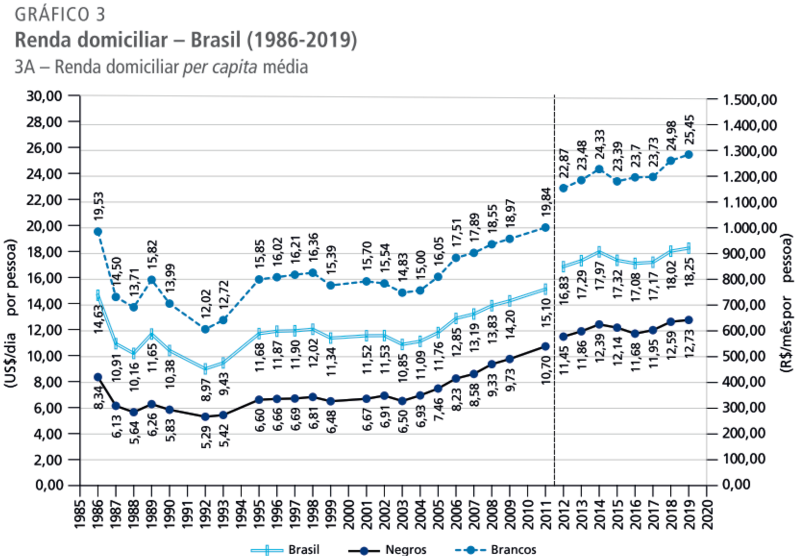
Desenvolvimento Econômico

Aula 5: Desigualdade, Gênero, Raça

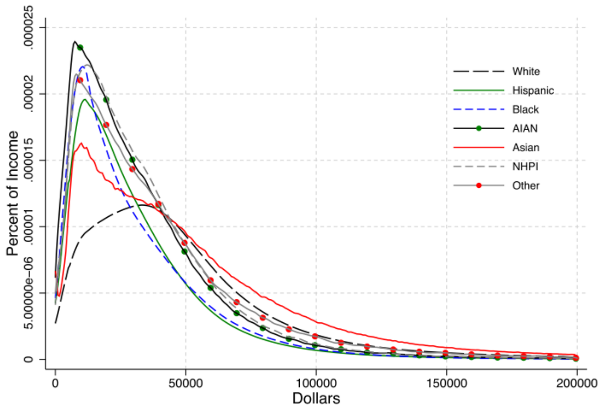
Ricardo Dahis

Desigualdade de renda no Brasil (Osorio, 2021)



Desigualdade de renda nos EUA (Akee et al., 2019)

Figure 2: Kernel Density in 2014 by Group



	White	Hispanic	Black	AIAN	Asian	NHPI	Other
Full sample mean	61,445	34,164	32,578	36,369	64,368	37,719	48,025
AGI<=200,000 mean	47,430	31,134	30,859	32,847	49,360	34,707	38,602

Source: Race and ethnicity file–Form 1040 data, 2000 and 2014.

Hoje

Origem histórica e persistência

Discriminação

Identidade

Conclusão

Hoje

Origem histórica e persistência

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Origem histórica e persistência

- Nunn (2008) estuda os efeitos do tráfico escravo em renda nas áreas de origem hoje (Africa).
- Usa dados principalmente do Trans-Atlantic Slave Trade Database construído por Eltis et al. (1999)
  - 34,584 viagens entre 1514 e 1866
- Literatura subsequente: Nunn and Wantchekon (2011), Michalopoulos and Papaioannou (2013)

Efeitos de tráfico escravo nas áreas de origem (Nunn, 2008)

