

# NCRN Meeting: “Job Market Signaling through Occupational Licensing”

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# Overview of My Research Agenda

- Applied micro economist specializing in labor and education
- How the educational system in concert with neighborhoods can promote equality in the labor market through expanding opportunity and access
- Higher education and post-secondary credentials such as occupational licensing as potential equalizers.
- **Talk today on Occupational Licensing as a labor market credential that reduces racial and gender wage gaps (joint w/ Bobby Chung, Clemson).**
- Examples of other work: (i) prestige as explanation for why elite schools have expanded slowly, (ii) effect of labor market flexibility on gender wage gaps, (iii) neighborhood tipping etc.
- PI BE-Lab: 5 PhD students, 2 undergraduates, faculty collaborators at: Clemson, Cornell, Duke, Harvard and Wharton.

## Meet the BE-Lab



## Occupational Licensing Defined

According to Bureau of Labor Statistics an occupational license is:

- a labor market credential issued by a *government agency*,
- that allows an individual to *lawfully* practice for payment.
- Some licenses have require passing an exam, completing a training or education component, or preclude felons from having one.

Licenses stand in contrast to professional *certificates*, which are:

- administered by a private or professional organization,
- do not restrict the right to practice but the right to title,
- and also may require passing an exam or satisfying some training requirement.

E.g. Teachers require a state-issued credential to teach and are *licensed* by this definition even though the credential is called a teaching certificate.

# Theory Predicts Licensing Increases Wages

- **Quantity Restriction:** Occupational licensing creates barriers to entry, restricting supply and increasing prices (Smith, 1937; Friedman, 1962).
- **Quality Restriction:** Occupational licensing imposing minimum quality standards, resulting in higher average prices to reflect higher average quality of workers. (Anderson et. al. 2016)

# Incidence of Occupational Licensing Increasing Over Time

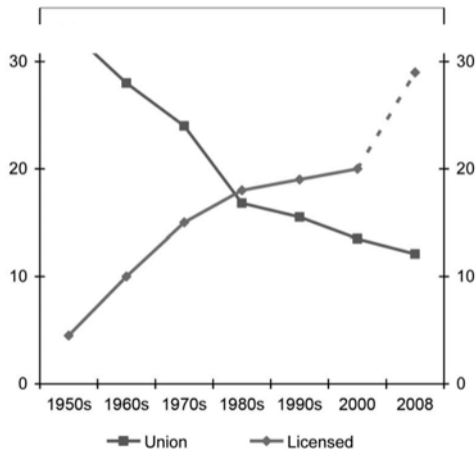


Figure: Courtesy of Kleiner & Krueger 2013

## Policy Makers are Advocating for Licensing Reform

- 1 Licensing restricts entry into occupations within state and restricts mobility in same occupations across states [FTC Commissioner](#).
- 2 Accepted wisdom: these frictions are particularly harmful for workers with felony records, returning veterans and trailing spouses.
- 3 Licensing reform rare issue with bipartisan political support.
- 4 Obama Administration designated \$7.5M to fund state efforts at licensing reform (2015): “New Steps to Reduce Unnecessary Occupation Licenses that are Limiting Worker Mobility and Reducing Wages.”
- 5 Current Labor Secretary Alexander Acosta urging states to reform licensing statutes and reduces barriers to entry.

# Our Key Insight: Licenses, like Education, is a Labor Market Signal

- Friedman (1962): occupational licensing just a barrier to entry
- Our idea: licensing is an informative signal *because* it is costly
- Labor market signals especially important for groups that face discrimination
- Akerlof (1970): asymmetric information → market failure
- Spence (1973): education a labor market signal that overcomes asymmetric information.
- Our idea: occupational licensing can play analogous role to education
- Reduce asymmetric information between firms and workers
- Firms rely less on race and gender as proxies of ability → less wage inequality



