mathcal{S}}} \pi_{ij} - \lambda\pi_{ji}$, implying it is optimal to rank all firms in $\bar{\mathcal{S}}$ above those in $\underline{\mathcal{S}}$. Moreover, $\sum_{i \in \bar{\mathcal{S}}} \sum_{j \in \mathcal{S} \text{ s.t. } d_j = d'} \pi_{ji} - \lambda\pi_{ij} > 0$ implies that it is optimal to tie firms in $\bar{\mathcal{S}}$ with firms in $\mathcal{S}$ that already have grade d', while $\sum_{j \in \underline{\mathcal{S}}} \sum_{i \in \mathcal{S} \text{ s.t. } d_i = d'} \pi_{ji} - \lambda\pi_{ij} < 0$ implies it is optimal to rank any firms in $\mathcal{S}$ that already have grade d' above those firms $\notin \mathcal{S}$ reassigned to grade m, and $\sum_{i \in \bar{\mathcal{S}}} \sum_{j \notin \mathcal{S} \text{ s.t. } d_j = \tilde{d}} \pi_{ji} - \lambda\pi_{ij} < 0$ implies it is optimal to rank firms in $\bar{\mathcal{S}}$ above any firms $\notin \mathcal{S}$ that currently have grade $\tilde{d}$. Comparisons to all firms with grades higher than d' are unaffected, as well as to any firms with grades below $\tilde{d}$. The top grades thus consist exclusively of firms in $\mathcal{S}$. To see that they also must be tied, note that because $\pi_{ji} - \lambda\pi_{ij} > 0 \; \forall (i, j) \in \mathcal{S}$, collapsing any two adjacent grades for firms in $\mathcal{S}$ must decrease risk. □

Appendix C Computing posteriors

This appendix details computation of posterior distributions for the firm contact gap analysis of Section 7. Computation of posteriors for the name contact rate analysis of Section 5 is a special case of this framework setting the dependence parameter β to zero and the standard error s_i for name i to $(4N_i)^{-1}$. Under the model in (8), the posterior density for $v_i = \theta_i/s_i^{\beta}$ given $Y_i = (\hat{\theta}_i, s_i)$ can be written

$$\begin{aligned} f_v(x|Y_i; G_v, \beta) =& \frac{\mathcal{L}(\hat{\theta}_i|v_i = x, s_i; \beta)dG_v(x)}{\int \mathcal{L}(\hat{\theta}_i|v_i = u, s_i; \beta)dG_v(u)}, \\ \mathcal{L}(\hat{\theta}_i|v_i = x, s_i; \beta) =& \frac{1}{s_i^{1-\beta}}\phi\left(\frac{(\hat{\theta}_i/s_i^{\beta}) - x}{s_i^{1-\beta}}\right). \end{aligned}$$

Taking $\hat{G}_v$ as a deconvolution estimate of G_v and $\hat{\beta}$ as a GMM estimate of β, posterior means for θ_i are computed as $s_i^{\hat{\beta}} \times \int x f_v(x|Y_i; \hat{G}_v, \hat{\beta})dx$, while the lower and upper limits of 95% credible intervals are given by the 2.5th and 97.5th percentiles of the posterior cumulative distribution $\mathcal{P}(t|\hat{\theta}_i, s_i; \hat{G}_v) = \int_{-\infty}^{t/s_i^{\hat{\beta}}} f_v(x|Y_i; \hat{G}_v, \hat{\beta})dx$.

We also use $\hat{G}_v$ and $\hat{\beta}$ to compute estimates of the matrix of pairwise posterior ranking probabilities π_{ij}. The oracle contrast probabilities are:

$$\begin{aligned} \pi_{ij} &= \Pr(\theta_i > \theta_j|Y_i, Y_j; G_v, \beta) \\ &= \Pr((s_i/s_j)^{\beta} v_i > v_j|Y_i, Y_j; G_v, \beta) \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{(s_i/s_j)^{\beta}x} f_v(x|Y_i; G_v, \beta) f_v(u|Y_j; G_v, \beta)dudx. \end{aligned}$$

We plug $\hat{G}_v$ and $\hat{\beta}$ into these formulas to construct empirical Bayes posterior contrast probabilities $\hat{\pi}_{ij}$ by numerical integration. Substituting with $\hat{\pi}_{ij}$ for π_{ij} in (5), the grades are computed by minimizing the posterior expected loss subject to the constraints in (4) using Gurobi.

C.1 Industry effects

Posteriors for the hierarchical industry effects model of Section 6.4 condition on the data for all firms in an industry. Let $\mathbf{Y}_k$ denote the $2n_k \times 1$ vector of estimates $\hat{\theta}_i$ and standard errors s_i for all firms in industry k, and let $\boldsymbol{\xi}_k$ denote the $n_k \times 1$ vector of within-industry deviations ξ_i for all firms in this industry. The joint posterior density for $\boldsymbol{\xi}_k$ and the industry effect η_k at the point where $\eta_k = x$ and $\boldsymbol{\xi}_k = \mathbf{z} = (z_1, ..., z_{n_k})'$ is given by:

$$f_{\eta,\boldsymbol{\xi}}(x, \mathbf{z}|\mathbf{Y}_k; G_\eta, G_\xi, \beta) = \frac{\left[\prod_{i:\mathrm{k}(i)=k} \mathcal{L}(\hat{\theta}_i|v_i = x \times z_i, s_i; \beta) dG_\xi(z_i)\right] dG_\eta(x)}{\int_u \int_{\mathbf{t}} \left[\prod_{i:\mathrm{k}(i)=k} \mathcal{L}(\hat{\theta}_i|v_i = u \times t_i, s_i; \beta) dG_\xi(t_i)\right] dG_\eta(u)}.$$

We form empirical Bayes joint posteriors given by $f_{\eta,\boldsymbol{\xi}}(x, \mathbf{z}|\mathbf{Y}_k; \hat{G}_\eta, \hat{G}_\xi, \hat{\beta})$, where $\hat{\beta}$ is the GMM estimate of β from column (2) of Table 3, and $\hat{G}_\xi$ and $\hat{G}_\eta$ are hierarchical deconvolution estimates from panel (a) of Figure 5. We then integrate over these joint posteriors by simulation to compute posterior means and quantiles for each random effect along with pairwise posterior probabilities π_{ij} for the model with industry effects.

C.2 Between grade variance

Letting M denote the total number of grades, the (firm-weighted) between grade variance of θ_i can be written

$$\sum_{g=1}^{M} w_g \bar{\theta}_g^2 - \left(\sum_{g=1}^{M} w_g \bar{\theta}_g\right)^2 = \sum_{g=1}^{M} w_g (1 - w_g) \bar{\theta}_g^2 - \sum_{g=1}^{M} \sum_{g' \neq g} w_g w_{g'} \bar{\theta}_g \bar{\theta}_{g'},$$

where $\bar{\theta}_g = \frac{\sum_{i=1}^n D_{ig}\theta_i}{\sum_{i=1}^n D_{ig}}$, $D_{ig} = 1\{d_i^* = g\}$ is an indicator for being assigned grade $g \in [M]$, and $w_g = n^{-1} \sum_{i=1}^n D_{ig}$ gives the share of firms assigned grade g.

We compute a Bayes unbiased estimate of each $\bar{\theta}_g$ by simply averaging the firm specific posterior firm means $\mathbb{E}[\theta_i|Y_i]$ within grade. The posterior mean estimate of each $\bar{\theta}_g^2$ is slightly harder to compute because

$$\begin{aligned}
\bar{\theta}_g^2 &= \frac{\sum_{i=1}^n D_{ig}\theta_i^2}{\left(\sum_{i=1}^n D_{ig}\right)^2} + \frac{\sum_{i=1}^n \sum_{i' \neq i} D_{ig} D_{i'g} \theta_i \theta_{i'}}{\left(\sum_{i=1}^n D_{ig}\right)^2} \\
&= (n w_g)^{-2} \left\{ \sum_{i=1}^n D_{ig}\theta_i^2 + \sum_{i=1}^n \sum_{i' \neq i} D_{ig} D_{i'g} \theta_i \theta_{i'} \right\}.
\end{aligned}$$

Our posterior mean estimate of this quantity is computed analogously as

$$\begin{aligned}
\mathbb{E}\left[\bar{\theta}_g^2|Y_i\right] &= (n w_g)^{-2} \left\{ \sum_{i=1}^n D_{ig} \mathbb{E}\left[\theta_i^2|Y_i\right] + \sum_{i=1}^n \sum_{i' \neq i} D_{ig} D_{i'g} \mathbb{E}[\theta_i|Y_i] \mathbb{E}[\theta_{i'}|Y_{i'}] \right\} \\
&= (n w_g)^{-2} \left\{ \sum_{i=1}^n D_{ig} \mathbb{E}\left[\theta_i^2|Y_i\right] + \left(\sum_{i=1}^n D_{ig} \mathbb{E}[\theta_i|Y_i]\right)^2 - \sum_{i=1}^n D_{ig} \mathbb{E}[\theta_i|Y_i]^2 \right\},
\end{aligned}$$

where each $\mathbb{E}[\theta_i|Y_i]$ and $\mathbb{E}[\theta_i^2|Y_i]$ is evaluated numerically using the relevant estimated $\hat{G}$.

Appendix D Hierarchical log-spline estimator

We extend the empirical Bayes log-spline deconvolution approach from Efron (2016), and corresponding penalized maximum likelihood estimator, to separately estimate within- and between-industry distributions of race and gender contact gaps. The between-industry distribution G_η is approximated with a discrete probability mass function defined on a set of M_η support points $\{\bar{\eta}_1, ..., \bar{\eta}_{M_\eta}\}$. The mass at the m-th support point $\bar{\eta}_m$ is given by

$$g_{\eta,m}(\alpha_\eta) = \exp\left(q'_{\eta,m}\alpha_\eta - \log\left(\sum_{\ell=1}^{M_\eta} \exp(q'_{\eta,\ell}\alpha_\eta)\right)\right),$$

where $q_{\eta,m}$ is a 5×1 vector of values of natural cubic spline basis functions for point m (as detailed in Efron 2016) and α_η is a 5×1 vector of coefficients. Similarly, we approximate the within-industry distribution G_ξ with a discrete distribution defined on support $\{\bar{\xi}_1, ..., \bar{\xi}_{M_\xi}\}$, with mass function

$$g_{\xi,m}(\alpha_\xi) = \exp\left(q'_{\xi,m}\alpha_\xi - \log\left(\sum_{\ell=1}^{M_\xi} \exp(q'_{\xi,\ell}\alpha_\xi)\right)\right)$$

for 5×1 spline basis and coefficient vectors $q_{\xi,m}$ and α_ξ, respectively.

With this specification of the mixing distributions the joint likelihood contribution for firms in industry k under our model for race contact gaps in Section 6.4 is given by:

$$\mathcal{L}\left(\hat{\boldsymbol{\theta}}_k | \boldsymbol{s}_k; \alpha_\eta, \alpha_\xi\right) = \sum_{\ell=1}^{M_\eta} g_{\eta,\ell}(\alpha_\eta) \left\{ \prod_{i:\mathrm{k}(i)=k} \left[\sum_{m=1}^{M_\xi} g_{\xi,m}(\alpha_\xi) \frac{1}{s_i^{1-\beta}} \phi\left(\frac{(\hat{\theta}_i / s_i^\beta) - \bar{\eta}_\ell \bar{\xi}_m}{s_i^{1-\beta}} \right) \right] \right\},$$

where $\hat{\boldsymbol{\theta}}_k$ and $\boldsymbol{s}_k$ are vectors collecting the $\hat{\theta}_i$ and s_i for firms with $\mathrm{k}(i) = k$. The likelihood function for gender gaps adapts this expression to the alternative model outlined in Section 8.

Following Efron (2016), we estimate the parameters α_η and α_ξ by penalized maximum likelihood. Our approach extends the Efron (2016) estimator to add a separate penalty for the within- and between-industry spline coefficients. Specifically, the parameter estimates are computed as:

$$(\hat{\alpha}_\eta, \hat{\alpha}_\xi) = \arg\max_{(\alpha_\eta, \alpha_\xi)} \sum_{k=1}^{K} \log \mathcal{L}\left(\hat{\boldsymbol{\theta}}_k | \boldsymbol{s}_k; \alpha_\eta, \alpha_\xi\right) - c_\eta \sqrt{\alpha'_\eta \alpha_\eta} - c_\xi \sqrt{\alpha'_\xi \alpha_\xi}.$$

In models with industry effects the number of support points is set equal to $M_\eta = M_\xi = 200$, with points equally spaced on the supports of η_k and ξ_i. Models without industry effects use $M_\xi = 1,000$ and $M_\eta = 1$ with $\bar{\eta}_1 = 1$ for race and $\bar{\eta}_1 = 0$ for gender, so that η_k has a degenerate distribution at unity (or zero for gender).

The upper limit of the support for each component is set equal to the maximum of the empirical distribution of corresponding estimates or five GMM-estimated standard deviations above the GMM-estimated mean, whichever is larger. For gender, the lower limit of the support is similarly set equal to the minimum of the empirical distribution and five standard deviations below the mean; for race we set the lower support limits equal to zero. To limit the influence of outliers, we truncate the support of each component in each model to not exceed seven GMM-estimated standard deviations from the GMM-estimated mean. Since the scales of the two mixing distributions are not separately identified we impose the constraint $\sum_m g_{\eta,m}(\alpha_m)\bar{\eta}_m = 1$ for race. For gender we impose corresponding constraints normalizing the means of both ξ_i and η_k to zero.

The penalty terms c_η and c_ξ are calibrated so that mean contact ratio and variances of the within- and between-industry components come as close as possible to matching GMM estimates of these same quantities. Specifically, we compute the log-spline estimator for a grid of values of the penalty parameters and compute model-implied moments of the resulting distribution, then compute the quadratic distance between log-spline and GMM moment estimates (scaled by the inverse variance matrix of the GMM estimates). We then choose the value of the penalty parameter that minimizes this distance. The model without industry effects chooses c_ξ to minimize the quadratic difference between model-implied and GMM estimates of the mean and total variance of contact gaps (or just the variance for gender, since the mean of the standardized gender gap is normalized to zero). In practice all parameters match well, as can be seen by comparing Tables 3 and F4.