TABLE IV
ESTIMATES OF THE RELATIONSHIP BETWEEN SLAVE EXPORTS AND INCOME

	(1)	(2)	(3)	(4)
Second Stage. Dependent variable is log income in 2000, ln y				
ln(exports/area)	−0.208***	−0.201***	−0.286*	−0.248***
	(0.053)	(0.047)	(0.153)	(0.071)
	[−0.51, −0.14]	[−0.42, −0.13]	[−∞, +∞]	[−0.62, −0.12]
Colonizer fixed effects	No	Yes	Yes	Yes
Geography controls	No	No	Yes	Yes
Restricted sample	No	No	No	Yes
F-stat	15.4	4.32	1.73	2.17
Number of obs.	52	52	52	42
First Stage. Dependent variable is slave exports, ln(exports/area)				
Atlantic distance	−1.31***	−1.74***	−1.32*	−1.69**
	(0.357)	(0.425)	(0.761)	(0.680)
Indian distance	−1.10***	−1.43***	−1.08	−1.57*
	(0.380)	(0.531)	(0.697)	(0.801)
Saharan distance	−2.43***	−3.00***	−1.14	−4.08**
	(0.823)	(1.05)	(1.59)	(1.55)
Red Sea distance	−0.002	−0.152	−1.22	2.13
	(0.710)	(0.813)	(1.82)	(2.40)
F-stat	4.55	2.38	1.82	4.01
Colonizer fixed effects	No	Yes	Yes	Yes
Geography controls	No	No	Yes	Yes
Restricted sample	No	No	No	Yes
Hausman test (p-value)	.02	.01	.02	.04
Sargan test (p-value)	.18	.30	.65	.51

Mecanismos?

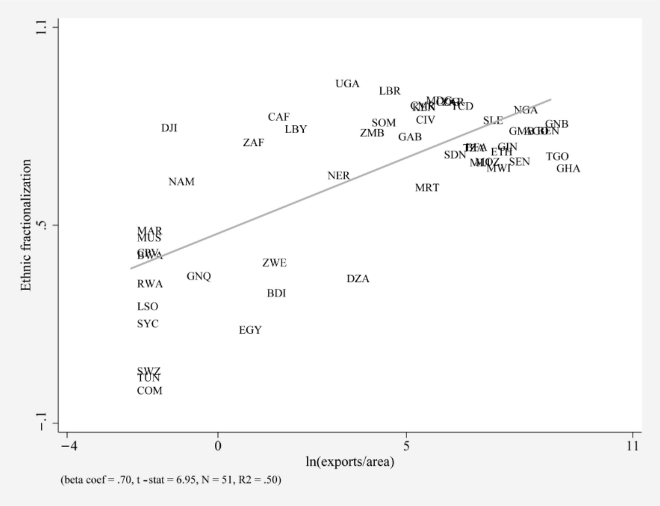


FIGURE VI
Relationship between Slave Exports and Current Ethnic Fractionalization

No Brasil e EUA, trajetórias segregadas

- Escravidão carrega consequências (diretas e indiretas) até hoje.
- Uma história de políticas segregacionistas: *Jim Crow*, *redlining*.
- Equalização de direitos e convergência social acontece em ritmo lento.
- Derenoncourt (2022) estuda as consequências da "Grande Migração"nos EUA, incluindo a reação de brancos e comunidades locais.

Derenoncourt (2022) Can You Move to Opportunity? Evidence from the Great Migration

- Artigo mostra que as respostas das cidades do norte à Grande Migração entre 1940 e 1970 acabaram reduzindo os ganhos de crescer nos locais de destino.
- Estratégia empírica
  - "The empirical strategy makes use of the fact that Black southern migrants settled in northern cities where previous migrants from their communities had moved, giving rise to highly specific linkages between southern locations and northern destinations."
  - Shift-share: "I combine information on pre-1940 Black southern migrants' location choices with supply-side variation in county out-migration from 1940 to 1970, predicted from southern economic variables."

Prevendo população negra

ing. More precisely, I replace the numerator in equation (1) with the predicted, as opposed to actual, increase in the Black population:

$$\text{(2)} \qquad \text{Predicted Black pop}_{CZ}^{1940\text{–}1970} = \frac{\widehat{\Delta b}_{\text{urban},CZ}^{1940\text{–}1970}}{\text{pop}_{\text{urban},CZ}^{1940}},$$

where $\widehat{\Delta b}_{\text{urban},CZ}^{1940-1970}$ denotes the predicted increase, which I define as follows:

$$\text{(3)} \qquad \widehat{\Delta b}_{\text{urban},CZ}^{1940\text{–}1970} = \sum_{j \in S} \sum_{c \in CZ} \omega_{jc}^{1935\text{–}1940} \times \hat{m}_j^{1940\text{–}1970}.$$