# Research Questions on Heterogeneous Licensing Premia

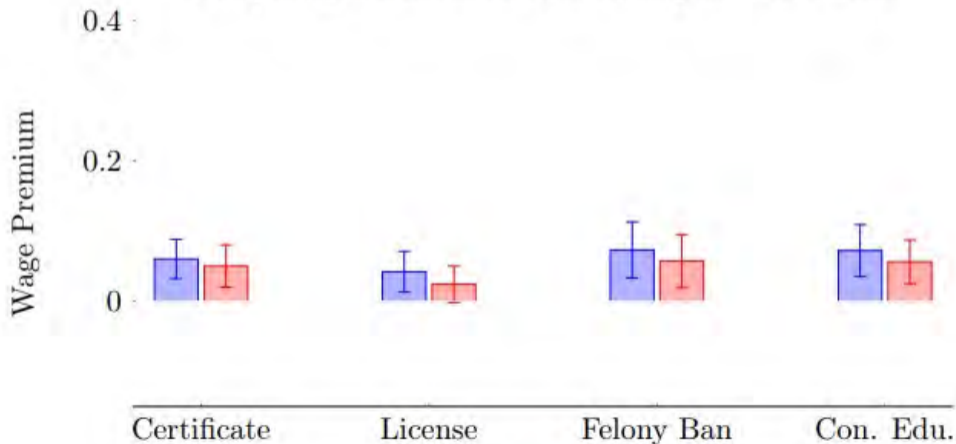
- 1 Is there heterogeneity in licensing premium by race and gender?
- 2 Does heterogeneity in licensing premium reduce or exacerbate the racial and wage gaps?
- 3 What is the mechanism generating the heterogeneity e.g. asymmetric information between firms and workers or human capital bundling?
- 4 Can certificates, which are less restrictive than occupational licenses, convey the same wage benefits of licenses for women and minority men?
- 5 What can policy makers learn from our work and the broader literature?

## Preview of Results: Licensing ↓ Gender and Racial Wage Gaps

- 1 Licensing reduces racial wage gap between black men and white men by 43%.
  - Remaining wage gap statistical indistinguishable from zero.
  - Mechanism: licensing a positive signal of non-felony status.
- 2 Licensing reduces the gender wage gap between women and white men by 36%-40%.
  - Mechanism: higher returns to training that is bundled with licensing.
- 3 Certificates convey the same wage benefit as licenses for white men.
- 4 Licensing conveys larger wage benefits than certificates for women and black men.
- 5 The results are robust to accounting for selection, measurement error and alternative hypotheses.

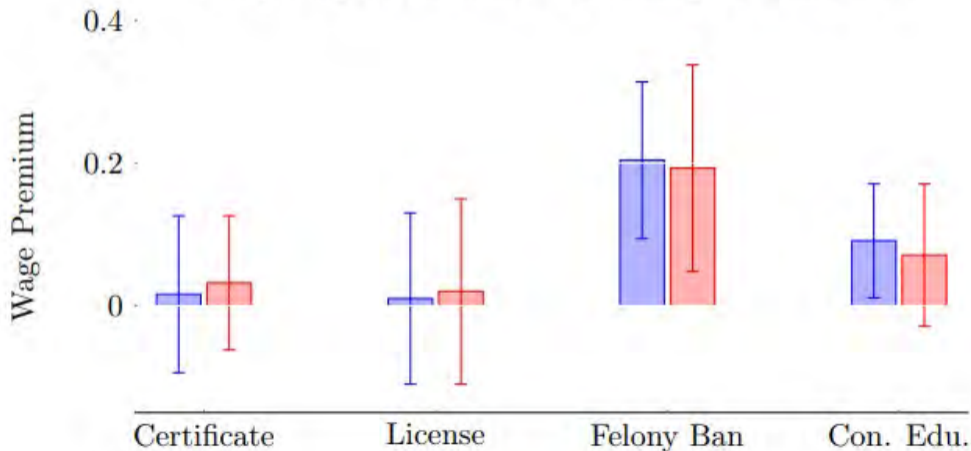
# Licensing and Certificate Premiums Similar for White Men