Appendix E Monte Carlo evaluation of grades

To evaluate the composite performance of the grading procedure, a Monte Carlo exercise was conducted that conditions on the standard errors and industries of the 97 firms used in the racial discrimination report card. Each simulation draws a new θ_i and $\hat{\theta}_i$ for each firm from the models described in Section 6. Optimal grades are then computed under $\lambda = 0.25$, both when treating the distribution G_v as known (to evaluate oracle risk) and when re-estimating G_v in each simulation (to evaluate empirical risk).

Table E1 reports the results of 250 simulations. Column (1) assumes G_v obeys the baseline log-spline form described in Section 6.3 and reported in the upper panel of Figure 4. The oracle grading rule d^* computes the optimal grades given knowledge of the true G_v underlying the simulation. The empirical rule $\hat{d}^*$ computes the optimal grades using an estimated G_v obtained by applying GMM followed by the log-spline procedure in each simulation draw.[16] Column (2) fits a log-normal G_v via the method of moments (i.e., matching the mean and bias corrected variance) and simulates from this distribution. The empirical rule relies on a GMM step in each simulation draw followed by a corresponding method of moments step that recovers the log-normal distribution parameters from the mean and bias corrected variance of estimated residuals. Column (3) uses estimates from the model with industry effects in Section 6.4 as the prior and the empirical rule re-estimates the model in each simulation via GMM followed by the hierarchical log-spline method.

For both the oracle and empirical procedures, we report the expected rank correlation, discordance proportion, and loss evaluated under the true mixing distribution G_v. Regret is expressed as the average difference between the losses produced by the empirical and oracle rules. In all cases the regret is small (ranging from 0.012 to 0.017) indicating that the EB grades are nearly Bayes optimal. The slightly larger regret generated by the industry effects specification reflects that it is more difficult to adapt to the richer parameter space entertained by the hierarchical model.

The final panel of Table E1 reports the average expected rank correlation and discordance proportion of the empirical and oracle procedures when evaluated under the estimated $\hat{G}_v$. The posterior mean estimates of the τ and DP of the oracle rule produced under $\hat{G}_v$ are roughly unbiased, differing only slightly from their estimates under G_v.[17] This finding suggests the $\hat{\pi}_{ij}$ provide accurate estimates of the π_{ij}. In contrast, the posterior expected τ and DP of the empirical rule, when computed under $\hat{G}_v$, tend to be

[16] GMM estimation was initialized at the true parameters and optimized using a trust region reflective search procedure. In both the initial (unweighted) step and the second (optimally weighted) step we capped the procedure at 10 iterations.

[17] In the industry effects specification the estimates under $\hat{G}_v$ are slightly pessimistic, suggesting a lower τ and higher DP for the oracle rule than actually prevails under G_v. This phenomenon emerges because in roughly 12% of the simulations GMM finds no within industry component. We throw such simulations out, leading to a mild selection bias.

overly optimistic. This optimism bias results from the fact that the empirical grades are highly nonlinear functions of the $\hat{\pi}_{ij}$. For reference, we also report the standard deviation of these biases across Monte Carlo simulations. Dividing these standard deviations by $\sqrt{250} \approx 15.8$ yields a pair of standard errors on the expected bias that can be used to assess whether the average biases are distinguishable from simulation error.

In the baseline specification, the $\bar{\tau}$ of the empirical grades is biased up by about 0.036, while the DR is biased down by roughly 0.018. While the standard deviation of each bias is large, the average biases are both statistically distinguishable from simulation error at the 1% level. These biases do not seem to be driven by over-parameterization of the log-spline: the more parsimonious log-normal model yields almost identical mean biases and greater variability of bias. The model with industry effects exhibits a similar degree of over-optimism but is more precise than the simpler one level models, yielding an average rank correlation estimate that is biased up by 0.023 and an estimated discordance rate that is biased down by 0.011. The standard deviation of both biases is roughly 1/3 smaller than found with the baseline procedure, suggesting that the industry effects model yields error rate estimates that are both more accurate and precise.

Notably, the optimism bias in the estimated DR is driven in part by its lower bound of zero, which generates a skewed distribution of estimation errors $\mathbb{E}_{\hat{G}}[\tau(\hat{d}^*, \theta)] - \mathbb{E}_G[\tau(\hat{d}^*, \theta)]$. In the industry model the 25th, 50th, and 75th percentiles of these errors are -0.017, -0.006, and -0.001 respectively. Hence, the median bias of the DR estimate is 0.006, which is roughly half its mean bias of 0.011.

In sum, the grades produced by EB procedure appear to be nearly optimal in the sense of producing risk close to that of a Bayesian oracle. The EB estimates of reliability and informativeness are somewhat over-optimistic. However, this optimism bias tends to be small, particularly for the industry effects model. If the bias in our data were the same as the average bias in our Monte Carlo DGP, then the estimated Discordance Rate of 5.6% in our industry effects model of race gaps would need to be adjusted up to 6.7%.

Table E1: Monte Carlo simulations

	Baseline	Log-normal	Industry effects
Oracle risk			
$\mathbb{E}[\mathbb{E}_G[\tau(d^*,\theta)]]$	0.191	0.209	0.385
$\mathbb{E}[\mathbb{E}_G[DP(d^*,\theta)]]$	0.042	0.047	0.053
$\mathbb{E}[\mathbb{E}_G[\mathcal{R}(d^*,\theta;\lambda=0.25)]]$	-0.016	-0.017	-0.056
Empirical risk			
$\mathbb{E}[\mathbb{E}_G[\tau(\hat{d}^*,\theta)]]$	0.212	0.203	0.316
$\mathbb{E}[\mathbb{E}_G[DP(\hat{d}^*,\theta)]]$	0.063	0.060	0.058
$\mathbb{E}[\mathbb{E}_G[\mathcal{R}(\hat{d}^*,\theta;\lambda=0.25)]]$	-0.006	-0.006	-0.035
Regret			
$\mathbb{E}[\mathbb{E}_G[\mathcal{R}(\hat{d}^*,\theta;\lambda=0.25)-\mathcal{R}(d^*,\theta;\lambda=0.25)]]$	0.010	0.011	0.021
Estimated risk components			
$\mathbb{E}[\mathbb{E}_{\hat{G}}[\tau(d^*,\theta)]]$	0.192	0.203	0.333
$\mathbb{E}[\mathbb{E}_{\hat{G}}[\tau(\hat{d}^*,\theta)]]$	0.248	0.238	0.339
$\mathbb{V}(\mathbb{E}_{\hat{G}}[\tau(\hat{d}^*,\theta)]-\mathbb{E}_G[\tau(\hat{d}^*,\theta)])^{0.5}$	0.059	0.064	0.054
$\mathbb{E}[\mathbb{E}_{\hat{G}}[DP(d^*,\theta)]]$	0.042	0.050	0.080
$\mathbb{E}[\mathbb{E}_{\hat{G}}[DP(\hat{d}^*,\theta)]]$	0.045	0.042	0.047
$\mathbb{V}(\mathbb{E}_{\hat{G}}[DP(\hat{d}^*,\theta)]-\mathbb{E}_G[DP(\hat{d}^*,\theta)])^{0.5}$	0.029	0.032	0.027

Notes: This table reports the results of 250 Monte Carlo evaluations of the performance of the grading procedure. Here $\mathbb{E}_G$ denotes integration against the posterior distribution of θ given the oracle prior G and $\hat{\theta}$ while $\mathbb{E}$ denotes integration against simulated draws of $\hat{\theta}$. $\mathbb{E}_{\hat{G}}$ denotes integration against the posterior distribution of θ given the estimated prior $\hat{G}$ and $\hat{\theta}$. $\mathbb{V}$ denotes the variance across simulation draws. The first panel reports the expected rank correlation, discordance proportion, and risk of an oracle rule that forms grades using $\lambda = 0.25$. The second panel reports the same statistics for a rule that relies on an estimated prior in each simulation. Regret is the expected difference in risk between the empirical rule and the oracle rule. The final panel reports average expected rank correlations and discordance proportions of the empirical rule evaluated under the estimated $\hat{G}$ instead of the true G, as well as the standard deviation of the difference between the two evaluations for the empirical rule. Column (1) simulates data from the prior estimated in Section 6.3. Column (2) is the same but assumes that G_v is log-normal, both for simulating data and estimating G in each simulation. Column (3) simulates data from the model including industry effects described in Section 6.4.

Appendix F Additional Figures and Tables

Table F2: First names assigned by race and gender

	Black male		White male		Black female		White female	
	Name (1)	Source (2)	Name (3)	Source (4)	Name (5)	Source (6)	Name (7)	Source (8)
1	Antwan	NC	Adam	NC	Aisha	Both	Allison	BM
2	Darnell	BM	Brad	Both	Ebony	Both	Amanda	NC
3	Donnell	NC	Bradley	NC	Keisha	BM	Amy	NC
4	Hakim	BM	Brendan	Both	Kenya	BM	Anne	BM
5	Jamal	Both	Brett	BM	Lakeisha	NC	Carrie	BM
6	Jermaine	Both	Chad	NC	Lakesha	NC	Emily	Both
7	Kareem	Both	Geoffrey	BM	Lakisha	Both	Erin	NC
8	Lamar	NC	Greg	BM	Lashonda	NC	Heather	NC
9	Lamont	NC	Jacob	NC	Latasha	NC	Jennifer	NC
10	Leroy	BM	Jason	NC	Latisha	NC	Jill	Both
11	Marquis	NC	Jay	BM	Latonya	Both	Julie	NC
12	Maurice	NC	Jeremy	NC	Latoya	Both	Kristen	Both
13	Rasheed	BM	Joshua	NC	Lawanda	NC	Laurie	BM
14	Reginald	NC	Justin	NC	Patrice	NC	Lori	NC
15	Roderick	NC	Matthew	Both	Tameka	NC	Meredith	BM
16	Terrance	NC	Nathan	NC	Tamika	Both	Misty	NC
17	Terrell	NC	Neil	BM	Tanisha	BM	Rebecca	NC
18	Tremayne	BM	Scott	NC	Tawanda	NC	Sarah	Both
19	Tyrone	Both	Todd	BM	Tomeka	NC	Susan	NC

Notes: This table lists the first names assigned by race and gender and their sources. "BM" indicates that the name appeared in original set of nine names used for each group in Bertrand and Mullainathan (2004). "NC" indicates the name was drawn from data on North Carolina speeding infractions and arrests. "Both" indicates the name appeared in both sources. Names from N.C. speeding tickets were selected from the most common names where at least 90% of individuals are reported to belong to the relevant race and gender group.

Table F3: Industries represented in firm sample

	# Firms (1)	# Jobs (2)	# Apps (3)
2-digit SIC industry (code)			
Food products (20)	5	470	3,333
Manufacturing (24-35)	4	382	2,931
Freight / transport (42-47)	4	458	3,300
Communications (48)	4	407	2,855
Electric / gas (49)	3	320	2,419
Wholesale trade (50-51)	8	817	6,186
Building materials (52)	3	377	2,755
General merchandise (53)	12	1,355	10,231
Food stores (54)	3	305	2,316
Auto dealers / services / parts (55)	9	1,016	7,857
Apparel stores (56)	5	550	4,303
Home furnishing stores (57)	3	351	2,708
Eating / drinking (58)	4	500	4,000
Other retail (59)	6	715	5,482
Banks / securities (61-64)	6	575	4,280
Accommodation / real estate (65-70)	4	397	3,024
Personal / business services (72-73)	5	550	4,177
Repair services (75-76)	3	340	2,551
Health and engineering services (80-87)	6	568	4,202

Notes: This table describes the number of firms in each two-digit SIC industry in the firm sample, along with the total number of jobs sampled and applicants sent. Industries were assigned using the most commonly reported SIC code of establishments listed in the InfoGroup Historical Datafiles database for 2019. In cases where InfoGroup reports a large share of establishments in multiple industries, we use the code that best reflects the jobs sampled in the experiment and ensures peer firms are grouped together. The resulting codes differ in 19 cases from those used in Kline, Rose and Walters (2022), which used SIC codes assigned before the experiment was conducted. Some industry codes are grouped to ensure that each category includes at least three firms. Labels for grouped industries were chosen to reflect the 2-digit codes of the firms actually included, rather than all potential industries in the grouping.

Table F4: Deconvolution estimates of random effect distributions

	No industry effects	With industry effects		
	Contact penalty (θ_i)	Industry effect (η_k)	Firm effect (ξ_i)	Contact penalty (θ_i)
	(1)	(2)	(3)	(4)
		a) Race estimates		
Mean	0.098	1.000	0.300	0.088
	(0.010)	-	(0.053)	(0.016)
Std. Dev.	0.076	0.619	0.115	0.076
	(0.012)	(0.186)	(0.038)	(0.019)
Skewness	2.027	1.365	1.611	2.885
	(0.457)	(0.800)	(0.865)	(0.918)
Excess kurtosis	7.610	0.384	8.320	15.369
	(3.799)	(2.406)	(6.045)	(12.445)
		b) Gender estimates		
Mean	-0.009	0.000	0.000	0.000
	(0.000)	-	-	(0.008)
Std. Dev.	0.184	0.644	0.686	0.163
	(0.037)	(0.257)	(0.191)	(0.035)
Skewness	-0.469	-3.094	0.702	-1.296
	(2.378)	(1.597)	(1.116)	(1.657)
Excess kurtosis	29.680	11.316	1.654	22.735
	(24.073)	(5.802)	(3.137)	(7.822)

Notes: This table reports estimated moments of the distributions of industry and firm effects for race and gender contact gaps. Results are derived from hierarchical log-spline deconvolution estimates, with spline parameters estimated by penalized maximum likelihood. Panel (a) displays results for race, while Panel (b) shows results for gender. Standard errors come from 1,000 iterations of a parametric bootstrap procedure that resamples from the estimated mixing distribution. Each bootstrap trial takes a draw of the latent parameters from the full-sample mixing distribution estimate and draws normally-distributed estimation error using firm-specific standard errors. We then re-estimate the mixing distribution in each trial and compute moments of the resulting estimate. Standard errors are standard deviations of these moment estimates across bootstrap trials.