Prevendo migração

The term $\hat{m}_j$ is predicted Black migration from southern county j over the decades 1940–1970, and ω_{jc} is the share of recently migrated pre-1940 Black southern migrants from county j living in city c in 1940. The term $\hat{m}_j^{1940\text{–}1970}$ consists of the sum of fitted values of decadal predictions of southern county net migration (from 1940 to 1950, 1950 to 1960, and 1960 to 1970) using lagged southern economic predictors of migration:

$$\hat{m}_j^{1940\text{–}1970} = \sum_{t=1950}^{1970} \widehat{\text{mig rate}}_{jt} \times \text{Black pop}_{jt},$$

where fitted values, $\widehat{\text{mig rate}}_{jt} = \text{mig rate}_{jt} - \varepsilon_{jt}$, come from the following prediction of net migration rates:

$$\text{mig rate}_{jt} = \beta_0 + Z'_{jt-10}\beta_1 + \varepsilon_{jt}.$$

$$\bar{y}_{p,CZ} = \alpha + \beta GM_{CZ} + \mathbb{X}'_{CZ}\Gamma + \varepsilon_{CZ} \tag{4}$$

$$\text{First Stage:} \quad GM_{CZ} = \gamma + \delta\widehat{GM}_{CZ} + \mathbb{X}'_{CZ}\mu + \epsilon_{CZ}. \tag{5}$$

Segundo estágio

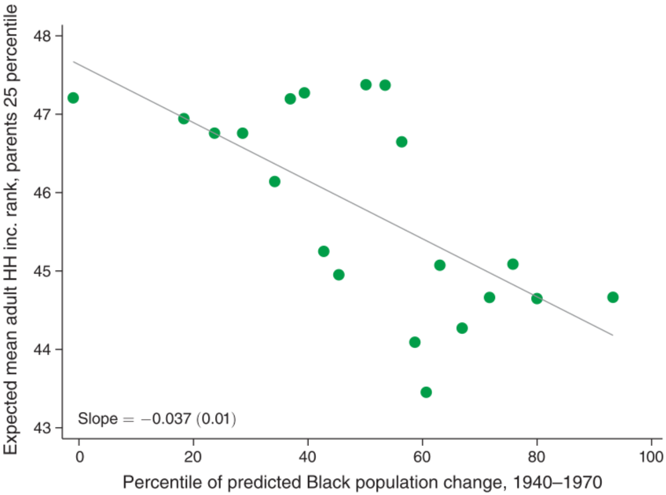


Figure 6. Great Migration Reduced Average Upward Mobility in Northern CZs

Hoje

Discriminação

1. Como medir discriminação?
2. Efeitos de discriminação
3. Discriminação explica disparidades raciais?

Medindo discriminação

- Desafio metodológico
  - Viés de variável omitida
  - Problema de auto-seleção das minorias
  - Variáveis de controle podem ter sido afetadas por discriminação (Guryan and Charles, 2013)
- Solução
  - Auditoria
  - Correspondência

Estudos de auditoria

- Compra de carros (Ayres and Siegelman, 1995)
- Aluguel de apartamento (Ahmed and Hammarstedt, 2008)
- Antecedentes criminais e *callback* (Pager, 2003)
- Tratamento médico (Schulman et al., 1999)
- Problemas
  - Auditores não são idênticos
  - Não é double-blind (auditor sabe o objetivo do estudo)

Estudos com correspondências

- Cria CVs falsos
- Vantagens
  - Candidatos perfeitamente comparáveis
  - Amostra maior
- Revisão da literatura de experimentos de campo em discriminação: Bertrand and Duflo (2017)
- Bertrand and Mullainathan (2004)
  - CVs dos homens brancos mais qualificados recebiam 30% mais chamada que CVs de homens brancos com menos qualificação
  - Mas esse efeito não aparece para homens negros = gap salarial aumenta com mais qualificação
  - Preferências lexicográficas?

Resultados (Bertrand and Mullainathan, 2004)

TABLE 5—EFFECT OF RESUME CHARACTERISTICS ON LIKELIHOOD OF CALLBACK

Dependent Variable: Callback Dummy Sample:	All resumes	White names	African-American names
Years of experience (*10)	0.07	0.13	0.02
	(0.03)	(0.04)	(0.03)
Years of experience^2 (*100)	−0.02	−0.04	−0.00
	(0.01)	(0.01)	(0.01)
Volunteering? (Y = 1)	−0.01	−0.01	0.01
	(0.01)	(0.01)	(0.01)
Military experience? (Y = 1)	−0.00	0.02	−0.01
	(0.01)	(0.03)	(0.02)
E-mail? (Y = 1)	0.02	0.03	−0.00
	(0.01)	(0.01)	(0.01)
Employment holes? (Y = 1)	0.02	0.03	0.01
	(0.01)	(0.02)	(0.01)
Work in school? (Y = 1)	0.01	0.02	−0.00
	(0.01)	(0.01)	(0.01)
Honors? (Y = 1)	0.05	0.06	0.03
	(0.02)	(0.03)	(0.02)
Computer skills? (Y = 1)	−0.02	−0.04	−0.00
	(0.01)	(0.02)	(0.01)
Special skills? (Y = 1)	0.05	0.06	0.04
	(0.01)	(0.02)	(0.01)
Ho: Resume characteristics effects are all zero (*p*-value)	54.50 (0.0000)	57.59 (0.0000)	23.85 (0.0080)
Standard deviation of predicted callback	0.047	0.062	0.037
Sample size	4,870	2,435	2,435