Comparing Certification to Licensing for White Men



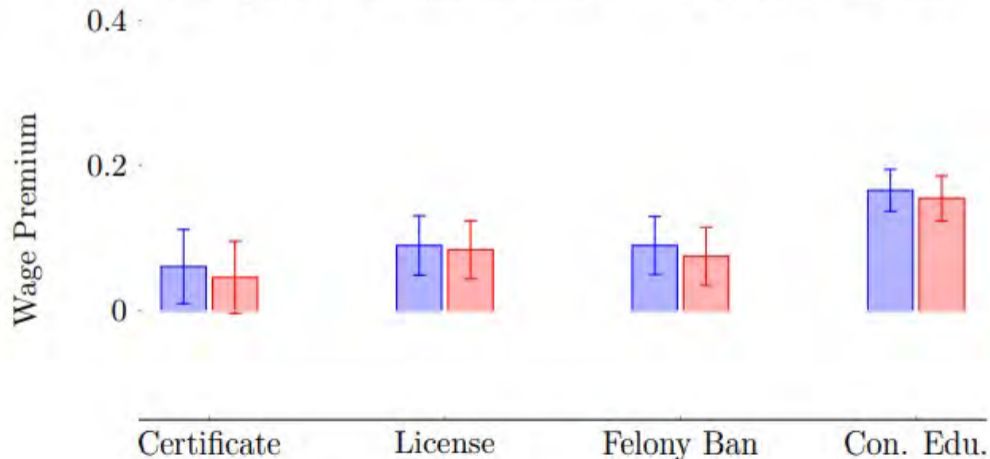
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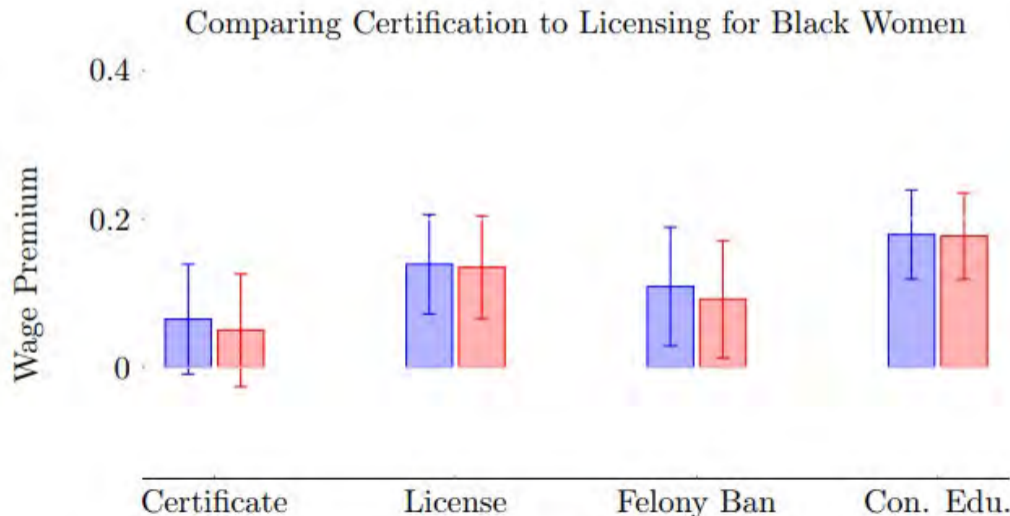


# Licensing and Certificate Premiums for White Women

Comparing Certification to Licensing for White Women



# Licensing and Certificate Premiums for Black Women



## Related Literature on Licensing & Education

- Education – Human Capital or Signalling: Spence (1973), Neal and Johnson (1996), Murnane et. al. (2000), Arcidiacono et. al (2010), Lang and Manove (2011), Artega (2016).
- Statistical Discrimination: Phelps (1972), Arrow (1973), Coate and Loury (1993), Altonji and Pierret (2001), Autor and Scarborough (2008), Wozniak (2015).
- Effects of Ban-the-Box Legislation: Doleac and Hansen (2017), Veuger and Shoag (2013), Agan and Star (2016).
- Theory of Occupational Licensing: Friedman (1962), Leland (1979).
- Measuring Licensing Premium: Gittleman et al. (2015), Kleiner and Krueger (2010, 2013), Law and Marks (2009), Pagliero (2010), Thornton and Timmons (2010), Pizzola and Tabarrok (2017).