Table F5: Race discrimination: Detailed results by firm

Firm (SIC group)	# apps	$\hat{p}_w$	$\hat{p}_b$	$\hat{\theta}_i$	Baseline model: Post. Mean	Baseline model: Post. CI	Baseline model: Grd	Baseline model: Cond. rank	Industry effect model: Post. Mean	Industry effect model: Post. CI	Industry effect model: Grd	Industry effect model: Cond. rank
Genuine Parts (Napa Auto) (55)	966	0.33 (0.03)	0.24 (0.03)	0.33 (0.07)	0.25	[0.12, 0.34]	1	1	0.23	[0.14, 0.35]	1	4
AutoNation (55)	869	0.14 (0.03)	0.09 (0.02)	0.43 (0.13)	0.23	[0.08, 0.45]	1	2	0.29	[0.15, 0.44]	1	1
Costco (53)	1000	0.07 (0.02)	0.05 (0.01)	0.38 (0.28)	0.19	[0.03, 0.38]	2	3	0.13	[0.05, 0.27]	2	22
Nationwide (61-64)	455	0.09 (0.03)	0.06 (0.02)	0.4 (0.22)	0.19	[0.04, 0.4]	2	4	0.10	[0.03, 0.22]	3	29
Builders FirstSource (24-35)	581	0.07 (0.02)	0.05 (0.02)	0.35 (0.29)	0.19	[0.03, 0.37]	2	5	0.12	[0.04, 0.29]	2	25
CVS Health (59)	787	0.05 (0.02)	0.04 (0.01)	0.34 (0.24)	0.18	[0.03, 0.35]	2	6	0.28	[0.08, 0.49]	1	2
Stanley Black & Decker (24-35)	790	0.05 (0.02)	0.04 (0.02)	0.17 (0.31)	0.17	[0.02, 0.34]	2	7	0.12	[0.03, 0.28]	2	24
Jones Lang LaSalle (65-70)	577	0.07 (0.02)	0.05 (0.02)	0.3 (0.23)	0.17	[0.03, 0.33]	2	8	0.11	[0.03, 0.29]	2	26
Aramark (72-73)	935	0.07 (0.02)	0.05 (0.02)	0.3 (0.19)	0.16	[0.03, 0.32]	2	9	0.10	[0.03, 0.24]	3	28
O'Reilly Automotive (55)	973	0.34 (0.03)	0.26 (0.03)	0.27 (0.08)	0.16	[0.06, 0.32]	2	10	0.21	[0.11, 0.32]	1	8
Dean Foods (20)	295	0.14 (0.05)	0.11 (0.04)	0.24 (0.24)	0.16	[0.03, 0.32]	2	11	0.09	[0.03, 0.19]	3	31
Tractor Supply (50-51)	943	0.2 (0.03)	0.15 (0.03)	0.29 (0.11)	0.16	[0.05, 0.33]	2	12	0.09	[0.03, 0.22]	3	35
Advance Auto Parts (55)	967	0.28 (0.03)	0.21 (0.03)	0.29 (0.11)	0.16	[0.05, 0.32]	2	13	0.24	[0.12, 0.36]	1	3
VFC (North Face / Vans) (56)	791	0.18 (0.04)	0.14 (0.03)	0.26 (0.09)	0.15	[0.06, 0.3]	2	14	0.19	[0.07, 0.31]	1	9
State Farm (61-64)	481	0.05 (0.02)	0.08 (0.04)	-0.54 (0.44)	0.16	[0.01, 0.34]	2	15	0.12	[0.03, 0.24]	2	23
GameStop (57)	790	0.06 (0.02)	0.05 (0.02)	0.17 (0.21)	0.14	[0.02, 0.28]	2	16	0.15	[0.04, 0.38]	2	18
Rite Aid (59)	962	0.22 (0.03)	0.17 (0.03)	0.24 (0.08)	0.14	[0.05, 0.27]	2	17	0.18	[0.06, 0.29]	2	11
Ascena (Ann Taylor / Loft) (56)	590	0.35 (0.04)	0.28 (0.04)	0.24 (0.09)	0.14	[0.05, 0.26]	2	18	0.18	[0.06, 0.3]	2	10
CBRE (65-70)	597	0.04 (0.02)	0.03 (0.02)	0.18 (0.19)	0.14	[0.02, 0.27]	2	19	0.10	[0.03, 0.25]	3	30
UGI (49)	546	0.11 (0.03)	0.09 (0.03)	0.22 (0.15)	0.14	[0.03, 0.26]	2	20	0.09	[0.03, 0.25]	3	32
PepsiCo (20)	916	0.05 (0.02)	0.04 (0.02)	0.2 (0.14)	0.13	[0.03, 0.24]	2	21	0.07	[0.02, 0.15]	3	43
Comcast (48)	231	0.42 (0.07)	0.34 (0.06)	0.22 (0.1)	0.13	[0.04, 0.23]	2	22	0.07	[0.02, 0.19]	3	44
Goodyear (55)	387	0.08 (0.04)	0.07 (0.03)	0.19 (0.14)	0.13	[0.02, 0.24]	2	23	0.23	[0.1, 0.37]	1	5
Estee Lauder (72-73)	579	0.14 (0.03)	0.12 (0.03)	0.14 (0.17)	0.13	[0.02, 0.24]	2	24	0.09	[0.03, 0.19]	3	33
Marriott (65-70)	964	0.16 (0.03)	0.13 (0.03)	0.19 (0.12)	0.12	[0.03, 0.22]	2	25	0.08	[0.02, 0.2]	3	39
Universal Health (80-87)	586	0.32 (0.04)	0.27 (0.04)	0.19 (0.08)	0.12	[0.03, 0.2]	2	26	0.06	[0.02, 0.13]	3	58
Pilot Flying J (55)	993	0.36 (0.03)	0.3 (0.03)	0.18 (0.08)	0.11	[0.04, 0.2]	2	27	0.17	[0.09, 0.27]	2	12
Gap (56)	996	0.33 (0.04)	0.27 (0.04)	0.17 (0.06)	0.11	[0.04, 0.19]	2	28	0.15	[0.05, 0.24]	2	15

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Disney (incl. stores) (59)	858	0.09 (0.02)	0.1 (0.03)	-0.12 (0.24)	0.12	[0.01, 0.25]	2	29	0.22	[0.05, 0.41]	1	7
Murphy USA (55)	927	0.3 (0.03)	0.25 (0.03)	0.17 (0.08)	0.11	[0.03, 0.19]	2	30	0.17	[0.08, 0.26]	2	13
Republic Services (49)	943	0.22 (0.03)	0.19 (0.03)	0.17 (0.08)	0.11	[0.03, 0.19]	2	31	0.07	[0.02, 0.19]	3	48
CarMax (55)	775	0.14 (0.03)	0.14 (0.03)	0.05 (0.17)	0.11	[0.01, 0.23]	2	32	0.22	[0.07, 0.38]	1	6
AT&T (48)	893	0.13 (0.02)	0.11 (0.02)	0.11 (0.14)	0.11	[0.02, 0.21]	2	33	0.08	[0.02, 0.17]	3	38
DISH (48)	771	0.28 (0.04)	0.25 (0.04)	0.13 (0.12)	0.11	[0.02, 0.21]	2	34	0.07	[0.02, 0.16]	3	41
Cardinal Health (50-51)	974	0.23 (0.03)	0.2 (0.03)	0.14 (0.11)	0.11	[0.02, 0.2]	2	35	0.07	[0.03, 0.14]	3	40
Best Buy (57)	920	0.18 (0.03)	0.16 (0.03)	0.14 (0.11)	0.11	[0.02, 0.2]	2	36	0.11	[0.03, 0.26]	3	27
Dick's (59)	975	0.38 (0.04)	0.32 (0.03)	0.15 (0.06)	0.10	[0.04, 0.17]	2	37	0.14	[0.05, 0.22]	2	16
AutoZone (55)	1000	0.38 (0.04)	0.33 (0.03)	0.15 (0.06)	0.10	[0.04, 0.17]	2	38	0.15	[0.08, 0.23]	2	14
Pizza Hut (58)	1000	0.42 (0.04)	0.36 (0.04)	0.14 (0.06)	0.10	[0.04, 0.16]	2	39	0.07	[0.03, 0.18]	3	45
Hertz (75-76)	786	0.24 (0.04)	0.21 (0.03)	0.13 (0.09)	0.10	[0.02, 0.18]	2	40	0.06	[0.02, 0.12]	3	60
Dillard's (53)	925	0.34 (0.03)	0.3 (0.03)	0.14 (0.05)	0.10	[0.04, 0.16]	2	41	0.06	[0.03, 0.13]	3	53
Bath & Body Works (59)	990	0.31 (0.03)	0.27 (0.03)	0.14 (0.06)	0.10	[0.03, 0.16]	2	42	0.13	[0.04, 0.22]	2	17
Walgreens (59)	910	0.41 (0.04)	0.35 (0.04)	0.14 (0.06)	0.09	[0.03, 0.16]	2	43	0.13	[0.04, 0.22]	2	21
JPMorgan Chase (61-64)	981	0.06 (0.02)	0.07 (0.02)	-0.19 (0.22)	0.10	[0.01, 0.22]	2	44	0.08	[0.02, 0.17]	3	34
LKQ Auto (50-51)	587	0.23 (0.04)	0.2 (0.04)	0.12 (0.08)	0.09	[0.02, 0.17]	2	45	0.06	[0.02, 0.13]	3	50
Edward Jones (61-64)	965	0.12 (0.02)	0.11 (0.02)	0.1 (0.1)	0.09	[0.02, 0.18]	2	46	0.06	[0.02, 0.12]	3	55
Ross Stores (53)	650	0.22 (0.03)	0.2 (0.03)	0.09 (0.1)	0.09	[0.01, 0.18]	2	47	0.07	[0.03, 0.14]	3	37
Dollar Tree (53)	998	0.28 (0.03)	0.25 (0.03)	0.11 (0.07)	0.09	[0.02, 0.16]	2	48	0.07	[0.02, 0.12]	3	47
Victoria's Secret (56)	931	0.38 (0.04)	0.34 (0.04)	0.12 (0.06)	0.09	[0.02, 0.15]	2	49	0.13	[0.05, 0.22]	2	20
Walmart (53)	400	0.64 (0.05)	0.57 (0.05)	0.12 (0.07)	0.09	[0.02, 0.15]	2	50	0.06	[0.02, 0.12]	3	51
Bed Bath & Beyond (57)	998	0.36 (0.04)	0.32 (0.04)	0.12 (0.05)	0.09	[0.03, 0.14]	2	51	0.08	[0.02, 0.17]	3	42
Cintas (72-73)	747	0.23 (0.04)	0.21 (0.03)	0.09 (0.09)	0.09	[0.02, 0.16]	2	52	0.06	[0.02, 0.13]	3	57
United Rentals (72-73)	917	0.12 (0.02)	0.12 (0.02)	0.03 (0.11)	0.08	[0.01, 0.17]	2	53	0.07	[0.02, 0.14]	3	46
Nordstrom (53)	941	0.21 (0.03)	0.19 (0.03)	0.09 (0.07)	0.08	[0.02, 0.15]	2	54	0.06	[0.02, 0.12]	3	52
J.C. Penney (53)	994	0.31 (0.04)	0.28 (0.04)	0.1 (0.05)	0.08	[0.02, 0.14]	2	55	0.06	[0.02, 0.11]	3	63
Tyson Foods (20)	797	0.36 (0.04)	0.33 (0.04)	0.09 (0.07)	0.08	[0.02, 0.14]	2	56	0.05	[0.01, 0.1]	3	78
US Foods (50-51)	961	0.29 (0.03)	0.27 (0.03)	0.1 (0.05)	0.08	[0.02, 0.13]	2	57	0.05	[0.02, 0.1]	3	71
Quest Diagnostics (80-87)	907	0.02 (0.01)	0.03 (0.01)	-0.27 (0.2)	0.08	[0.01, 0.19]	2	58	0.08	[0.02, 0.15]	3	36
Foot Locker (56)	995	0.15 (0.03)	0.14 (0.03)	0.04 (0.09)	0.07	[0.01, 0.15]	2	59	0.13	[0.04, 0.23]	2	19

