Racial Screening on the Big Screen? Evidence from the Motion Picture Industry

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Introduction

- In many contexts, a decision-maker must screen applicants using only imperfect information about their quality.
  - An employer hires a job applicant.
  - An admission committee admits a candidate to freshman class.
  - A journal editor accepts an article for publication.
- The decision-maker may use information about the applicant's race or gender to guide their decision, potentially resulting in discrimination.

Econometrician's Problem

- Can only observe ex-post outcomes *of applicants that pass the screening process*: the worker's productivity, the student's grades, or the number of citations received by an article.

- Using data on the group differences in the output of applicants that pass the screening process, is it possible to assess the extent and nature of discrimination?

This Paper

- We answer this in the context of the **motion picture industry**.
  The industry
- Develop a model that allows to interpret differences in box-office revenue, conditional on production.
  - Nests three types of discrimination: employer (taste-based), customer, and statistical discrimination.
- Test for racial differences in box office revenue of almost 7000 motion pictures released between 1997 and 2017.

Model: Setup

- "White movie": a movie in which the leading roles are solely played by whites (represented as "w").
- "Non-white movie": a movie in which the leading roles also include non-whites (represented as "b").
- Log revenue for movie of type $t \in \{w, b\}$: π_t .
- Prior distribution: $\pi_t \sim N(\mu_t, \sigma^2_{\pi t})$.

Model: Information

- Producers receive offers to produce movies ("scripts"), but cannot observe revenue ex-ante.
- Instead, they observe the expected racial composition of the cast and a noisy signal of the movie's expected box office revenue (genre, director's ability, etc.), y.
- Signal is well-calibrated, but precision varies by type:

$$y \mid \pi_t \sim N(\pi_t, \sigma_{yt}^2).$$

Model: Decision to produce

- Movie is produced if expected log revenue, conditional on the signal and the movie's type, exceeds some threshold π_{0t} (*revenue threshold*):

$$E(\pi|y,t) > \pi_{0t}.$$

- Movie will be produced if and only if the signal exceeds some threshold, $\bar{y}_t$ (*signal threshold*).

$$\bar{y}_t = \pi_{0t} + (\pi_{0t} - \mu_t)\frac{\sigma^2_{yt}}{\sigma^2_{\pi t}}$$

Comparative statics

- Can calculate closed form solution for $E_t \equiv E(\pi_t|y_t > \bar{y}_t)$ and $V_t \equiv V(\pi_t|y_t > \bar{y}_t)$, mean and variance of box-office log revenue, *conditional on production*. Observed Revenue

Types of Discrimination

Type	Math Def	Exp Value	Var
Taste-based The producer bears utility cost from producing non-white movies	$\pi_{0b} > \pi_{0w}$ Production threshold is higher for non-white movies	$E_b > E_w$	$V_b < V_w$

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Customer The viewing public has a preference for white movies over non-white	$\mu_b < \mu_w$ The distribution of box-office revenue for white movies is shifted to the right	$E_b < E_w$	$V_b < V_w$

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Customer The viewing public has a preference for white movies over non-white	$\mu_b < \mu_w$ The distribution of box-office revenue for white movies is shifted to the right	$E_b < E_w$	$V_b < V_w$
Statistical Producer has "less" or "worse" information on non-white movie potential	$\sigma^2_{yb} > \sigma^2_{yw}$ Signal for non-white movies is less informative	$E_b < E_w$	$V_b > V_w$

Data

- A novel data set for almost 7000 motion pictures released in the United States between 1997 and 2017, from `www.opusdata.com`.
- Main Variables: gross box-office revenue, production costs, and the name, gender, and age of the four top-billed performers.
- Machine learning algorithm trained on the Chicago Face Database to classify artists as white or non-white (Anwar and Islam, 2017).
  ▸ Classifying movies
- Baseline: A movie is "non-white" if two of the four top billed performers are classified as non-white.