# Framework for the Rest of Talk

- 1 Model
- 2 Data
- 3 Empirical Specification
- 4 Results
- 5 Robustness checks
- 6 Policy Implications
- 7 Future Work



## Two Sector, Two Period Model of Firms and Workers

- Two sectors: licensed sector and unlicensed sector
- One representative profit maximizing firm in each sector
- Unit measure of workers: heterogeneous tastes for sectors and ability
- Licensing costly and cost varies by worker ability.
- Licensing bundled with human capital  $0 \leq h \leq 1$  (training).

# Timing in the Model

Two period sequential game:

- 1 Period 1: firms set wages  $\omega_L$  and  $\omega_U$  to maximize profits.
- 2 Period 2: Workers observe wages sort into sector that delivers highest utility given wages, ability and preferences (sector taste).

Solution Concept: Subgame Perfect Equilibrium (backwards induction)

Details of the Model: [Model of Workers](#) [Model of Firms](#) [Model Equilibrium](#)

## Defining the Licensing Premium

### Definition

The *licensing premium*, describes the percentage difference in the wages of a licensed and an unlicensed worker.

$$\text{licensing premium} = \frac{\omega_L^* - \omega_U^*}{\omega_U^*} \quad (1)$$

## Predictions of the Model

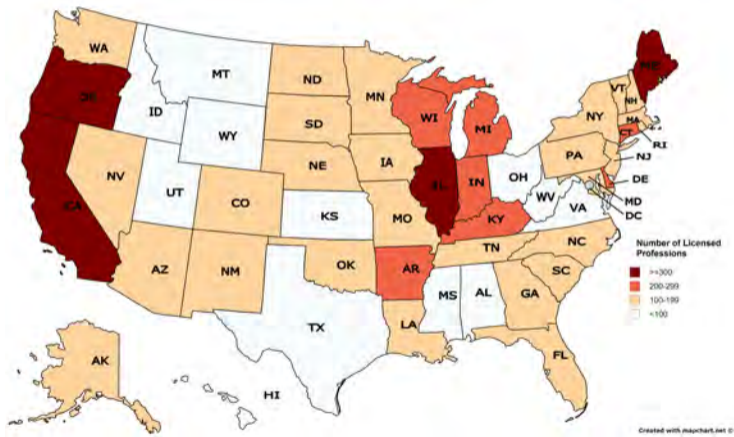
- 1 The licensing premium is unambiguously *increasing* in the average cost of the occupational license.
- 2 The licensing premium is *increasing* in the level of human capital bundled with the license so long as the licensing premium is less than 100%.
- 3 The licensing premium is unambiguously *decreasing* in the average ability of workers, if there is no relative preference for the licensed sector.
- 4 Sum of worker and firm surplus is maximized by non-zero cost of licensing. Industry Surplus

# Data on Licensing and Wages

## • Survey of Income and Program Participation (SIPP)

- Nationally representative: 20,000+ individuals 400+ occupations
- From May 2012 to Nov 2013 (Wave 13 to Wave 16)
- Data: wages, demographics, education, licensing
- Topical Module on Occupational Licensing:
  - Record if license used in *current* occupation (↓ measurement error)
  - Record if license obtained for professional or personal reasons (taste)
  - Report whether license requires continuous education, training, or an exam (human capital bundling)
  - In total 9 licensing questions
- Sample selection:
  - age of 18 through 64
  - observations with imputed license status and wage are dropped
  - included certified and all races
  - control for license not required by current job