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UnitedHealth (80-87)	942	0.1 (0.03)	0.1 (0.03)	0.05 (0.08)	0.07	[0.01, 0.15]	2	60	0.05	[0.02, 0.1]	3	72
Honeywell (50-51)	556	0.16 (0.04)	0.15 (0.04)	0.06 (0.08)	0.07	[0.01, 0.14]	2	61	0.06	[0.02, 0.11]	3	62
Safeway (54)	429	0.25 (0.05)	0.25 (0.05)	0 (0.11)	0.07	[0.01, 0.16]	2	62	0.06	[0.02, 0.11]	3	61
International Paper (24-35)	954	0.22 (0.03)	0.2 (0.03)	0.06 (0.07)	0.07	[0.01, 0.14]	2	63	0.06	[0.02, 0.12]	3	66
Olive Garden (58)	1000	0.4 (0.04)	0.37 (0.04)	0.09 (0.04)	0.07	[0.02, 0.12]	2	64	0.06	[0.02, 0.13]	3	64
US Bank (61-64)	966	0.18 (0.03)	0.17 (0.03)	0.05 (0.08)	0.07	[0.01, 0.15]	2	65	0.05	[0.02, 0.1]	3	68
Dollar General (53)	787	0.48 (0.04)	0.45 (0.04)	0.08 (0.05)	0.07	[0.02, 0.12]	2	66	0.05	[0.02, 0.1]	3	70
XPO Logistics (42-47)	861	0.16 (0.03)	0.16 (0.03)	0.02 (0.09)	0.07	[0.01, 0.15]	2	67	0.05	[0.01, 0.1]	3	75
Performance Food Group (50-51)	520	0.35 (0.05)	0.33 (0.05)	0.06 (0.07)	0.07	[0.01, 0.13]	2	68	0.05	[0.02, 0.1]	3	65
Sherwin-Williams (52)	980	0.48 (0.04)	0.44 (0.04)	0.08 (0.03)	0.07	[0.02, 0.11]	2	69	0.04	[0.02, 0.09]	3	84
Home Depot (52)	987	0.06 (0.02)	0.06 (0.02)	-0.01 (0.1)	0.07	[0.01, 0.15]	2	70	0.06	[0.02, 0.12]	3	59
Macy's (53)	851	0.19 (0.03)	0.19 (0.03)	0.02 (0.09)	0.07	[0.01, 0.14]	2	71	0.06	[0.02, 0.12]	3	49
TJX (53)	767	0.53 (0.04)	0.49 (0.04)	0.07 (0.04)	0.06	[0.02, 0.11]	2	72	0.05	[0.02, 0.09]	3	77
Starbucks (58)	1000	0.3 (0.03)	0.28 (0.03)	0.05 (0.07)	0.06	[0.01, 0.13]	2	73	0.06	[0.02, 0.15]	3	56
Sears (incl. repair / auto) (75-76)	968	0.3 (0.04)	0.29 (0.04)	0.06 (0.06)	0.06	[0.01, 0.12]	2	74	0.05	[0.01, 0.09]	3	82
KFC (58)	1000	0.35 (0.04)	0.33 (0.04)	0.06 (0.05)	0.06	[0.01, 0.11]	2	75	0.06	[0.02, 0.12]	3	69
Lab Corp (80-87)	826	0.14 (0.02)	0.14 (0.03)	-0.01 (0.09)	0.06	[0.01, 0.13]	2	76	0.05	[0.02, 0.1]	3	73
Kindred Healthcare (80-87)	567	0.11 (0.03)	0.14 (0.03)	-0.18 (0.14)	0.06	[0, 0.15]	2	77	0.06	[0.02, 0.12]	3	54
J.B. Hunt (42-47)	877	0.25 (0.04)	0.25 (0.04)	-0.01 (0.08)	0.06	[0.01, 0.13]	2	78	0.05	[0.01, 0.09]	3	81
Geico (61-64)	432	0.43 (0.06)	0.44 (0.06)	-0.02 (0.09)	0.06	[0.01, 0.13]	2	79	0.05	[0.01, 0.1]	3	74
WestRock (24-35)	606	0.21 (0.04)	0.21 (0.04)	-0.02 (0.09)	0.06	[0.01, 0.13]	2	80	0.05	[0.02, 0.11]	3	67
Publix (54)	947	0.76 (0.03)	0.72 (0.03)	0.06 (0.04)	0.05	[0.01, 0.1]	2	81	0.04	[0.01, 0.07]	4	89
Ulta Beauty (72-73)	999	0.24 (0.03)	0.23 (0.03)	0.01 (0.07)	0.05	[0.01, 0.11]	2	82	0.05	[0.01, 0.1]	3	79
AECOM (80-87)	374	0.12 (0.05)	0.12 (0.05)	0.04 (0.04)	0.05	[0.01, 0.1]	2	83	0.04	[0.01, 0.07]	4	88
McLane Company (50-51)	704	0.4 (0.04)	0.4 (0.04)	-0.01 (0.06)	0.05	[0, 0.1]	3	84	0.05	[0.01, 0.09]	3	80
Target (53)	974	0.2 (0.03)	0.2 (0.03)	-0.01 (0.06)	0.05	[0, 0.1]	3	85	0.05	[0.02, 0.09]	3	76
FedEx (42-47)	648	0.19 (0.04)	0.2 (0.04)	-0.03 (0.07)	0.04	[0, 0.1]	3	86	0.04	[0.01, 0.08]	3	86
Lowe's (52)	788	0.36 (0.04)	0.36 (0.04)	0 (0.05)	0.04	[0, 0.09]	3	87	0.04	[0.01, 0.08]	3	85
Ryder System (42-47)	914	0.18 (0.03)	0.19 (0.03)	-0.03 (0.06)	0.04	[0, 0.1]	3	88	0.04	[0.01, 0.07]	4	87
Kohl's (53)	944	0.53 (0.04)	0.52 (0.04)	0.02 (0.03)	0.03	[0, 0.07]	3	89	0.04	[0.01, 0.06]	4	90
Mondelez (20)	788	0.44 (0.04)	0.44 (0.04)	-0.01 (0.04)	0.03	[0, 0.08]	3	90	0.03	[0.01, 0.06]	4	93

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Hilton (65-70)	886	0.24 (0.04)	0.26 (0.04)	-0.11 (0.07)	0.03	[0, 0.09]	3	91	0.04	[0.01, 0.09]	3	83
Sysco (50-51)	941	0.18 (0.03)	0.18 (0.03)	0 (0.04)	0.03	[0, 0.07]	3	92	0.04	[0.01, 0.07]	4	91
Waste Management (49)	930	0.45 (0.04)	0.46 (0.04)	-0.03 (0.04)	0.03	[0, 0.07]	3	93	0.04	[0.01, 0.07]	4	92
Kroger (54)	940	0.46 (0.04)	0.46 (0.04)	0 (0.03)	0.02	[0, 0.05]	3	94	0.02	[0.01, 0.05]	4	96
Avis-Budget (75-76)	797	0.31 (0.04)	0.32 (0.04)	-0.05 (0.04)	0.02	[0, 0.06]	3	95	0.03	[0.01, 0.06]	4	94
Dr Pepper (20)	537	0.88 (0.04)	0.94 (0.02)	-0.07 (0.04)	0.02	[0, 0.05]	3	96	0.03	[0.01, 0.05]	4	95
Charter / Spectrum (48)	960	0.45 (0.04)	0.46 (0.04)	-0.03 (0.03)	0.02	[0, 0.04]	3	97	0.02	[0.01, 0.05]	4	97

Notes: This table reports estimated contact penalties and the results of empirical Bayes and grading exercises for race. Each firm's industry (2-digit SIC code group) is shown in parentheses. The next column reports the total number of applications sent to this firm. The columns $\hat{p}_w$ and $\hat{p}_b$ give estimates of the probability that a white and Black application (respectively) is contacted at the average job sampled from the firm in question. The column $\hat{\theta}_i$ reports contact penalties (with positive values indicating discrimination against Black applicants). Job-clustered standard errors are reported in parentheses. The remaining columns report posterior means (Post. mean), 95% credible intervals (Post. CI), assigned grades using $\lambda = 0.25$ (Grd), and Condorcet ranks (Cond. rank), which are grades under $\lambda = 1$, in the baseline model and the model with industry effects.

Table F6: Gender discrimination: Detailed results by firm

Firm (SIC group)	# apps	$\hat{p}_m$	$\hat{p}_f$	$\hat{\theta}_i$	Baseline model: Post. Mean	Baseline model: Post. CI	Baseline model: Grd	Baseline model: Cond. rank	Industry effect model: Post. Mean	Industry effect model: Post. CI	Industry effect model: Grd	Industry effect model: Cond. rank
Builders FirstSource (24-35)	581	0.11 (0.03)	0.02 (0.01)	1.57 (0.55)	0.90	[0.15, 1.63]	1	1	0.67	[-0.09, 1.44]	1	1
LKQ Auto (50-51)	587	0.29 (0.05)	0.15 (0.04)	0.66 (0.21)	0.30	[0.04, 0.55]	2	2	0.26	[-0.01, 0.54]	2	2
JPMorgan Chase (61-64)	981	0.08 (0.02)	0.05 (0.02)	0.45 (0.26)	0.19	[-0.11, 0.51]	2	3	0.13	[-0.16, 0.48]	3	4
Honeywell (50-51)	556	0.19 (0.05)	0.12 (0.03)	0.42 (0.19)	0.17	[-0.05, 0.4]	2	4	0.15	[-0.06, 0.41]	2	3
CVS Health (59)	787	0.05 (0.02)	0.04 (0.01)	0.38 (0.28)	0.15	[-0.16, 0.5]	3	5	0.11	[-0.19, 0.49]	3	6
Goodyear (55)	387	0.08 (0.04)	0.06 (0.03)	0.3 (0.27)	0.11	[-0.17, 0.44]	3	6	0.11	[-0.15, 0.46]	3	5
AutoNation (55)	869	0.13 (0.03)	0.1 (0.02)	0.28 (0.24)	0.10	[-0.15, 0.38]	3	7	0.10	[-0.13, 0.41]	3	7
UGI (49)	546	0.11 (0.03)	0.08 (0.03)	0.27 (0.25)	0.10	[-0.16, 0.39]	3	8	0.07	[-0.17, 0.4]	3	12
Target (53)	974	0.23 (0.04)	0.18 (0.03)	0.26 (0.14)	0.09	[-0.05, 0.25]	3	9	0.08	[-0.06, 0.26]	3	9
WestRock (24-35)	606	0.24 (0.05)	0.19 (0.04)	0.24 (0.18)	0.08	[-0.1, 0.3]	3	10	0.08	[-0.1, 0.32]	3	8
Costco (53)	1000	0.07 (0.02)	0.05 (0.01)	0.24 (0.29)	0.08	[-0.21, 0.43]	3	11	0.07	[-0.2, 0.44]	3	15
O'Reilly Automotive (55)	973	0.33 (0.03)	0.26 (0.03)	0.22 (0.12)	0.07	[-0.05, 0.2]	3	12	0.07	[-0.05, 0.22]	3	10
Avis-Budget (75-76)	797	0.34 (0.04)	0.29 (0.04)	0.19 (0.09)	0.06	[-0.04, 0.16]	3	13	0.06	[-0.03, 0.18]	3	11
KFC (58)	1000	0.37 (0.04)	0.31 (0.04)	0.17 (0.1)	0.05	[-0.04, 0.15]	3	14	0.05	[-0.04, 0.17]	3	17
Sherwin-Williams (52)	980	0.5 (0.04)	0.42 (0.04)	0.16 (0.08)	0.04	[-0.03, 0.12]	3	15	0.05	[-0.03, 0.14]	3	19
Disney (incl. stores) (59)	858	0.1 (0.03)	0.08 (0.02)	0.17 (0.24)	0.05	[-0.19, 0.33]	3	16	0.04	[-0.18, 0.34]	3	23
XPO Logistics (42-47)	861	0.17 (0.03)	0.14 (0.03)	0.16 (0.16)	0.05	[-0.11, 0.23]	3	17	0.04	[-0.11, 0.25]	3	21
McLane Company (50-51)	704	0.43 (0.05)	0.37 (0.05)	0.15 (0.11)	0.04	[-0.06, 0.16]	3	18	0.05	[-0.05, 0.19]	3	14
Sears (incl. repair / auto) (75-76)	968	0.32 (0.04)	0.27 (0.04)	0.15 (0.11)	0.04	[-0.06, 0.16]	3	19	0.05	[-0.05, 0.19]	3	18
Hertz (75-76)	786	0.25 (0.04)	0.21 (0.04)	0.15 (0.16)	0.04	[-0.1, 0.21]	3	20	0.06	[-0.08, 0.25]	3	13
Quest Diagnostics (80-87)	907	0.03 (0.02)	0.03 (0.01)	0.17 (0.46)	0.05	[-0.43, 0.6]	3	21	0.00	[-0.43, 0.59]	3	69
Tractor Supply (50-51)	943	0.19 (0.03)	0.17 (0.03)	0.13 (0.16)	0.04	[-0.12, 0.22]	3	22	0.06	[-0.09, 0.25]	3	16
Starbucks (58)	1000	0.31 (0.04)	0.28 (0.03)	0.1 (0.09)	0.02	[-0.06, 0.12]	3	23	0.03	[-0.05, 0.14]	3	22
Walmart (53)	400	0.63 (0.05)	0.57 (0.05)	0.1 (0.08)	0.02	[-0.05, 0.1]	3	24	0.03	[-0.04, 0.12]	3	25
UnitedHealth (80-87)	942	0.11 (0.03)	0.09 (0.03)	0.11 (0.2)	0.03	[-0.16, 0.25]	3	25	0.01	[-0.17, 0.26]	3	48
Nordstrom (53)	941	0.21 (0.04)	0.19 (0.03)	0.1 (0.13)	0.02	[-0.09, 0.16]	3	26	0.03	[-0.08, 0.18]	3	28
Cintas (72-73)	747	0.23 (0.04)	0.21 (0.04)	0.1 (0.15)	0.02	[-0.11, 0.19]	3	27	0.01	[-0.13, 0.2]	3	41
US Foods (50-51)	961	0.29 (0.04)	0.27 (0.03)	0.09 (0.1)	0.02	[-0.07, 0.13]	3	28	0.04	[-0.05, 0.16]	3	20