Estudos com correspondências

- Efeito para além do mercado de trabalho
  - Empréstimos (Pope and Sydnor, 2011)
- Críticas:
  - Vagas muitas vezes são preenchidas via social network (e não anúncio)
  - Pessoas otimizam a estratégia de procurar emprego
  - Só mede discriminação para entrar, e não dentro da firma (ex: promoção)
  - Questões éticas: usar tempo de pessoas que não sabem que estão participando de um estudo

Métodos para medir discriminação

1. Implicit Association Tests (IATs)
   - Boa medida da propensão a discriminar
   - Poucos estudos com evidência em campo (Green et al., 2007)
   - Exemplos
     - Julgamento negativo sobre comportamento ambíguo de negros (Rudman and Lee, 2002)
     - Comportamento não-verbal mais agressivo (McConnell and Leibold, 2001)
     - Mais rigoroso com agressividade em negros do que em brancos (Hugenberg and Bodenhausen, 2004)

Métodos para medir discriminação

2. Propensão a pagar
   - Testar predição de Becker (utilidade em discriminar)
   - Crianças estão dispostas a abrir mão de prêmio para socializar com crianças ricas ao invés de pobres (Rao, 2019)

3. Aleatorização de lista
   - Medir discriminação a nível do grupo
   - Consegue capturar o que não é reportado em surveys usuais (Kuklinski et al., 1997; Martinez and Craig, 2010; Holbrook and Krosnick, 2010; Tsuchiya et al., 2007)
   - Ainda pouco usado por economistas (Karlan and Zinman, 2012)

Efeitos de discriminação: profecia auto-realizada

- Lundberg and Startz (1983) e Coate and Loury (1993)
  - Mostraram como a discriminação estatística poderia deprimir os investimentos em habilidades das minorias, levando as minorias a acreditar corretamente que esses investimentos não seriam totalmente recompensados.
  - Como resultado, a discriminação estatística pode levar a uma profecia auto-realizável em que as crenças prévias adversas dos empregadores sobre os níveis de habilidade das minorias são autoconfirmadas em equilíbrio.
- Evidência supermercado na França (Glover et al., 2017)
  - Performance é endogenamente menor quando tem discriminação

TABLE III

EFFECT OF MANAGER BIAS ON TIME SPENT AT WORK

Panel A: Dependent variable: absence indicator				
Minority worker × manager bias	0.0098**	0.0095**	0.0117***	0.0118***
	(0.0039)	(0.0040)	(0.0042)	(0.0043)
Manager bias	−0.0021	−0.0021	−0.0050	−0.0052
	(0.0031)	(0.0032)	(0.0040)	(0.0042)
Minority worker × minority manager				0.0081
				(0.0972)
Minority manager				−0.0057
				(0.0153)
Observations	4,371	4,371	4,371	4,371
Dependent variable mean	0.0162	0.0162	0.0162	0.0162
R-squared	0.0005	0.0031	0.0835	0.0835
Panel B: Dependent variable: minutes worked in excess of schedule				
Minority worker × manager bias	−3.295**	−3.279**	−3.327*	−3.237*
	(1.550)	(1.588)	(1.687)	(1.678)
Manager bias	−0.002	−0.002	−0.005	−0.005
	(1.141)	(1.167)	(0.969)	(1.009)
Minority worker × minority nanager				0.349
				(10.501)
Minority manager				−3.712
				(4.592)
Observations	4,163	4,163	4,163	4,163
Dependent variable mean	−0.068	−0.068	−0.068	−0.068
R-squared	0.001	0.008	0.129	0.129
Individual fixed effects	Yes	Yes	Yes	Yes
Day of the week fixed effects	No	Yes	No	No
Morning/evening fixed effects	No	Yes	Yes	Yes
Date fixed effects	No	No	Yes	Yes