# States Vary in Level of Licensing

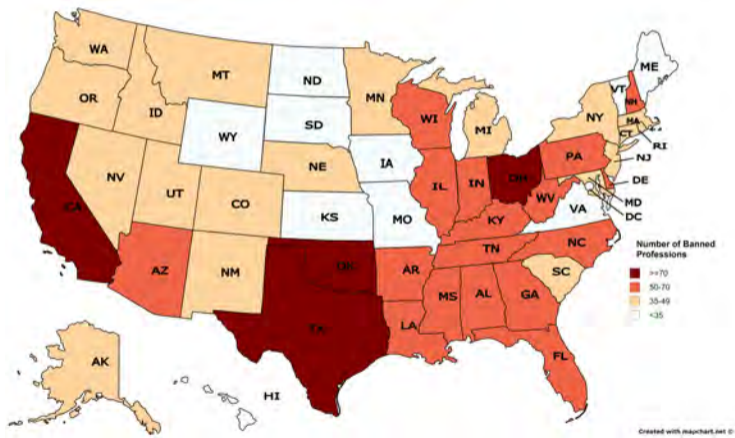


# New Data on Occupations with Felony Restrictions on Licenses

We construct a new data-set on occupational licensing restrictions facing ex-offenders

- **Criminal Justice Section of American Bar Association (ABA)**
- 16,343 legal restrictions facing ex-offenders in licensed occupations license restrictions on ex-offenders
- Content: the law citation, title, triggering offense, consequence type, and duration.
- Match each citation to a given state and occupation using web-scraping tool.

# States Vary in Licensed Occupations w/ Felony Restrictions





Licensed workers more likely to be: educated, female, gov't employee, service industry, and self-employed.

	Unlicensed		Certified		Nonban-licensed		Ban-licensed	
	mean	sd	mean	sd	mean	sd	mean	sd
blackmen	0.048	0.213	0.039	0.193	0.031	0.173	0.019	0.138
whitewomen	0.426	0.495	0.394	0.489	0.499	0.5	0.61	0.488
blackwomen	0.061	0.24	0.047	0.212	0.06	0.237	0.072	0.258
age	41.65	12.50	42.69	11.26	44.08	11.27	43.97	10.95
other ethnicity	0.081	0.273	0.073	0.26	0.063	0.242	0.072	0.258
hispan	0.144	0.351	0.078	0.268	0.07	0.255	0.078	0.268
high school drop-out	0.075	0.263	0.023	0.15	0.015	0.121	0.015	0.122
somecollege	0.176	0.381	0.139	0.346	0.106	0.308	0.069	0.254
college	0.213	0.41	0.228	0.42	0.279	0.449	0.312	0.463
postgrad	0.089	0.285	0.152	0.359	0.218	0.413	0.305	0.461
union membership	0.1	0.3	0.132	0.339	0.231	0.421	0.283	0.451
government worker	0.155	0.362	0.124	0.329	0.35	0.477	0.374	0.484
self employed	0.022	0.148	0.036	0.186	0.04	0.195	0.027	0.162
service worker	0.487	0.5	0.59	0.492	0.707	0.455	0.825	0.38
N	198,412		20,725		28,151		14,878	

# Occupations with Felony Bans in the Most States

Occupation	Permanent	Temporary	Total
Driver/sales workers and truck drivers	19	32	51
Nursing, psychiatric, and home health aides	36	12	48
Loan counselors and officers	21	25	46
Lawyers	24	20	44
Social Workers	27	16	43
Medical and health services managers	29	13	42
Motor vehicle operators	19	23	42
Post-secondary school teachers	22	17	39
Registered nurses	28	11	39
Counselors	28	10	38

Source: *Criminal Justice Section, American Bar Association*

Notes: Occupations are defined by Standard Occupation Classification. The total number of unique mandatory bans is 2,512. Temporary bans refer to restrictions with specific terms or with relief. The 'total' represents the total number of states with mandatory felon restrictions in that particular occupation.