Output of facial classification

Recognize following as White

Recognize following as Non-White

Figure 1: output of facial classification

Non-white performers and the revenue distribution

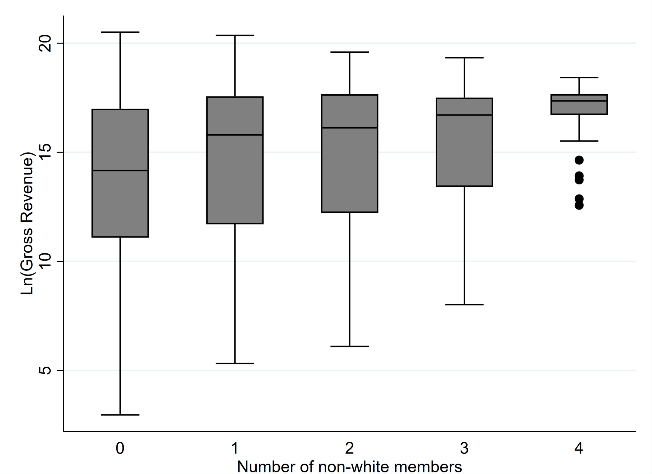

Figure 2: Box-whisker plot

The non-white revenue premium

Table 1: The non-white revenue premium

	(1)	(2)	(3)	(4)
Sample:	Full	Full	Full	Non-missing cost variable
	Ln(Gross Revenue)	Ln(Gross Revenue)	Ln(Gross Revenue)	Ln(Gross Revenue)
Race: At least two non-white	1.093***	1.058***	0.560***	0.628***
	(0.169)	(0.159)	(0.094)	(0.096)
Cast controls	N	Y	Y	Y
Movie controls	N	N	Y	Y
N	6943	6943	6943	3853
R^2	0.006	0.125	0.697	0.597

- The coefficient appears to be driven down primarily by the inclusion of the Metacritic score and the cost of production variables

Main results

- After controlling for cast characteristics and movie characteristics, clear evidence that non-white movies have higher box-office revenue (about 60 log points $\approx$ 82 %)
- Not consistent with models of customer discrimination or statistical discrimination (unless discrimination *in favor* of non-white movies, or signal by non-white movies *more* precise)
- Consistent with taste-based discrimination: non-white movies are held to a higher standard, produced only if expected revenue surpasses a higher threshold

Additional predictions

- Taste-based discrimination model also makes predictions about:
  - How the gap changes at different points of the distribution
  - Variance of box-office revenue conditional on production
- If non-white movies held to higher standards:
  - non-white premium becomes smaller at higher quantiles of the distribution
  - lower variance

Coefficients are decreasing over Quantiles

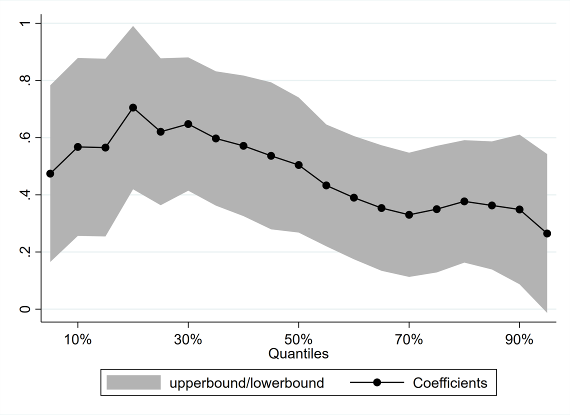

Figure 3: Quantile plots

Robustness check

Heterogeneity

- By distributor: large non-white premium for both Big-6 and Non-Big-6 distributed movies (latter slightly larger).
- By genre: results mostly driven by dramas and comedies, less so action/adventure movies.
- By year: non-white premium slightly larger in pre-2007 period than post-2007.
- By gender: non-white premium more pronounced in movies with predominantly female cast.