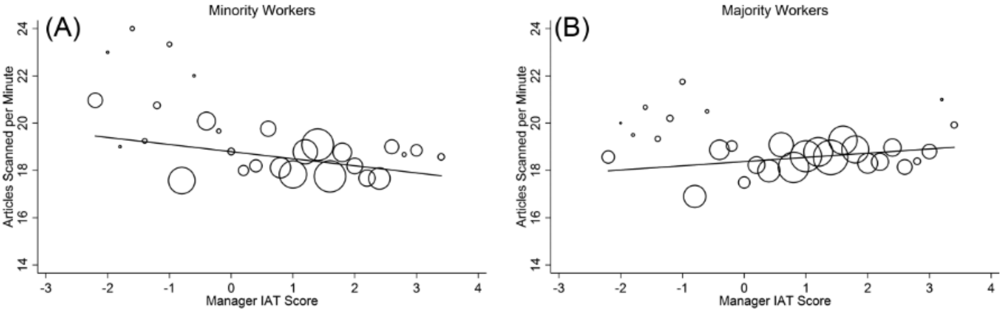


FIGURE I

Manager Bias and Worker Performance

TABLE V

WORKER-MANAGER AFFECTION AND TASK ASSIGNMENT

Panel A: Worker-manager affection

	Manager liked you best	Manager most likely to recommend you for promotion	You enjoyed working with manager best	Manager initially made you feel most confident
Minority worker × manager bias	0.019	0.078	0.243	0.194
	(0.246)	(0.212)	(0.234)	(0.196)
Manager bias	0.152	0.251*	−0.061	0.134
	(0.131)	(0.148)	(0.162)	(0.127)
Observations	3,036	2,862	3,209	3,189
Dependent variable mean	3.991	4.053	4.062	4.073
R-squared	0.015	0.042	0.010	0.026

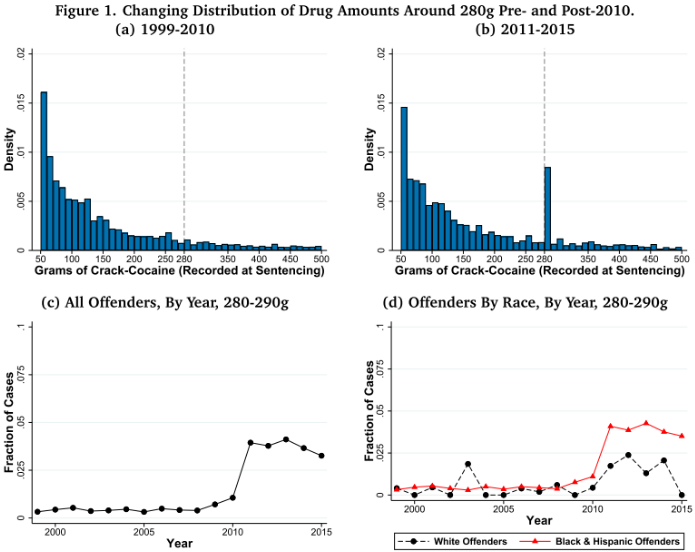
Panel B: Task assignment

	Manager assigned to preferred register type	Manager assigned best breaks	Management of lines and customer flows encouraged performance	Manager assigned to fewest cleaning duties
Minority worker × manager bias	−0.035	0.146	−0.153	0.673***
	(0.391)	(0.469)	(0.308)	(0.189)
Manager bias	0.021	−0.083	0.129	−0.276
	(0.157)	(0.146)	(0.137)	(0.182)
Observations	2,288	2,553	2,864	2,235
Dependent variable mean	4.010	3.922	4.215	3.373
R-squared	0.002	0.008	0.018	0.045

Efeitos de discriminação: justiça

- A pena para crimes contra brancos é mais severa do que para crime contra negros (Alesina and La Ferrara, 2014)
- Taxa de encarceramento é maior se o criminoso é negro (Abrams et al., 2012)
- Não ter negros no juri aumenta em 16 pp a chance de condenar um negro (Anwar et al., 2012)
  - Efeito some se tem pelo menos 1 negro no juri
- Discricionariedade do promotor (Tuttle, 2021)

Sentenças por porte de craque e cocaína (Tuttle, 2021)



Discriminação

- Discriminação explica disparidades raciais?
- Fryer (2011) faz exercício de decomposição.
  - Segue as coortes de 1979 e 1997 na NLSY nos EUA.
- Argumenta que o diferencial que importa é em educação e oportunidades.
  - "Important critiques such as racial bias in the achievement measure (Darity and Mason, 1998; Jencks, 1998), labor market dropouts, or the potential that forward-looking minorities underinvest in human capital because they anticipate discrimination in the market cannot explain the stark results."