## Licensing Premium for White Men Smaller than for Women or Black Men

Unconditional Wage Premia: white men (12%), black men (28%), white women (34%), black women (36%).

	Not Licensed					Licensed				
	Mean	Std. Dev.	N	Min.	Max.	Mean	Std. Dev.	N	Min.	Max.
white										
Male	25.48	15.97	59,993	5	100	28.48	15.21	15,353	5	99
Female	19.36	12.41	55,646	5	98	25.92	13.89	21,159	5	100
black										
Male	18.83	12.57	7,969	5	100	24.11	13.98	1,280	5	88
Female	16.11	10.53	10,364	5	100	21.93	13.11	2,850	5	83

Similar pattern holds in raw data when we condition on license type (ordinary, felony, human capital). [More](#)

# Wage Regression Model

Regress log wages on:

- 1 indicator for type of license: ordinary (lic), felony restriction (ban), bundled with human capital (hcap) Examples
- 2 interact licensing variables with race and gender dummies: BM (black man), WW (white woman), BW (black woman),
- 3 and control for individual characteristics ( $X$ ), state ( $\theta_o$ ), occupation ( $\theta_o$ ), month of survey ( $\theta_m$ )

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$$\begin{aligned}
 \log(w_{ijsm}) = & \tau_0 + \tau_1 BM_i + \tau_2 WW_i + \tau_3 BW_i \\
 & + \tau_4 lic_i + \tau_5 lic_i \times BM_i + \tau_6 lic_i \times WW_i + \tau_7 lic_i \times BW_i \\
 & + \tau_8 ban_i + \tau_9 ban_i \times BM_i + \tau_{10} ban_i \times WW_i + \tau_{11} ban_i \times BW_i \\
 & + \tau_{12} hcap_i + \tau_{13} hcap_i \times BM_i + \tau_{14} hcap_i \times WW_i + \tau_{15} hcap_i \times BW_i \\
 & + \Gamma X_i + \theta_s + \theta_o + \theta_m + \epsilon_{ijsm}
 \end{aligned}$$

# Estimated Licensing Premia

## Ordinary License

- 1 White Men:  $\tau_4$
- 2 Black Men:  $\tau_4 + \tau_5$
- 3 White Women:  $\tau_4 + \tau_6$
- 4 Black Women:  $\tau_4 + \tau_7$

# Estimated Licensing Premia

## Ordinary License

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- ④ Black Women:  $\tau_4 + \tau_7$

## License w/ Felony Bans

- ① White Men:  $\tau_4 + \tau_8$
- ② Black Men:  $\tau_4 + \tau_5 + \tau_8 + \tau_9$
- ③ White Women:  $\tau_4 + \tau_6 + \tau_8 + \tau_{10}$
- ④ Black Women:  $\tau_4 + \tau_7 + \tau_8 + \tau_{11}$

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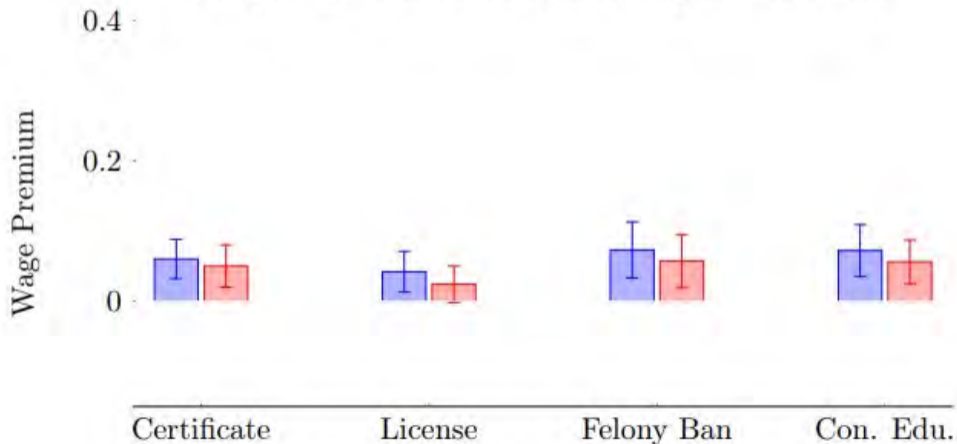
## License w/ Human Capital Bundled