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Kohl's (53)	944	0.54 (0.04)	0.5 (0.04)	0.09 (0.06)	0.02	[-0.04, 0.08]	3	29	0.02	[-0.03, 0.1]	3	26
DISH (48)	771	0.28 (0.04)	0.26 (0.04)	0.09 (0.16)	0.02	[-0.12, 0.19]	3	30	0.01	[-0.13, 0.2]	3	43
Safeway (54)	429	0.26 (0.06)	0.24 (0.05)	0.09 (0.19)	0.02	[-0.15, 0.23]	3	31	0.03	[-0.14, 0.25]	3	29
Olive Garden (58)	1000	0.4 (0.04)	0.38 (0.04)	0.06 (0.08)	0.01	[-0.05, 0.08]	3	32	0.02	[-0.05, 0.11]	3	31
Best Buy (57)	920	0.18 (0.03)	0.17 (0.03)	0.07 (0.15)	0.01	[-0.12, 0.17]	3	33	0.02	[-0.11, 0.2]	3	33
Publix (54)	947	0.76 (0.03)	0.72 (0.03)	0.05 (0.04)	0.01	[-0.02, 0.04]	3	34	0.01	[-0.02, 0.06]	3	34
Murphy USA (55)	927	0.28 (0.04)	0.27 (0.03)	0.06 (0.12)	0.01	[-0.09, 0.13]	3	35	0.03	[-0.07, 0.16]	3	27
AT&T (48)	893	0.12 (0.02)	0.12 (0.02)	0.07 (0.18)	0.01	[-0.15, 0.2]	3	36	0.00	[-0.15, 0.21]	3	54
United Rentals (72-73)	917	0.13 (0.02)	0.12 (0.03)	0.07 (0.19)	0.01	[-0.16, 0.22]	3	37	0.00	[-0.17, 0.23]	3	62
Genuine Parts (Napa Auto) (55)	966	0.29 (0.04)	0.28 (0.03)	0.05 (0.11)	0.01	[-0.09, 0.12]	3	38	0.02	[-0.07, 0.15]	3	30
AutoZone (55)	1000	0.36 (0.04)	0.35 (0.04)	0.04 (0.09)	0.00	[-0.07, 0.09]	3	39	0.02	[-0.05, 0.11]	3	32
Dick's (59)	975	0.36 (0.04)	0.35 (0.04)	0.02 (0.09)	0.00	[-0.07, 0.08]	3	40	0.00	[-0.06, 0.1]	3	42
Bed Bath & Beyond (57)	998	0.34 (0.04)	0.34 (0.04)	0.02 (0.09)	0.00	[-0.07, 0.08]	3	41	0.01	[-0.06, 0.1]	3	38
Dillard's (53)	925	0.32 (0.04)	0.32 (0.04)	0.01 (0.11)	0.00	[-0.09, 0.1]	3	42	0.01	[-0.08, 0.13]	3	39
J.B. Hunt (42-47)	877	0.25 (0.04)	0.25 (0.04)	0.01 (0.13)	0.00	[-0.12, 0.13]	3	43	0.01	[-0.11, 0.15]	3	44
Advance Auto Parts (55)	967	0.25 (0.03)	0.25 (0.03)	0.01 (0.13)	-0.01	[-0.11, 0.12]	3	44	0.02	[-0.09, 0.15]	3	35
Dr Pepper (20)	537	0.9 (0.03)	0.92 (0.03)	-0.02 (0.04)	-0.01	[-0.04, 0.02]	3	45	0.00	[-0.03, 0.04]	3	52
US Bank (61-64)	966	0.17 (0.03)	0.17 (0.03)	0.01 (0.14)	-0.01	[-0.13, 0.13]	3	46	0.00	[-0.12, 0.15]	3	59
Waste Management (49)	930	0.45 (0.04)	0.46 (0.04)	-0.01 (0.07)	-0.01	[-0.06, 0.05]	3	47	0.00	[-0.06, 0.07]	3	49
Geico (61-64)	432	0.44 (0.06)	0.44 (0.06)	0.01 (0.13)	-0.01	[-0.11, 0.12]	3	48	0.00	[-0.11, 0.13]	3	56
Ryder System (42-47)	914	0.18 (0.03)	0.18 (0.03)	0.01 (0.16)	-0.01	[-0.15, 0.16]	3	49	0.01	[-0.13, 0.19]	3	46
Tyson Foods (20)	797	0.34 (0.04)	0.34 (0.04)	-0.01 (0.11)	-0.01	[-0.1, 0.09]	3	50	0.00	[-0.09, 0.11]	3	58
Jones Lang LaSalle (65-70)	577	0.06 (0.02)	0.06 (0.03)	0.03 (0.27)	0.00	[-0.27, 0.29]	3	51	-0.03	[-0.29, 0.3]	3	77
Dollar General (53)	787	0.46 (0.05)	0.47 (0.05)	-0.03 (0.07)	-0.01	[-0.07, 0.05]	3	52	0.00	[-0.06, 0.07]	3	50
Macy's (53)	851	0.19 (0.03)	0.19 (0.03)	-0.01 (0.14)	-0.01	[-0.13, 0.12]	3	52	0.00	[-0.11, 0.15]	3	47
Lowe's (52)	788	0.35 (0.04)	0.36 (0.04)	-0.03 (0.1)	-0.02	[-0.1, 0.08]	3	53	0.00	[-0.08, 0.11]	3	45
Mondelez (20)	788	0.43 (0.04)	0.45 (0.05)	-0.04 (0.08)	-0.02	[-0.08, 0.05]	3	54	-0.01	[-0.07, 0.07]	3	61
Bath & Body Works (59)	990	0.29 (0.04)	0.3 (0.03)	-0.05 (0.11)	-0.02	[-0.1, 0.07]	3	55	-0.01	[-0.09, 0.1]	3	62
Cardinal Health (50-51)	974	0.21 (0.03)	0.22 (0.03)	-0.04 (0.12)	-0.02	[-0.12, 0.09]	3	56	0.01	[-0.08, 0.13]	3	36
Dollar Tree (53)	998	0.26 (0.03)	0.27 (0.04)	-0.05 (0.11)	-0.02	[-0.11, 0.08]	3	57	0.00	[-0.09, 0.1]	3	55
AECOM (80-87)	374	0.12 (0.05)	0.12 (0.05)	0 (0.26)	-0.02	[-0.27, 0.27]	3	58	-0.02	[-0.25, 0.28]	3	74

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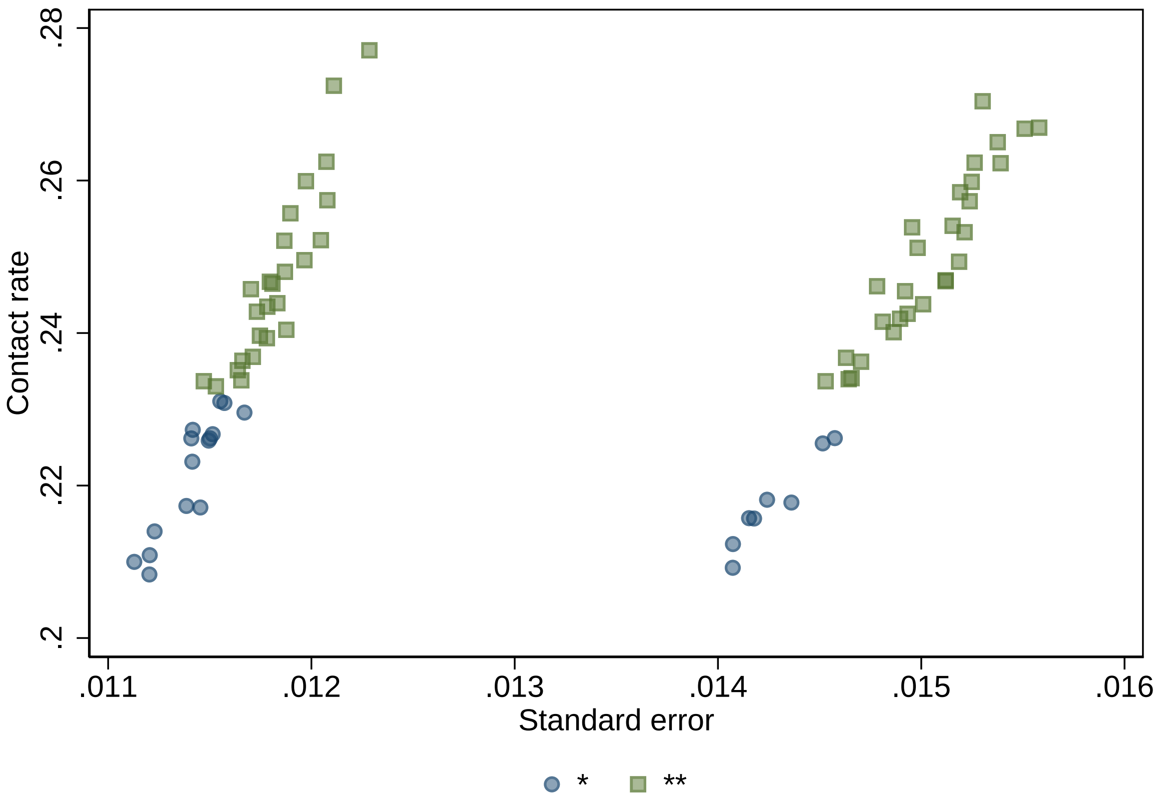
Kroger (54)	940	0.44 (0.04)	0.48 (0.04)	-0.09 (0.07)	-0.03	[-0.08, 0.03]	3	59	-0.01	[-0.07, 0.05]	3	63
Pilot Flying J (55)	993	0.31 (0.03)	0.34 (0.03)	-0.09 (0.09)	-0.03	[-0.1, 0.04]	3	60	0.00	[-0.07, 0.07]	3	53
Stanley Black & Decker (24-35)	790	0.04 (0.02)	0.04 (0.02)	0 (0.33)	-0.02	[-0.34, 0.35]	3	61	0.04	[-0.26, 0.41]	3	24
Pizza Hut (58)	1000	0.37 (0.04)	0.41 (0.04)	-0.1 (0.08)	-0.03	[-0.09, 0.03]	3	62	-0.01	[-0.07, 0.07]	3	57
Home Depot (52)	987	0.06 (0.02)	0.06 (0.02)	-0.02 (0.32)	-0.03	[-0.34, 0.32]	3	63	0.02	[-0.26, 0.38]	3	37
Sysco (50-51)	941	0.17 (0.03)	0.19 (0.04)	-0.11 (0.13)	-0.04	[-0.15, 0.08]	3	64	0.01	[-0.1, 0.13]	3	40
Charter / Spectrum (48)	960	0.42 (0.04)	0.49 (0.05)	-0.15 (0.08)	-0.04	[-0.11, 0.02]	3	65	-0.03	[-0.09, 0.04]	3	73
TJX (53)	767	0.48 (0.04)	0.55 (0.04)	-0.15 (0.08)	-0.04	[-0.11, 0.02]	3	66	-0.02	[-0.09, 0.05]	3	66
Walgreens (59)	910	0.35 (0.04)	0.41 (0.04)	-0.15 (0.09)	-0.04	[-0.11, 0.02]	3	67	-0.02	[-0.09, 0.05]	3	70
International Paper (24-35)	954	0.2 (0.03)	0.22 (0.04)	-0.13 (0.12)	-0.05	[-0.14, 0.06]	3	68	-0.01	[-0.11, 0.1]	3	60
Rite Aid (59)	962	0.18 (0.03)	0.21 (0.03)	-0.14 (0.12)	-0.05	[-0.14, 0.06]	3	69	-0.02	[-0.12, 0.09]	3	71
J.C. Penney (53)	994	0.27 (0.04)	0.32 (0.04)	-0.15 (0.11)	-0.05	[-0.13, 0.04]	3	70	-0.02	[-0.11, 0.07]	3	68
Ross Stores (53)	650	0.2 (0.03)	0.22 (0.03)	-0.13 (0.15)	-0.05	[-0.17, 0.08]	3	71	-0.02	[-0.13, 0.12]	3	67
Ulta Beauty (72-73)	999	0.22 (0.03)	0.25 (0.04)	-0.16 (0.12)	-0.05	[-0.15, 0.05]	3	72	-0.04	[-0.14, 0.07]	3	78
Universal Health (80-87)	586	0.27 (0.05)	0.32 (0.05)	-0.15 (0.15)	-0.05	[-0.17, 0.08]	3	73	-0.04	[-0.15, 0.1]	3	79
Performance Food Group (50-51)	520	0.32 (0.05)	0.37 (0.05)	-0.15 (0.14)	-0.05	[-0.17, 0.07]	3	74	0.00	[-0.11, 0.12]	3	51
Marriott (65-70)	964	0.14 (0.03)	0.16 (0.03)	-0.13 (0.17)	-0.05	[-0.19, 0.11]	3	75	-0.05	[-0.2, 0.12]	3	83
GameStop (57)	790	0.05 (0.02)	0.06 (0.02)	-0.09 (0.25)	-0.05	[-0.28, 0.21]	3	76	-0.01	[-0.23, 0.26]	3	65
FedEx (42-47)	648	0.18 (0.04)	0.21 (0.04)	-0.16 (0.14)	-0.05	[-0.17, 0.07]	3	77	-0.02	[-0.13, 0.1]	3	72
PepsiCo (20)	916	0.05 (0.02)	0.05 (0.02)	-0.1 (0.24)	-0.05	[-0.27, 0.19]	3	78	-0.03	[-0.23, 0.23]	3	76
Hilton (65-70)	886	0.23 (0.04)	0.27 (0.04)	-0.18 (0.13)	-0.06	[-0.17, 0.06]	3	79	-0.05	[-0.17, 0.08]	3	81
Gap (56)	996	0.27 (0.04)	0.33 (0.04)	-0.2 (0.12)	-0.06	[-0.16, 0.03]	3	80	-0.25	[-0.34, -0.11]	4	93
CarMax (55)	775	0.13 (0.02)	0.15 (0.03)	-0.16 (0.17)	-0.06	[-0.21, 0.1]	3	81	-0.01	[-0.15, 0.15]	3	64
Republic Services (49)	943	0.19 (0.03)	0.23 (0.04)	-0.21 (0.14)	-0.07	[-0.18, 0.05]	3	82	-0.03	[-0.15, 0.09]	3	75
Foot Locker (56)	995	0.13 (0.03)	0.16 (0.03)	-0.18 (0.17)	-0.07	[-0.21, 0.09]	3	83	-0.34	[-0.5, -0.12]	5	94
Dean Foods (20)	295	0.12 (0.05)	0.13 (0.05)	-0.12 (0.29)	-0.06	[-0.33, 0.24]	3	84	-0.04	[-0.29, 0.27]	3	80
Victoria's Secret (56)	931	0.32 (0.04)	0.4 (0.04)	-0.23 (0.1)	-0.07	[-0.2, 0.01]	3	85	-0.22	[-0.29, -0.12]	4	92
Edward Jones (61-64)	965	0.1 (0.02)	0.13 (0.02)	-0.21 (0.17)	-0.08	[-0.22, 0.08]	3	86	-0.04	[-0.19, 0.12]	3	82
Lab Corp (80-87)	826	0.12 (0.02)	0.16 (0.03)	-0.29 (0.16)	-0.10	[-0.24, 0.04]	3	87	-0.06	[-0.2, 0.08]	3	84
Estee Lauder (72-73)	579	0.11 (0.03)	0.15 (0.03)	-0.31 (0.21)	-0.11	[-0.29, 0.07]	3	88	-0.08	[-0.25, 0.11]	3	85
Comcast (48)	231	0.31 (0.07)	0.45 (0.08)	-0.37 (0.22)	-0.13	[-0.33, 0.07]	3	89	-0.08	[-0.28, 0.11]	3	86

Continued on next page

Kindred Healthcare (80-87)	567	0.1 (0.03)	0.15 (0.04)	-0.36 (0.25)	-0.14	[-0.36, 0.1]	3	90	-0.09	[-0.3, 0.14]	3	87
VFC (North Face / Vans) (56)	791	0.12 (0.03)	0.19 (0.04)	-0.42 (0.18)	-0.15	[-0.35, 0.02]	4	91	-0.42	[-0.55, -0.22]	5	95
Aramark (72-73)	935	0.05 (0.01)	0.07 (0.02)	-0.38 (0.25)	-0.14	[-0.36, 0.09]	3	92	-0.09	[-0.31, 0.13]	3	88
CBRE (65-70)	597	0.02 (0.01)	0.05 (0.02)	-0.72 (0.38)	-0.29	[-0.66, 0.08]	4	93	-0.19	[-0.61, 0.16]	4	91
State Farm (61-64)	481	0.05 (0.03)	0.08 (0.04)	-0.53 (0.66)	-0.28	[-0.96, 0.45]	3	94	-0.15	[-0.75, 0.54]	3	89
Nationwide (61-64)	455	0.05 (0.02)	0.1 (0.04)	-0.73 (0.48)	-0.32	[-0.8, 0.17]	4	95	-0.17	[-0.61, 0.29]	3	90
Ascena (Ann Taylor / Loft) (56)	590	0.21 (0.04)	0.42 (0.05)	-0.66 (0.17)	-0.44	[-0.68, -0.09]	4	96	-0.44	[-0.57, -0.3]	5	96

Notes: This table reports estimated contact differences and the results of empirical Bayes and grading exercises for gender. Each firm's industry (2-digit SIC code group) is shown in parentheses. The next column reports the total number of applications sent to this firm. The columns $\hat{p}_w$ and $\hat{p}_b$ give estimates of the probability that a male and female application (respectively) is contacted at the average job sampled from the firm in question. The column $\hat{\theta}_i$ reports contact differences (with positive values indicating favoring male applicants). Job-clustered standard errors are reported in parentheses. The remaining columns report posterior means (Post. mean), 95% credible intervals (Post. CI), assigned grades using $\lambda = 0.25$ (Grd), and Condorcet ranks (Cond. rank), which are grades under $\lambda = 1$, in the baseline model and the model with industry effects.