Discriminação explica disparidades raciais?

Table 1 The importance of educational achievement on racial differences in labor market outcomes (NLSY79).

	Wage				Unemployment			
	Men		Women		Men		Women	
Black	−0.394	−0.109	−0.131	0.127	2.312	1.332	3.779	2.901
	(0.043)	(0.046)	(0.043)	(0.046)	(0.642)	(0.384)	(1.160)	(1.042)
Hispanic	−0.148	0.039	−0.060	0.161	2.170	1.529	2.759	2.181
	(0.049)	(0.047)	(0.051)	(0.051)	(0.691)	(0.485)	(0.973)	(0.871)
Age	0.027	0.012	−0.011	0.016	1.191	1.202	0.956	0.941
	(0.023)	(0.022)	(0.024)	(0.022)	(0.175)	(0.178)	(0.131)	(0.133)
AFQT		0.270		0.288		0.561		0.735
		(0.021)		(0.023)		(0.082)		(0.123)
$AFQT^2$		0.039		−0.009		1.005		1.276
		(0.019)		(0.020)		(0.151)		(0.161)
Obs.	1167	1167	1044	1044	1315	1315	1229	1229
R^2	0.068	0.206	0.009	0.135	0.022	0.050	0.040	0.058
% Reduction		72		197		75		32

Discriminação explica disparidades raciais?

Table 2 The importance of educational achievement on racial differences in labor market outcomes (NLSY97).

	Wage				**Unemployment**			
	Men		**Women**		**Men**		**Women**	
Black	−0.179	−0.109	−0.153	−0.044	2.848	2.085	2.596	1.759
	(0.023)	(0.024)	(0.020)	(0.021)	(0.377)	(0.298)	(0.380)	(0.278)
Hispanic	−0.065	−0.014	−0.057	0.035	1.250	0.994	1.507	1.065
	(0.023)	(0.024)	(0.023)	(0.023)	(0.205)	(0.170)	(0.267)	(0.202)
Mixed race	0.007	0.009	−0.090	−0.057	3.268	3.216	1.317	1.278
	(0.143)	(0.145)	(0.072)	(0.065)	(1.661)	(1.618)	(0.975)	(0.911)
Age	0.064	0.062	0.039	0.039	0.934	0.937	1.084	1.081
	(0.006)	(0.006)	(0.006)	(0.006)	(0.038)	(0.038)	(0.048)	(0.048)
AFQT		0.089		0.148		0.664		0.595
		(0.011)		(0.012)		(0.049)		(0.052)
$AFQT^2$		−0.022		−0.035		1.248		1.140
		(0.012)		(0.012)		(0.095)		(0.107)
Obs.	3278	3278	3204	3204	3294	3294	3053	3053
R^2	0.047	0.065	0.029	0.081	0.032	0.051	0.026	0.049
% Reduction		39		71		41		52

Discriminação explica disparidades raciais?

Table 3 The importance of educational achievement on racial differences in incarceration and health outcomes.

	Incarceration								Physical health			
	NLSY79				NLSY97				NLSY79			
	Men		Women		Men		Women		Men		Women	
Black	3.494	1.777	1.054	0.418	2.325	1.417	1.218	0.710	−0.151	0.011	−0.230	−0.111
	(0.549)	(0.304)	(0.484)	(0.226)	(0.245)	(0.159)	(0.244)	(0.148)	(0.053)	(0.061)	(0.068)	(0.076)
Hispanic	2.599	1.549	1.135	0.497	1.641	1.120	0.908	0.591	−0.140	−0.035	0.030	0.125
	(0.476)	(0.300)	(0.573)	(0.275)	(0.196)	(0.136)	(0.216)	(0.146)	(0.061)	(0.063)	(0.065)	(0.071)
Mixed race					0.851	0.887	5.306	4.760				
					(0.511)	(0.557)	(2.428)	(2.207)				
Age	1.044	1.077	1.424	1.341	1.070	1.072	1.012	1.002	−0.035	−0.038	0.064	0.068
	(0.087)	(0.092)	(0.400)	(0.387)	(0.034)	(0.035)	(0.062)	(0.062)	(0.028)	(0.027)	(0.035)	(0.035)
AFQT		0.352		0.346		0.447		0.458		0.164		0.127
		(0.052)		(0.138)		(0.033)		(0.057)		(0.028)		(0.036)
$AFQT^2$		0.746		1.187		0.905		1.166		−0.023		−0.035
		(0.089)		(0.291)		(0.063)		(0.158)		(0.023)		(0.030)
Obs.	1989	1989	1894	1894	4599	4599	4385	4385	1588	1588	1576	1576
R^2	0.046	0.114	0.007	0.078	0.021	0.066	0.009	0.050	0.008	0.033	0.012	0.020
% Reduction		69		1178		69		233		107		52

Discriminação explica disparidades raciais?