Conclusion

- Present a model that delivers a rich set of testable predictions to tell different discrimination sources apart
- Take predictions to the data in the context of racial differences in the U.S. motion picture industry
- Find that non-white movies earn box-office premium, especially in the left tail of the revenue distribution
- Results consistent with pure taste-based discrimination among producers.
  - Alternative explanation: systematic underestimation of non-white movie revenue potential. Is the industry surprised?

Thank You!

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Supplementary Slides

Motion picture industry

- Significant debate recently on the underrepresentation of African American actors, directors and producers in the American motion picture industry.
  - In the 2010s, only 7% of nominees for Oscars were African Americans, far less than their proportion in the population.
    Black Oscar Nominees
- Studying discrimination in the motion picture industry has one crucial advantage: a good measure of productivity (box-office revenue).

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Preview of the Results

- Movies with non-white cast earn substantially *more* at the box-office, after controlling for movie and cast characteristics.
- Results are robust to different definitions of "non-white" movie.
- Difference in box-office revenue driven by left tail of the revenue distribution: low-potential non-white movies are never produced.
- Evidence consistent with taste-based discrimination: non-white movies are held to a higher standard for production.
- Relative to white movies, non-white movies substantially overperform relative to expectations.

Literature Review

- Identifying different discrimination mechanisms in the data (Altonji and Pierret, 2001; Knowles et al., 2001; List, 2004; Charles and Guryan, 2008; Zussman, 2013; Doleac and Stein, 2013; Bohren et al., 2019)
    - Our paper: proposes a simple theoretical framework that nests customer, producer taste-based, and statistical discrimination and delivers testable predictions for each.
- Documenting racial discrimination in the movie industry (Weaver, 2011; Fowdur et al., 2012; Kuppuswamy and Younkin, 2020)
    - Our paper: corroborates Kuppuswamy and Younkin's (2020) experimental finding of no customer discrimination through machine learning approach.

Black oscar nominees

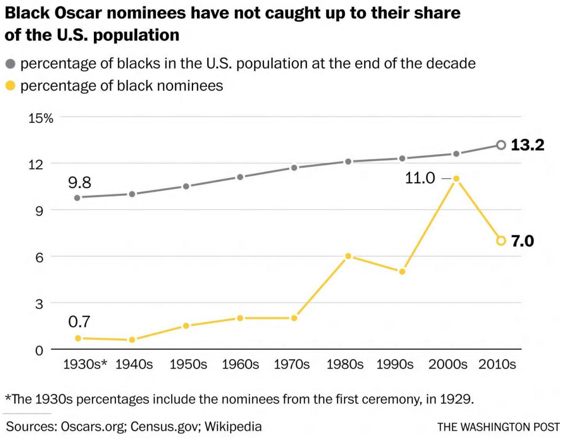

Figure 4: Black oscar nominees

Model: the signal threshold

- The signal threshold is type-specific:

$$\bar{y}_t = \pi_{0t} + (\pi_{0t} - \mu_t)\frac{\sigma_{yt}^2}{\sigma_{\pi t}^2}$$

- Comparative statics:
  - $\bar{y}_t$ increases in π_0: when the revenue threshold is high, the signal must be excellent to produce the movie.

Model: the signal threshold

- The signal threshold is type-specific:

$$\bar{y}_t = \pi_{0t} + (\pi_{0t} - \mu_t)\frac{\sigma^2_{yt}}{\sigma^2_{\pi t}}$$

- Comparative statics:
  - $\bar{y}_t$ decreases in μ_t: if movies are on average high-revenue, can afford to produce even if bad signal.

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Model: the signal threshold

- The signal threshold is type-specific:

$$\bar{y}_t = \pi_{0t} + (\pi_{0t} - \mu_t)\frac{\sigma^2_{yt}}{\sigma^2_{\pi t}}$$

- Comparative statics:

  - If $\pi_0 > \mu_t$, $\bar{y}_t$ increases in σ^2_{yt}: If the signal is imprecise and I only want to produce very high-quality movies ($\pi_0 > \mu_t$), then set a high threshold to make sure I pick the right tail.