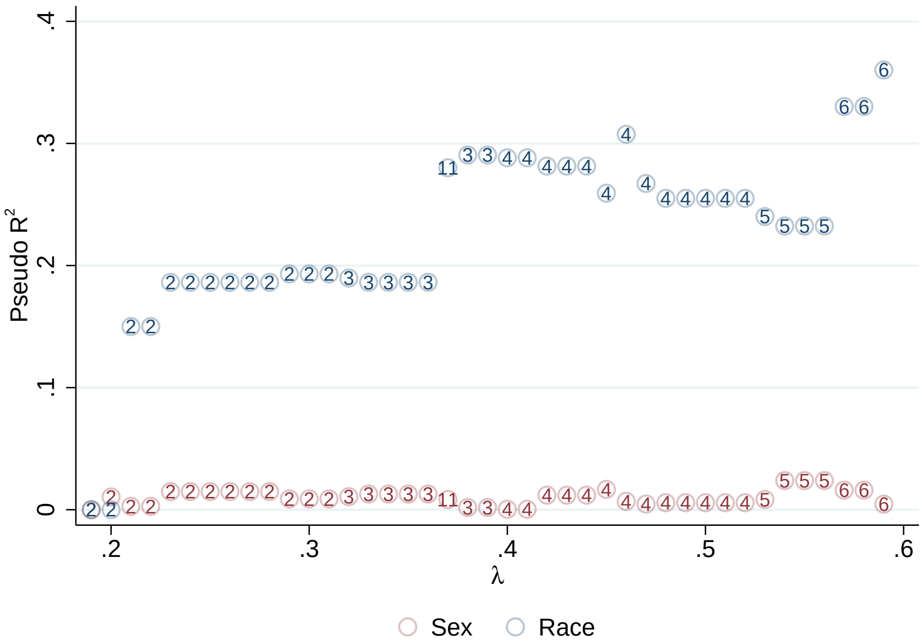
Figure F1: Contact rates, standard errors, and name grades



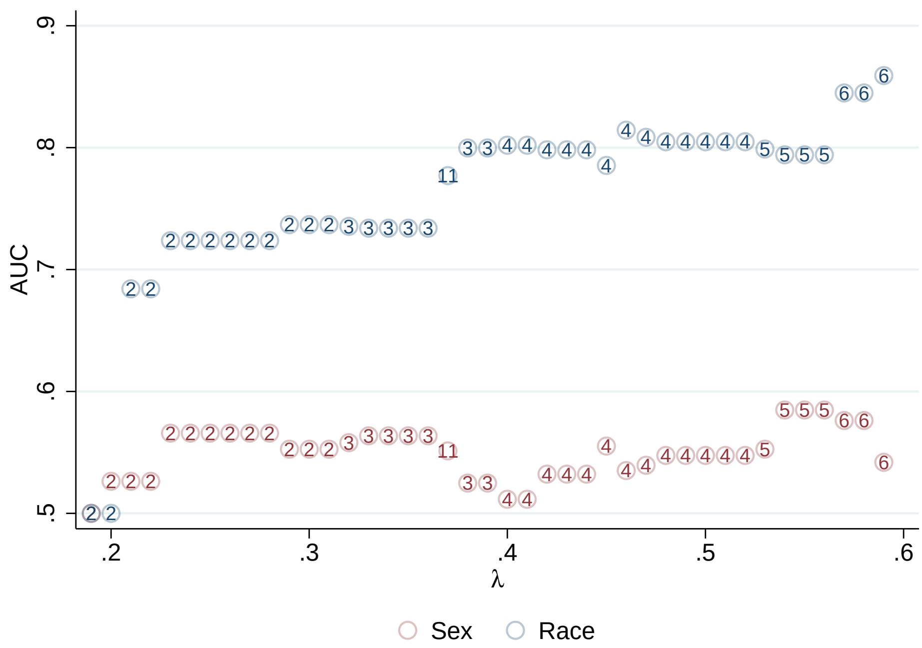
Notes: This figure plots the estimated contact rates for each name against its standard error. The shape and color of each point indicate the grade assigned to the name using the same specification as Figure 3.

Figure F2: Predictive power of grades name for race and sex labels

a) Pseudo R^2



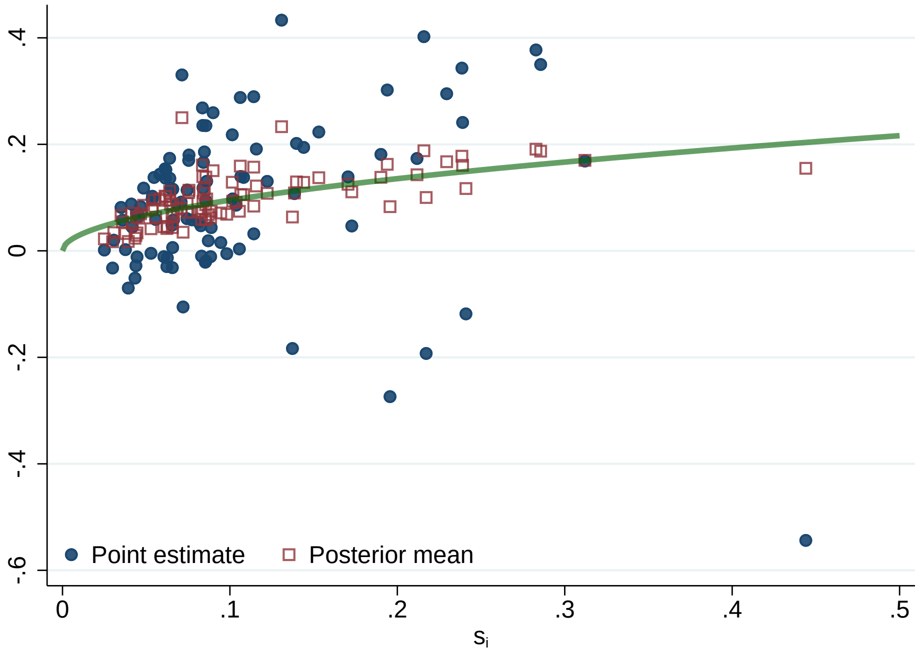
b) Area under the curve



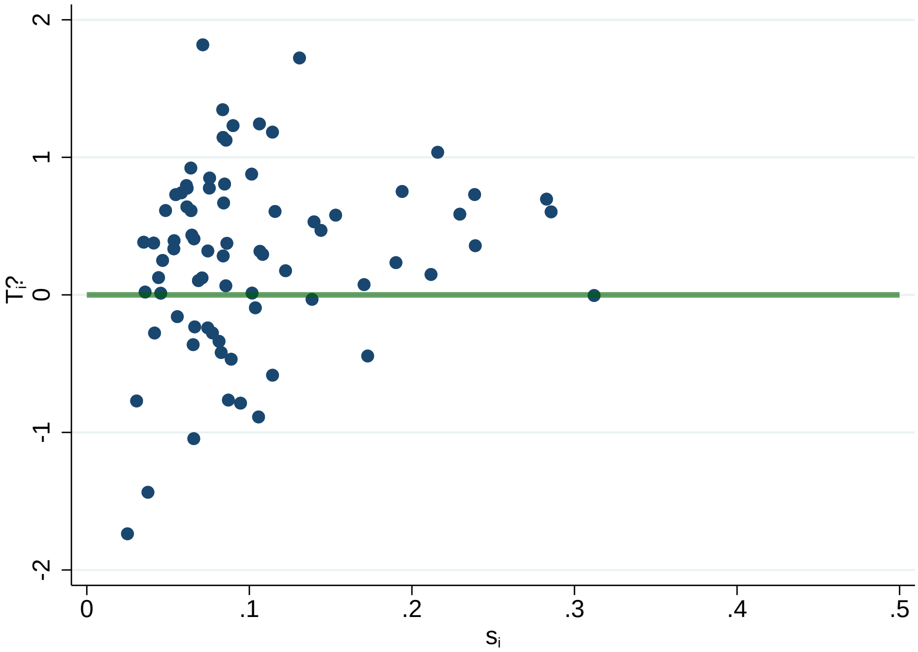
Notes: This figure plots the psuedo-R^2 (Panel (a)) and AUC (Panel (b)) for a series of logistic regressions using an indicator for the race or sex of the name as the outcome and dummies for assigned grades as the explanatory variables for an intermediate range of λ. The number shown indicates the number of grades assigned.

Figure F3: Unadjusted and studentized racial contact gaps against standard errors

a) $\hat{\theta}_i$ vs. s_i



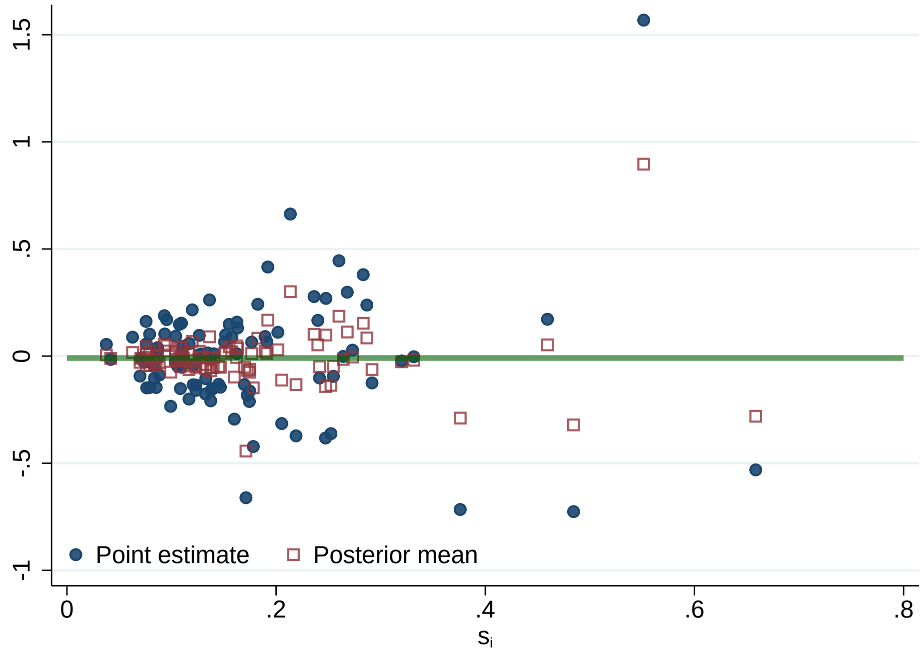
b) $\hat{T}_i$ vs. s_i



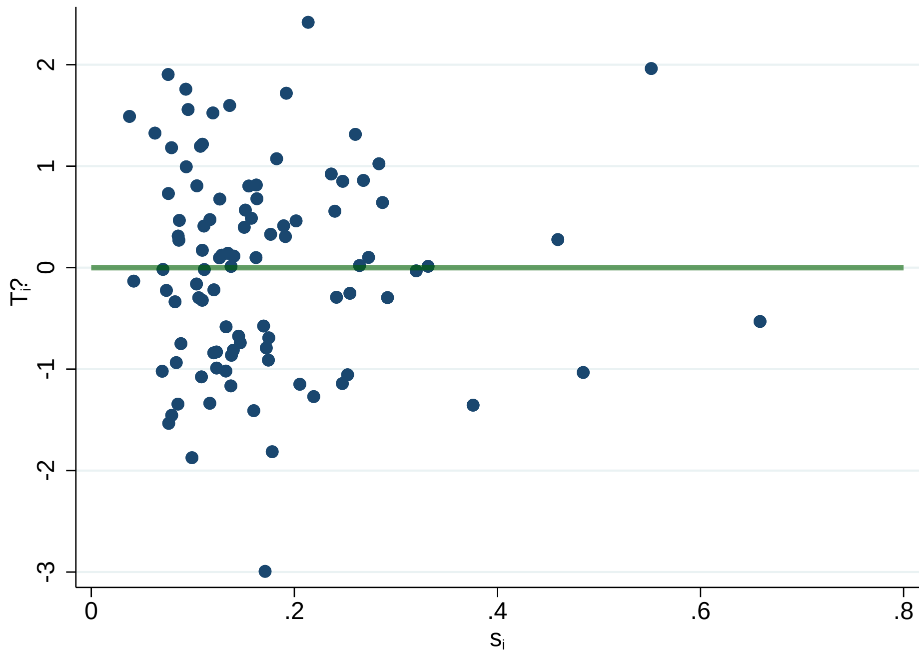
Notes: Panel (a) of this figure plots estimated race contact gaps against their standard errors. The green line plots the conditional mean of θ_i given s_i implied by the GMM estimates. Posterior mean estimates $\bar{\theta}_i$ from the baseline model are superimposed on this panel to illustrate EB shrinkage of contact gaps towards the conditional mean. Panel (b) plots studentized contact gaps $\hat{T}_i$ against standard errors. The green line plots the relationship implied by the model.