Table 4 The importance of educational achievement on racial differences in labor market outcomes (C&B 76).

	Men		Women	
Black	−0.273	−0.152	0.186	0.286
	(0.042)	(0.047)	(0.035)	(0.031)
Hispanic	−0.038	−0.007	0.005	0.059
	(0.081)	(0.077)	(0.094)	(0.088)
Other race	0.153	0.147	0.271	0.270
	(0.066)	(0.062)	(0.048)	(0.049)
SAT		0.003		0.001
		(0.001)		(0.001)
SAT^2		−0.000		−0.000
		(0.000)		(0.000)
Obs.	11,088	11,088	8976	8976
R^2	0.007	0.015	0.004	0.012
% Reduction		44		53

Hoje

Origem histórica e persistência

Discriminação

Identidade

Conclusão

Identidade

- Akerlof and Kranton (2000) incorporam identidade a modelos econômicos e mostram sua importância em previsões teóricas.
  - Indivíduos tem categorias com atributos e comportamentos prescritos. Utilidade de seguir ou violar (própria ou terceiros).
  - "because identity is fundamental to behavior, choice of identity may be the most important 'economic' decision people make."

Escolhendo identidade nos EUA

- Dahis et al. (2019) estudam a escolha de classificação racial nos EUA no contexto de alta discriminação em Jim Crow.
  - Exclusão institucionalizada. Leis anti-miscigenação, escolas só para negros.
  - *One-drop rule*: negro se tinha qualquer antepassado negro.
- Metodologia
  - *Linking*: encontrar a mesma pessoa entre censos na ausência de Social Security Number (Abramitzky et al., 2021)
  - Achar pares únicos em ambas direções, baseado em características (nome completo, idade, estado de nascimento, etc.). Taxa de $\approx 8\%$.
- Resultados: Passar associado com altos custos pessoais, mas ganhos em renda.
- Artigos relacionados nessa literatura
  - Internacional: Cassan (2015), Jia and Persson (2019)
  - Brasil: Cornwell et al. (2017), Janusz (2021)

Table 1: The Correlation Between Discrimination and Passing

	Dependent Variable: White in year t+10								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. Var. Mean	**0.169**	**0.169**	**0.170**	**0.170**	**0.171**	**0.170**	**0.170**	**0.170**	**0.170**
Number of Black Lynchings	0.00316**								0.00238
	(0.00143)								(0.00160)
KKK presence		-0.00445							-0.00357
		(0.00527)							(0.00665)
Congress Democratic Vote Share			0.000172						-0.000240
			(0.000307)						(0.000269)
President Democratic Vote Share				0.000686***					-9.57e-05
				(0.000230)					(0.000288)
Dissimilarity Index					0.0495***				0.0391**
					(0.0128)				(0.0154)
Miscegenation Illegal						0.309***			0.314***
						(0.106)			(0.106)
Oklahoma x Post 1930							0.0712***		0.125***
							(0.00903)		(0.0188)
Log Distance to Tulsa x Post 1930								0.00233	0.00836
								(0.00459)	(0.00611)
Observations	77,116	77,116	70,374	74,126	74,757	77,401	77,401	76,717	68,102
R-squared	0.043	0.043	0.045	0.043	0.012	0.011	0.011	0.043	0.013
Region FE	County	County	County	County	State	State	State	County	State
Standard Errors Cluster	County	County	County	County	State	State	State	County	State

Table 3: Marital Status, the Race of the Spouse and Passing

	t	t+10	$Black_t$ Obs. (1)	$Black_t$ Pass Rate (2)	$White_t$ Obs. (3)	$White_t$ Pass Rate (4)
A.	Single	Single	569	18.3%	3565	0.3%
B.	Single	Married to Black	1132	0.2%	58	98.3%
C.	Single	Married to White	411	98.0%	3260	0.0%
D.	Married to Black	Single	2298	35.7%	3	66.7%
E.	Married to Black	Married to Black	37013	0.2%	15	86.7%
F.	Married to Black	Married to White	6508	98.6%	16	0.0%
G.	Married to White	Single	15	66.7%	3388	4.8%
H.	Married to White	Married to Black	97	0.0%	1097	99.4%
I.	Married to White	Married to White	212	91.0%	175522	0.0%