Model: the signal threshold

- The signal threshold is type-specific:

$$\bar{y}_t = \pi_{0t} + (\pi_{0t} - \mu_t)\frac{\sigma^2_{yt}}{\sigma^2_{\pi t}}$$

- Comparative statics:

  - If $\pi_0 < \mu_t$, $\bar{y}_t$ decreases in σ^2_{yt}: If the signal is imprecise and I only want to make sure that I weed out shallow quality movies ($\pi_0 < \mu_t$), then I can lower threshold and still get movies that are OK.

Observed revenue

- We only observe the box-office revenue of movies that are produced and released to the public.
- Expected value and variance of box-office revenue, conditional on production:

$$E_t \equiv E(\pi_t \mid y_t > \bar{y}_t) = \mu_t + \sigma \frac{\phi(\frac{\pi_0 - \mu_t}{\sigma})}{1 - \Phi(\frac{\pi_0 - \mu_t}{\sigma})}$$

$$V_t \equiv var(\pi_t \mid y_t > \bar{y}_t)$$

where $\sigma = \frac{\sigma^2_{\pi t}}{\sqrt{\sigma^2_{\pi t} + \sigma^2_{yt}}}$ and $\lambda(x) = \frac{\phi(x)}{(1 - \Phi(x))}$. Comparative statics

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Comparative Statics in Observed Revenue

- $V_t = \sigma^2(1 + \sigma_{yt}^2 + \lambda(\frac{\pi_{0t} - \mu_t}{\sigma})(\frac{\pi_{0t} - \mu_t}{\sigma} - \lambda(\frac{\pi_{0t} - \mu_t}{\sigma})))$
- One can show that E_t expected observed revenue:
  1. Increases in π_{0t}.
  2. Increase in μ_t.
  3. Decreases in σ_{yt}, regardless of whether $\pi_{0t} \lesseqgtr \mu_t$.
- First two results intuitively obvious.
- Intuition for third result: if signal is perfectly uninformative, on average one will produce an average movie, even if threshold for producing is higher.

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Classifying Movies

- Obtained facial image of each performer by scraping the popular website `http://www.imdb.com`.
- Machine learning algorithm for classifying each image as either "white" or non-white.
  - Convolutional neural network and support vector machine (Anwar and Islam, 2017).
  - Training dataset: Chicago Face Database (CFD).
  - The non-white category includes mostly African-Americans, but may also include Asians, Hispanics, and other ethnicities.
- Classification accuracy of more than 95% in our validation data set, considered quite good in the image classification literature.

Sample from CFD

Figure 5: small sample of training dataset

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Variable definitions

- We define a movie as "non-white" if two of the four top billed performers are classified as non-white.
  - Also, robustness to other definitions of "non-white" movies
- Regression equation:

$$lny_t = \beta_0 + \beta_1 D_t + \beta_2 X_t + \delta_t + \epsilon_t$$

  - y_t: real domestic box-office revenue, in 2005 dollars
  - D_t: "non-white" dummy
  - X_t control variables, contains cast (average age, gender, star power) and movie (production budget, MPAA rating, Metacritic score, run time, genre, indicator for "Big 6" studio) characteristics
  - δ_t year of release fixed effects

Summary Statistics

Table 2: Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
PANEL A: Classification of movies by type					
Share of non-white performers	7,840	0.11	0.22	0	1
At least one non-white	7,840	0.23	0.42	0	1
At least two non-whites	7,840	0.05	0.23	0	1
Distribution of the number of non-white performers (percentages):					
0	77.2%				
1	17.3				
2	3.6				
3	1.6				
4	0.3				