Figure F4: Unadjusted and studentized gender contact gaps against standard errors

a) $\hat{\theta}_i$ vs. s_i

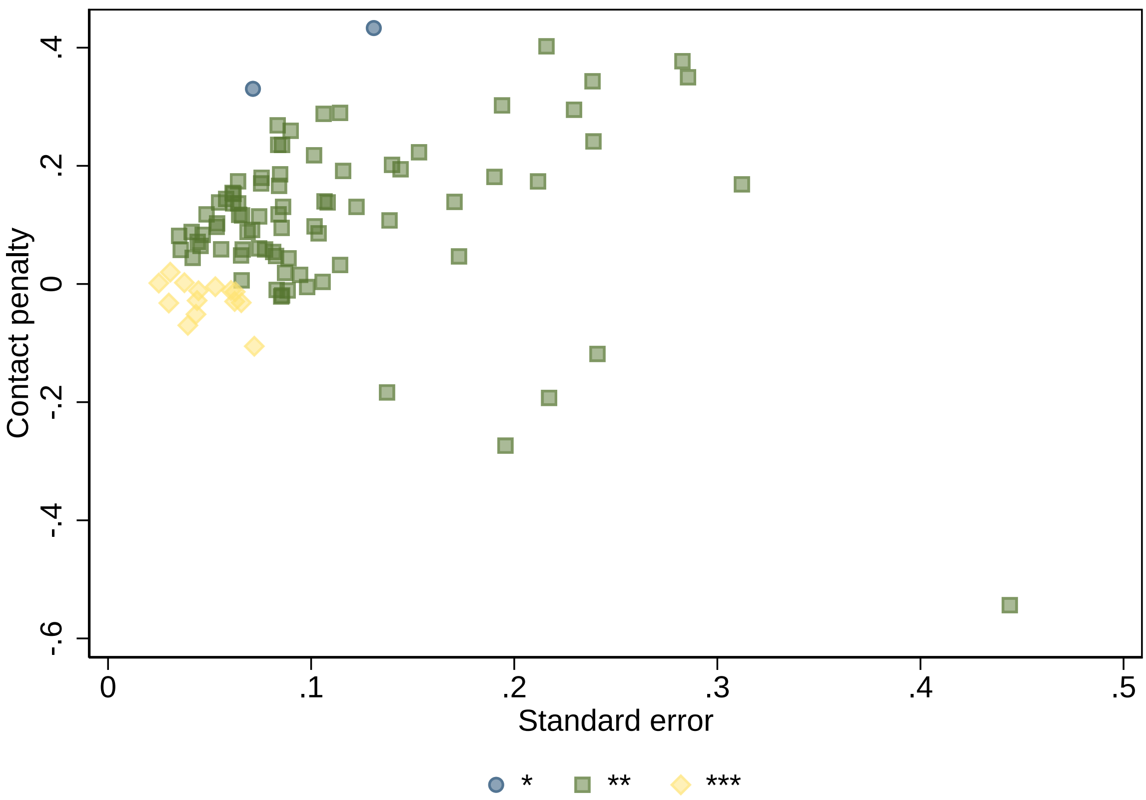


b) $\hat{T}_i$ vs. s_i



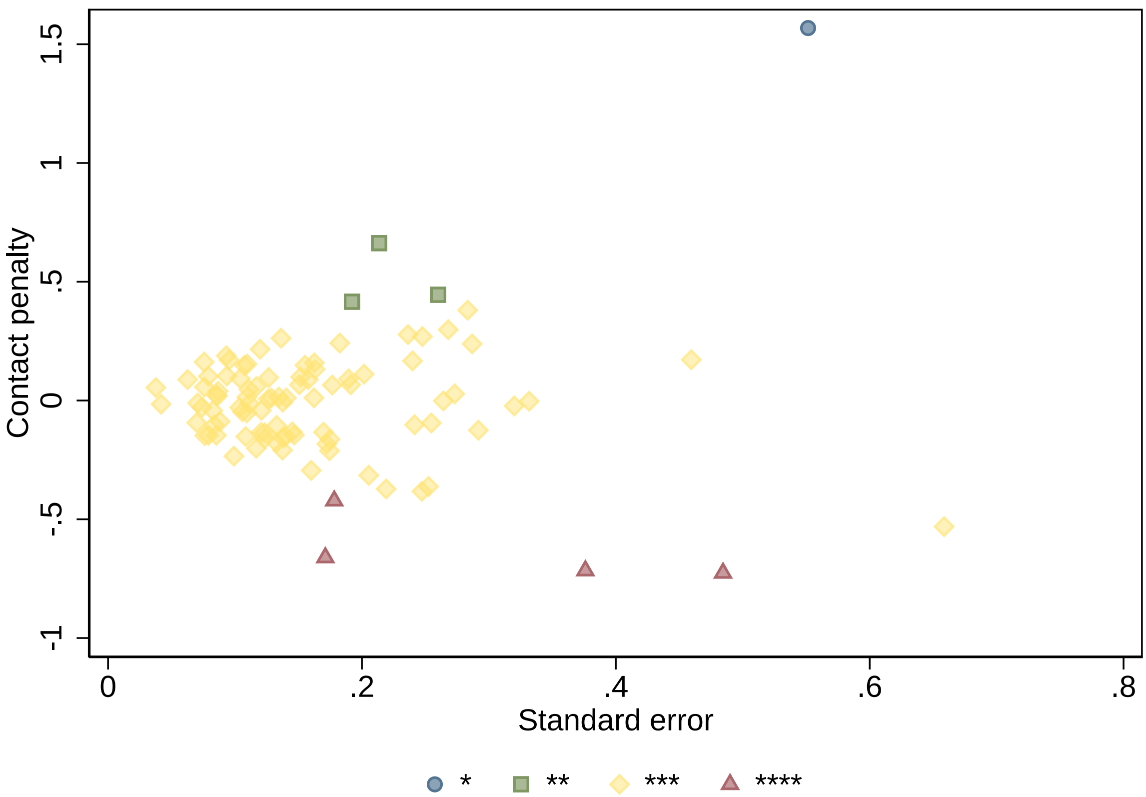
Notes: Panel (a) of this figure plots estimated gender contact gaps against their standard errors. The green line plots the conditional mean of θ_i given s_i implied by the GMM estimates. Posterior mean estimates $\bar{\theta}_i$ from the baseline model are superimposed on this panel to illustrate EB shrinkage of contact gaps towards the conditional mean. Panel (b) plots studentized contact gaps $\hat{T}_i$ against standard errors. The green line plots the relationship implied by the model.

Figure F5: Race: Contact penalties, standard errors, and report card grades



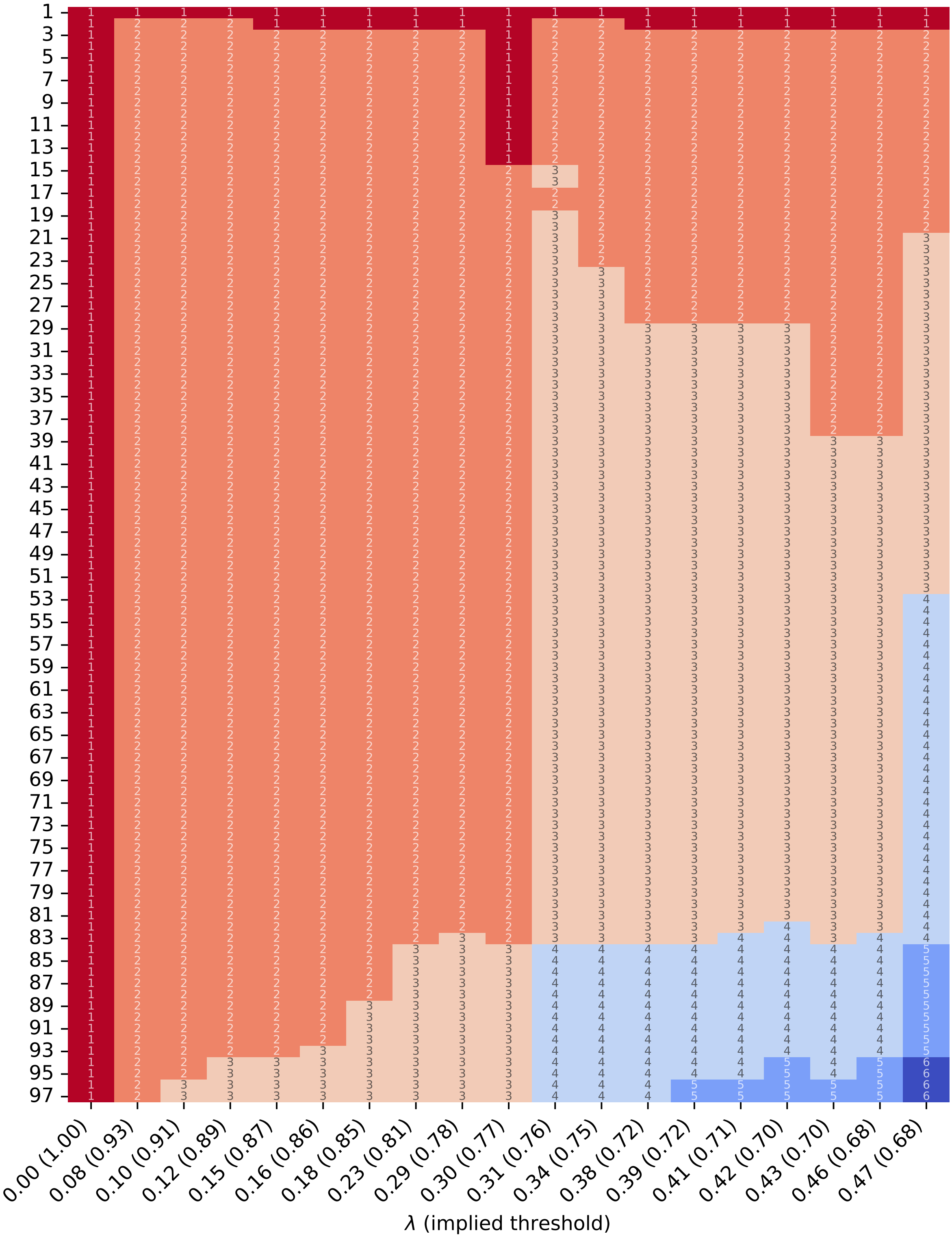
Notes: This figure plots the estimated contact penalty for a Black name at each firm against the standard error of the contact penalty estimate. The shape and color of each point indicate the grade assigned to the firm using the same specification as Figure 7.

Figure F6: Gender: Contact penalties, standard errors, and report card grades



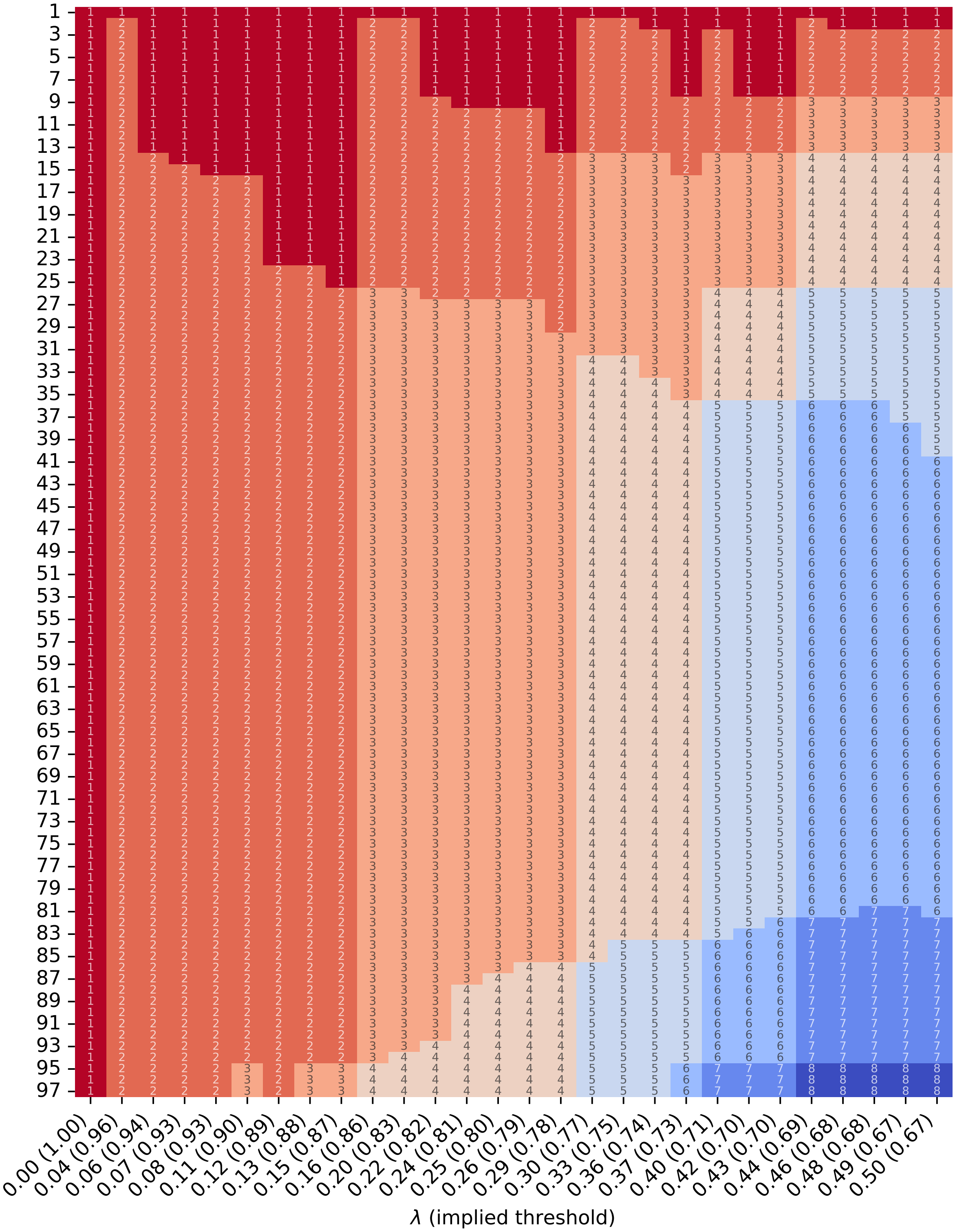
Notes: This figure plots the estimated gender contact difference for each firm against the standard error of the contact difference estimate. The shape and color of each point indicate the grade assigned to the firm using the same specification as Figure 14.