- ① White Men:  $\tau_4 + \tau_{12}$
- ② Black Men:  $\tau_4 + \tau_5 + \tau_{12} + \tau_{13}$
- ③ White Women:  $\tau_4 + \tau_6 + \tau_{12} + \tau_{14}$
- ④ Black Women:  $\tau_4 + \tau_7 + \tau_{12} + \tau_{15}$



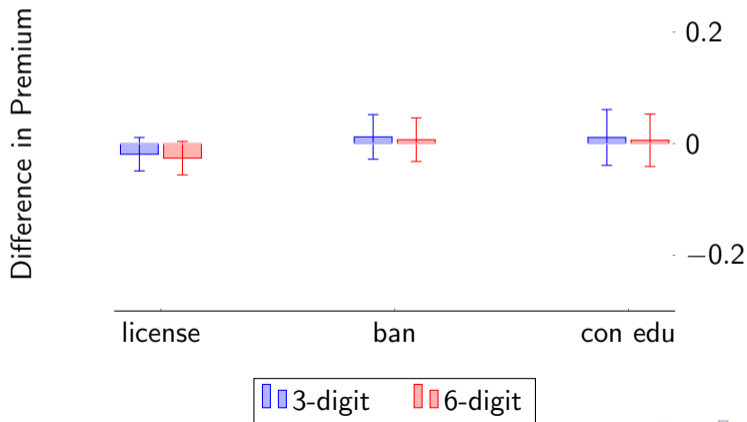
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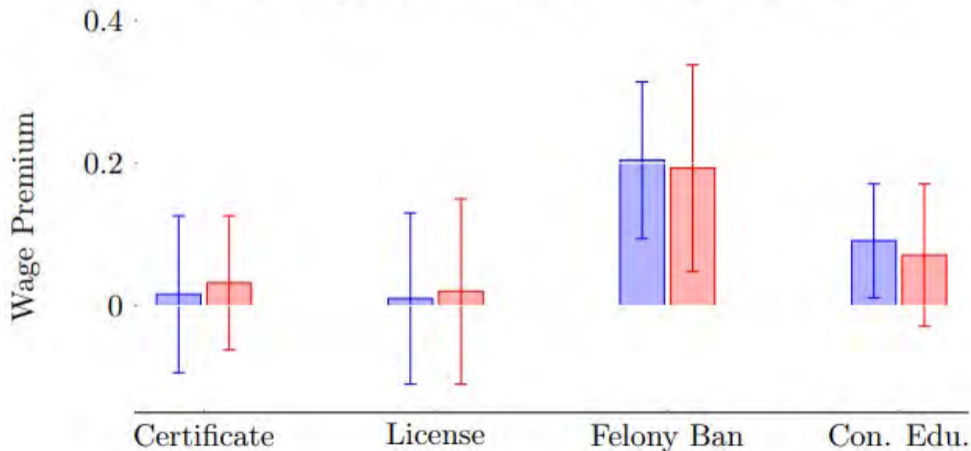
# White Men: No Advantage of Licensing over Certification

License Premium Compared to Certification (White Men)