Robustness: different definitions of "non-white" movies

Table 3: Alternative definitions of "non-white" movies

	(1)	(2)	(3)	(4)
Race:	At least two non-white	At least one non-white	Share of non-white	Leading role is non-white
	Ln(Gross Revenue)	Ln(Gross Revenue)	Ln(Gross revenue)	Ln(Gross revenue)
Race	0.560***	0.221***	0.623***	0.436***
	(0.094)	(0.053)	(0.101)	(0.075)
Q10	0.574***	0.191**	0.642***	0.417***
	(0.164)	(0.097)	(0.178)	(0.135)
Q25	0.613***	0.227***	0.740***	0.430***
	(0.131)	(0.075)	(0.139)	(0.107)
Q50	0.492***	0.184***	0.576***	0.315***
	(0.121)	(0.069)	(0.135)	(0.097)
Q75	0.344***	0.181***	0.424***	0.312***
	(0.111)	(0.064)	(0.121)	(0.087)
Q90	0.350***	0.217**	0.509***	0.325***
	(0.134)	(0.073)	(0.139)	(0.109)
Cast's control	Y	Y	Y	Y
Movie's control	Y	Y	Y	Y
N	6943	6943	6943	6943

Robustness: different definitions of "non-white" movies

- Non-white revenue premium between 22 and 62 log points.
- Smaller premium and less clear pattern of declining quantile coefficients if only one non-white performer. Tokenism?

Robustness: different dependent variables

Table 4: Different dependent variables

Sample:	(1) Non-missing cost variable Ln(Profit Margin+1)	(2) Non-missing cost variable Profit(in million)	(3) Non-missing cost variable Revenue(in million)
Race: At least two non-white	0.660***	10.57***	4.76
	(0.098)	(3.19)	(3.33)
Q10	0.591**	7.09***	3.96***
	(0.231)	(2.64)	(1.25)
Q25	0.524***	8.11***	6.31***
	(0.142)	(2.00)	(1.86)
Q50	0.576***	9.42***	5.64**
	(0.092)	(1.99)	(2.68)
Q75	0.450***	12.56***	8.40*
	(0.088)	(3.56)	(4.71)
Q90	0.399***	13.21*	9.18
	(0.116)	(7.93)	(8.96)
Cast's control	Y	Y	Y
Movie's control	Y	Y	Y
N	3853	3853	3853

Robustness: different dependent variables

- Profits instead of revenue: similar results.
- Functional form is important.

Variance of box-office revenue.

Table 5: Breusch-Pagan regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Race definition	At least two	At least two	At least two	At least one	Share	Leading role
	Dependent variable: Ln(residual square)					
Race	-0.493***	-0.490***	-0.340***	-0.074	-0.334***	-0.104
	(0.116)	(0.116)	(0.110)	(0.061)	(0.118)	(0.088)
Cast's Control		Y	Y	Y	Y	Y
Movie's Control			Y	Y	Y	Y
N	6943	6943	6943	6943	6943	6943
R^2	0.003	0.012	0.121	0.122	0.123	0.120

"Non-white" movies have lower residual variance, confirming box-whisker plots.

Robustness of variance test

Table 6: Variance regression respect to different dependent variables

	(1) Ln(Profit Margin+1)	(2) Profit(in million)	(3) Revenue(in million)
Race: At least two non-white	-0.289*	-0.124	-0.053
	(0.149)	(0.152)	(0.145)
Cast Controls	Y	Y	Y
Movie Controls	Y	Y	Y
N	3853	3853	3853
R^2	0.133	0.132	0.144

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Discussion

- Taste-based discrimination or incorrect beliefs: why do they survive in the long run?
- Industry is concentrated, (Big-6 have 80% of market share), but presumably lots of competition between the Big-6.
- Are there enough opportunities for learning?

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Is the Industry Surprised?

- Is it taste-based discrimination or incorrect beliefs?
- Test for incorrect beliefs in industry: look at distributors' decision making.
- Conjecture: distributors choose number of screens as function of expected customer demand.
  - If non-white movies have same level of customer demand but are displayed in fewer theaters, distributors must underestimate revenue potential (Moretti, 2011).

Testing For Incorrect Beliefs

- Regress log of first-weekend revenues on log number of theaters
  - $R^2 = 89\%$, stable as movie and cast controls are added
- Find that residuals for non-white movies are significantly larger than those for white movies
  - Average residual for white movies approximately zero

▸ Discussion