SUPPLEMENTAL ONLINE APPENDIX

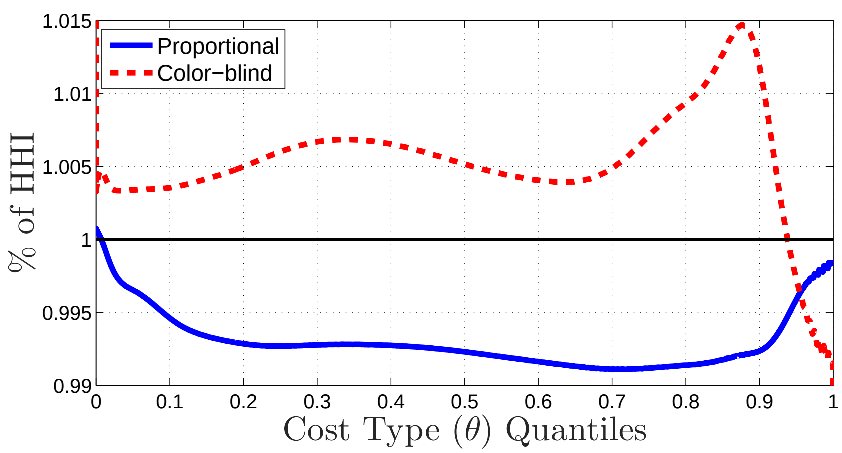
TO ACCOMPANY

Pre-College Human Capital Investment and Affirmative Action: A Structural Policy Analysis of US College Admissions

BY AARON L. BODOH-CREED AND BRENT R. HICKMAN

6.1. **Additional Figures.** Figure 12 displays the equivalent variation for the nonminority students for the color-blind and proportional quota. The horizontal axis represents quantiles of the nonminority student type distribution. The equivalent variation is of opposite sign for nonminority students, relative to minorities, but the magnitudes are much smaller. For example, the effect of a color-blind system is equivalent to a 0.5% increase in the wage for the bottom 80% of the learning cost distribution. Interestingly, we predict that nonminority students in the highest 5% of the learning cost distribution are hurt by moving to a color-blind system. Virtually all of the nonminority students are hurt by moving to a proportional quota. The middle 80% of the distribution have an equivalent variation equal to between -0.6% to -0.8% of household income, and the effect vanishes for the very highest and lowest learning cost students.

FIGURE 12. Nonminority Equivalent Variations



6.2. **Solving the Model Numerically.** Counterfactuals that compare different AA regimes necessarily require solving the model to determine the student behavior (i.e., human capital investments), which in turn determines college enrollments and final outcomes. There are two endogenous objects that need to be computed for each demographic group: the student strategies and the assignment functions that map NHC to college assignment.

We numerically approximate all four objects: two group-specific strategies and two group-specific inverse assignment functions. B-splines were used for the numerical approximations because these functions allow for accurate approximations of both a function and it's derivatives using relatively few parameters. We chose to approximate the inverse assignment function because while the range of these functions (the colleges) are known ex ante, the domain (the noisy human capitals) is endogenous. We used six knots in our approximation, but found that using up to 20 knots had a negligible effect on our results. We insist that the strategies be consistent with the first order conditions for the student's decision problem in the AA regime of interest (Equation 1). The assignment functions (i.e., the inverse of the inverse assignment function approximated by our B-splines) are required to be consistent with the human capital choices of the students.[17]

We solved the model using an optimization algorithm that tries to minimize the inconsistencies between the approximated objects and the theoretical analogs described above. The optimization algorithm adjusts the variables describing all four of the numerical approximations simultaneously. Our first step within each iteration is to compute the *induced inverse assignment function* for each group, which is simply the inverse of the assignment function generated by the approximate student strategies and the contest structure generated by the form of AA we are studying. We then use an L_2 penalty function for the distance between the B-spline fit of the inverse assignment function and the induced inverse assignment function, which is computed at 50 points evenly spaced across the support of the distribution of college qualities. The measure applied in the L_2 norm is the estimated CDF of the distribution of college qualities available to that demographic group.[18]

We now turn to our metric of the inconsistency between the approximate and exact equilibrium strategies. Our third step within each iteration is to compute the assignment function implied by our B-spline of the inverse assignment function. The fourth step of our algorithm is to calculate the first order condition given the assignment function for each group implied by the associate d B-spline of the inverse assignment function and the B-spline of the strategy for that group. Our error function was an L_2 penalty function enforced at 50 evenly gridded values over the support of θ. The measure used in the L_2-norm is the type distribution of the respective group.

The complete objective function for the optimization problem is the sum of the penalty functions for the inverse assignment mapping and the first order condition, which we chose for simplicity and the fact that the weighting did not seem to significantly affect the optimization results. If an optimal value of 0 is found, then the approximated inverse assignment functions and the approximate strategies are consistent with the first order conditions of the decision problem. In addition, an optimal value of 0 implies that the approximation strategies and inverse assignment functions are also consistent with each other as required by equilibrium.

E-mail address: Corresponding Author (Brent Hickman): hickmanbr@gmail.com

[17]We solved for the status-quo system as a quality assurance check on our algorithms. Because quota and admissions preference schemes are outcome equivalent (Bodoh-Creed and Hickman [13]), we treated the status quo admissions preference scheme as quota wherein each group competed separately for the distribution of seats allocated to members of that group in the status quo.

[18]In the color-blind and proportional quota counterfactuals, this is the total measure of college qualities. In the status-quo model, the distribution of school available to students in a given demographic group is equal to the distribution of college qualities in which those students enroll.