Figure F7: Race: All firm grades (baseline)



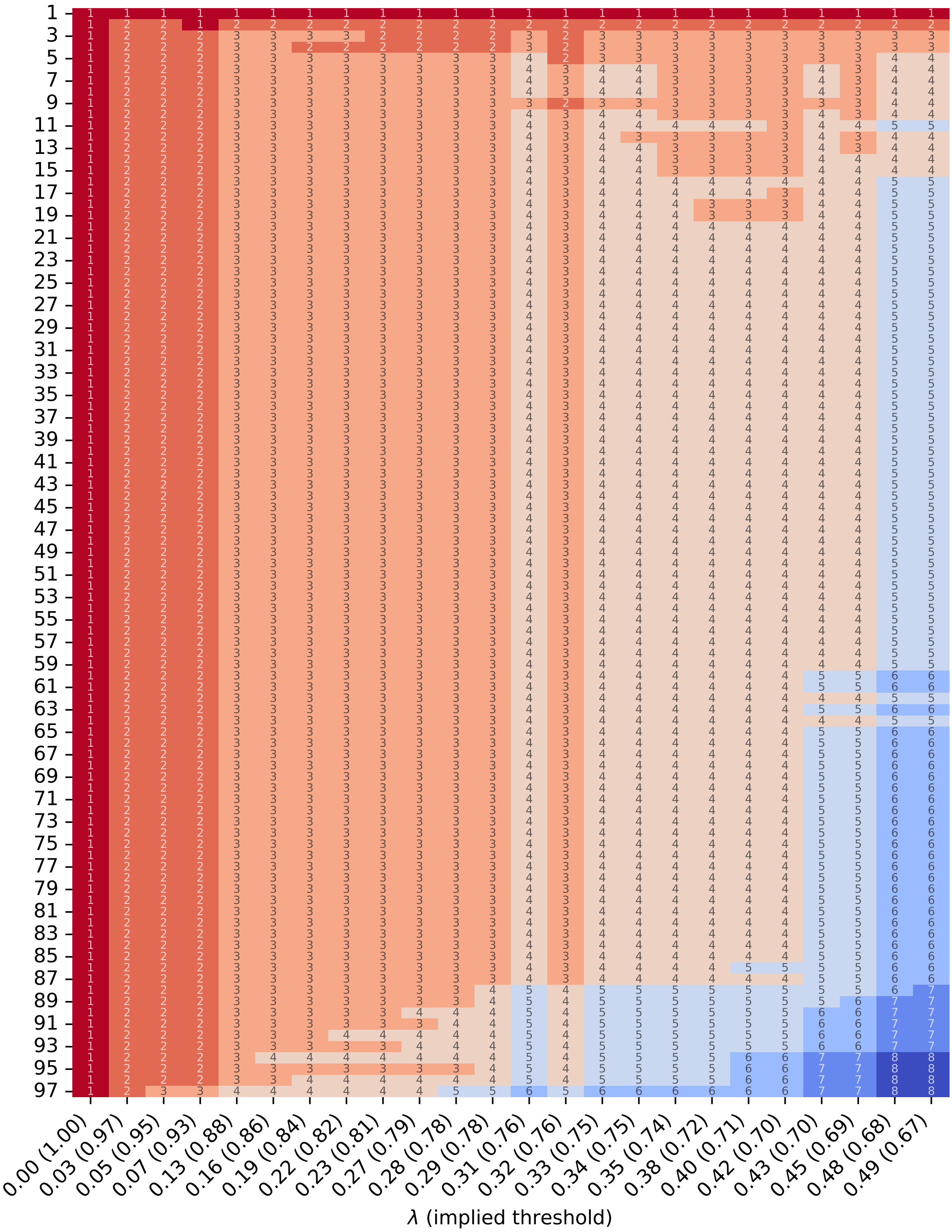
Notes: This figure shows race grade assignments for each value of $\lambda <= 0.5$ from a baseline model without industry effects. To increase readability, only the smallest λ that yields each unique set of grades is retained. The horizontal axis reports this λ and the corresponding value of $1/(1+\lambda)$, which is the implied posterior threshold for pairwise ranking decisions. Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade.

Figure F8: Race: All firm grades (industry effects)



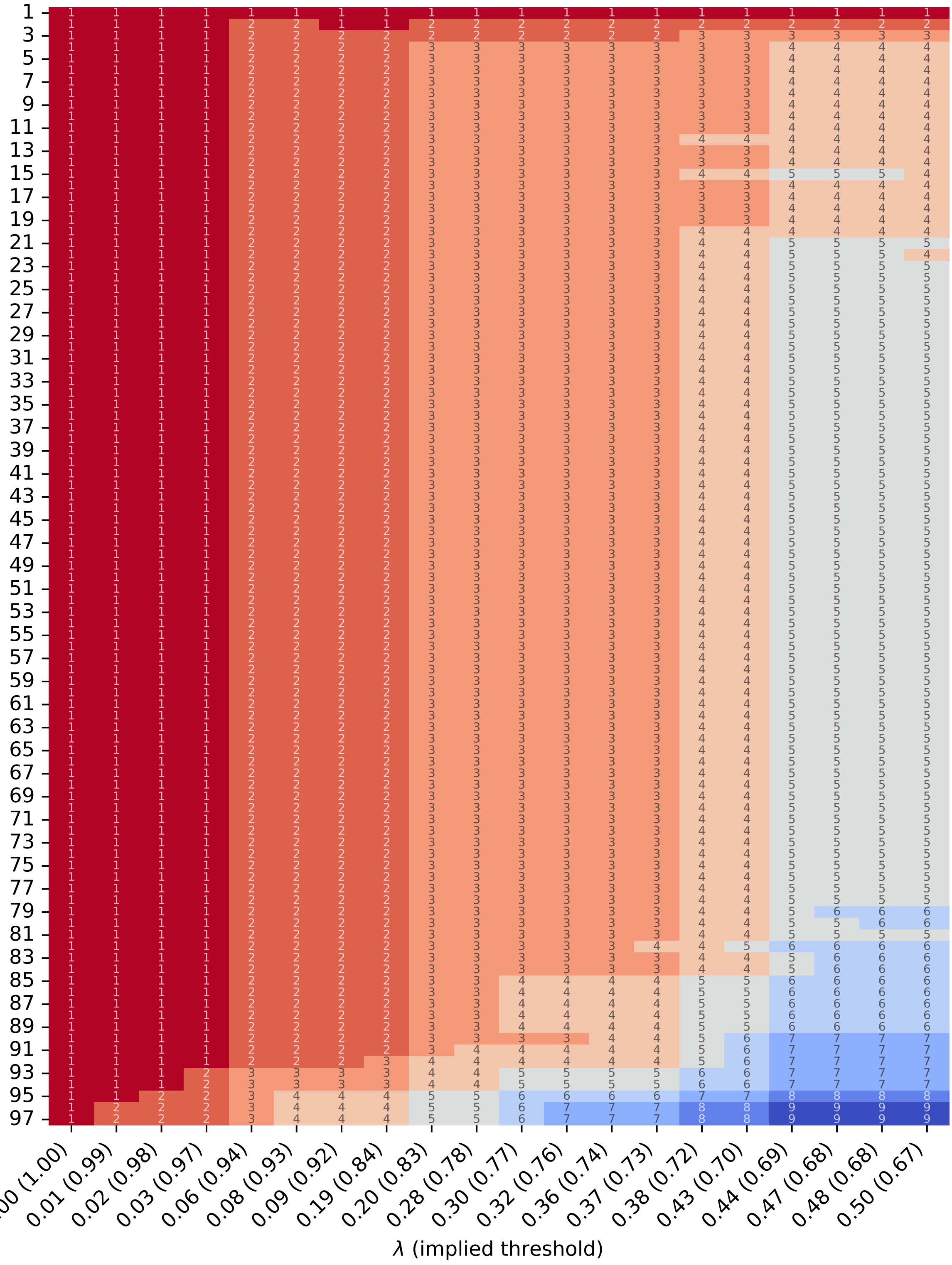
Notes: This figure shows race grade assignments for each value of $\lambda \leq 0.5$ from a model with industry effects. To increase readability, only the smallest λ that yields each unique set of grades is retained. The horizontal axis reports this λ and the corresponding value of $1/(1+\lambda)$, which is the implied posterior threshold for pairwise ranking decisions. Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade.

Figure F9: Gender: All firm grades (baseline)



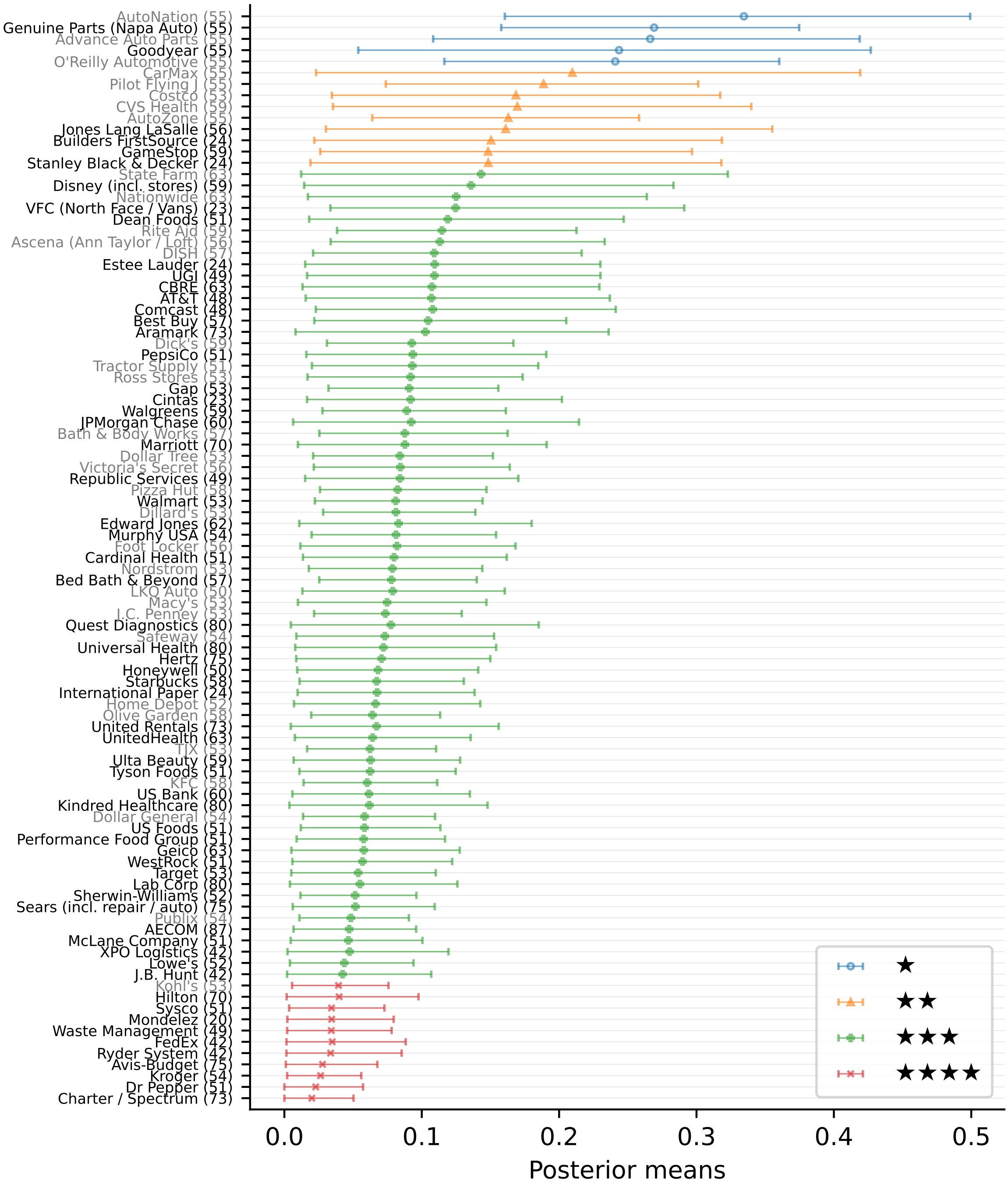
Notes: This figure shows gender grade assignments for each value of $\lambda <= 0.5$ from a baseline model without industry effects. To increase readability, only the smallest λ that yields each unique set of grades is retained. The horizontal axis reports this λ and the corresponding value of $1/(1+\lambda)$, which is the implied posterior threshold for pairwise ranking decisions. Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade.

Figure F10: Gender: All firm grades (industry effects)



Notes: This figure shows gender grade assignments for each value of $\lambda \leq 0.5$ from a model with industry effects. To increase readability, only the smallest λ that yields each unique set of grades is retained. The horizontal axis reports this λ and the corresponding value of $1/(1+\lambda)$, which is the implied posterior threshold for pairwise ranking decisions. Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade.

Figure F11: Race report card using alternative industry codings



Notes: This figure shows posterior mean proportional contact penalties for distinctively Black names, 95% credible intervals, and assigned grades from the industry random effect model. Grades are shown for $\lambda = 0.25$, implying an 80% threshold for posterior ranking probabilities. Posterior estimates come from a model with industry effects using the same industry assignments and groupings as in Kline, Rose and Walters (2022). Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade. Firms labeled with black text are federal contractors, whereas firms in gray are not.

Figure F12: Gender report card using alternative industry codings

Notes: This figure shows posterior mean proportional gender contact differences between distinctively male and female names, 95% credible intervals, and assigned grades from the industry random effect model. Negative differences imply favoring female applications on average, while positive differences imply favoring men. Grades are shown for $\lambda = 0.25$, implying an 80% threshold for posterior ranking probabilities. Posterior estimates come from a model with industry effects using the same industry assignments and groupings as in Kline, Rose and Walters (2022). Firms are ordered by their rank under $\lambda = 1$, when each firm is assigned its own grade. Firms labeled with black text are federal contractors, whereas firms in gray are not.