Table 5: The Correlation between Passing and Income

	Dependent Variables						
	Occ. Score$_{t+10}$	Occ. Score$_{t+10}$	Occ. Score$_{t+10}$	Occ. Score$_{t+10}$	Occ. Score$_{t+10}$	Occ. Score$_{t+10}$	WTB Occupational Income Score $_{t+10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var. Mean (Std. Dev.)	**16.4 (9.76)**	**16.4 (9.76)**	**16.4 (9.76)**	**16.4 (9.76)**	**16.4 (9.76)**	**16.4 (9.76)**	**1.57 (0.31)**
White$_{t+10}$	3.014***	1.507	4.555***	4.743***	1.835***	1.682***	-0.0518***
	(0.120)	(1.069)	(0.334)	(0.349)	(0.306)	(0.324)	(0.00405)
Occupational Score$_t$ x White$_{t+10}$			-0.0837***	-0.0638***			
			(0.0165)	(0.0175)			
Literacy$_t$ x White$_{t+10}$			-0.258	0.0727			
			(0.290)	(0.297)			
Mulatto$_t$ x White$_{t+10}$			-1.129***	-1.126***			
			(0.375)	(0.375)			
Mulatto$_t$			0.447***	0.450***			
			(0.130)	(0.130)			
Occupational Score$_t$	0.122***	0.122***	0.137***	0.133***	0.118***	0.118***	5.09e-05
	(0.00738)	(0.00738)	(0.00801)	(0.00811)	(0.00735)	(0.00735)	(0.000152)
Urban$_t$	1.404***	1.406***	1.395***	1.639***	2.796***	2.795***	-0.00913**
	(0.125)	(0.125)	(0.125)	(0.127)	(0.128)	(0.128)	(0.00438)
Married$_t$	0.126	0.127	0.118	0.162	0.171*	0.172*	0.000860
	(0.0974)	(0.0974)	(0.0973)	(0.0988)	(0.0966)	(0.0966)	(0.00342)
Literacy$_t$	0.596***	0.596***	0.635***	0.582***	0.504***	0.503***	0.00104
	(0.0838)	(0.0838)	(0.0807)	(0.0805)	(0.0826)	(0.0826)	(0.00341)
Passed$_{t+10}$ x Moved County$_{t+10}$					0.919**	1.040***	
					(0.358)	(0.370)	
Passed$_{t+10}$ x Moved State$_{t+10}$					1.017***	1.078***	
					(0.360)	(0.363)	
Passed$_{t+10}$ x Rural to Urban$_{t+10}$					2.768***	2.748***	
					(0.349)	(0.351)	
Passed$_{t+10}$ x Move North$_{t+10}$						0.433	
						(0.315)	

Hoje

Origem histórica e persistência

Discriminação

Identidade

Conclusão

Melhor alocação de talentos

- Menores barreiras à acumulação de capital humano, discriminação e normas de gênero $\implies$ uso de vantagens comparativas e ganho de produtividade.
- Hsieh et al. (2019) estimam que 20-40% do crescimento do PIB americano entre 1960 e 2010 se deve à melhor alocação de talentos de mulheres e homens pretos.

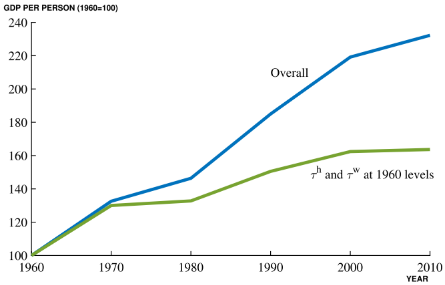


FIGURE 7.—GDP per person, data and model counterfactual. Note: The graph shows the cumulative growth in GDP per person (market), in the data (overall), and in the model with no changes in τ's as in Table V.

Conclusão

- Literatura sobre desigualdade é ampla e cruza horizontalmente diversas outras.
- *Low-hanging fruits* parecem ter sido pegas. Fronteira está em detalhar mecanismos por trás de disparidades nos dados.
  - Exemplo: Roussille (2021) estudando o *ask gap*.

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