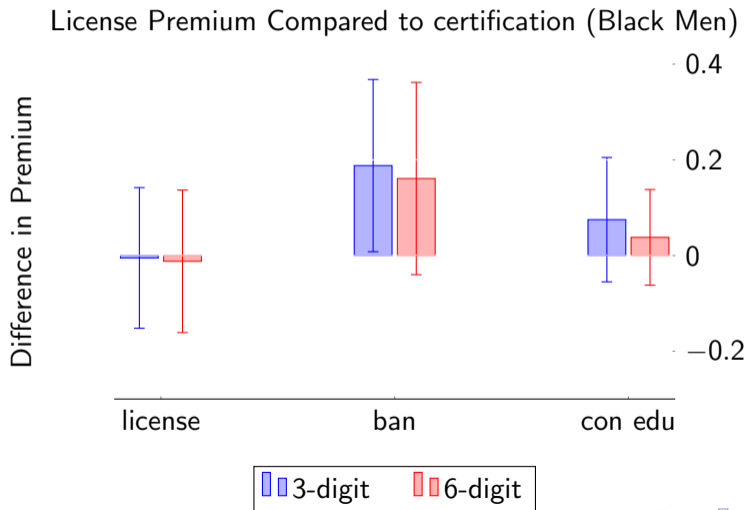


# Licensing and Certificate Premiums for Black Men

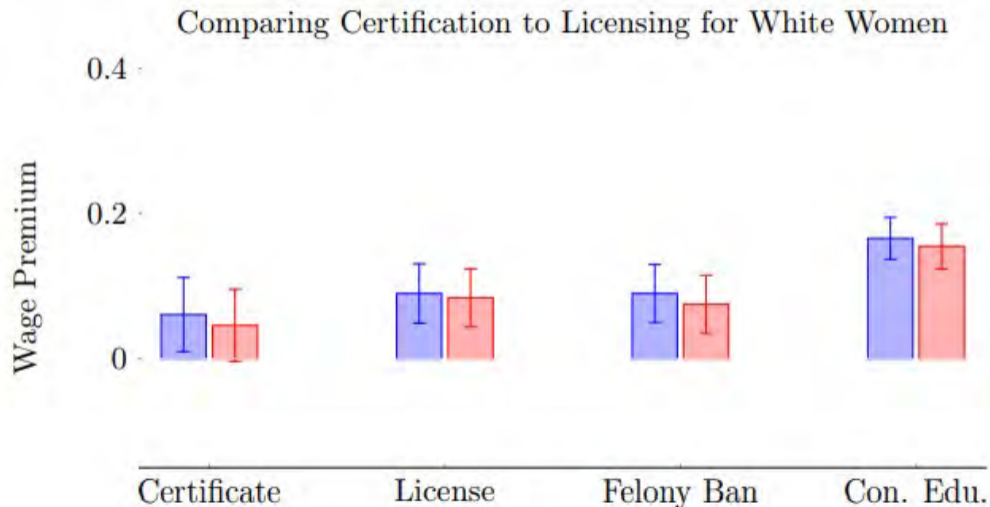
## Comparing Certification to Licensing for Black Men



# Black Men: Largest Premium in Felony Ban Occupations

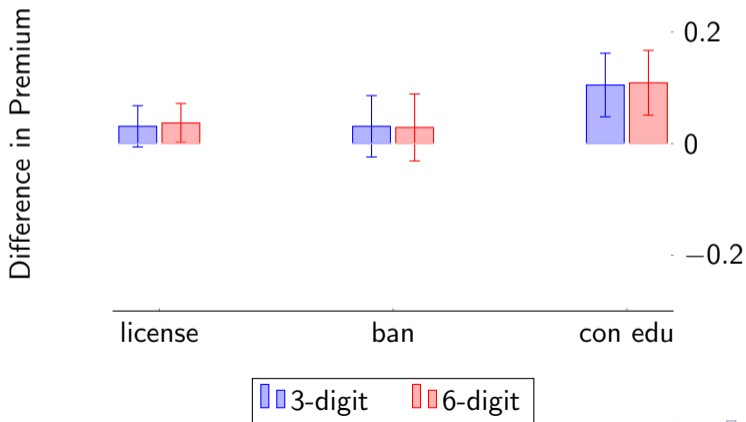


# Licensing and Certificate Premiums for White Women

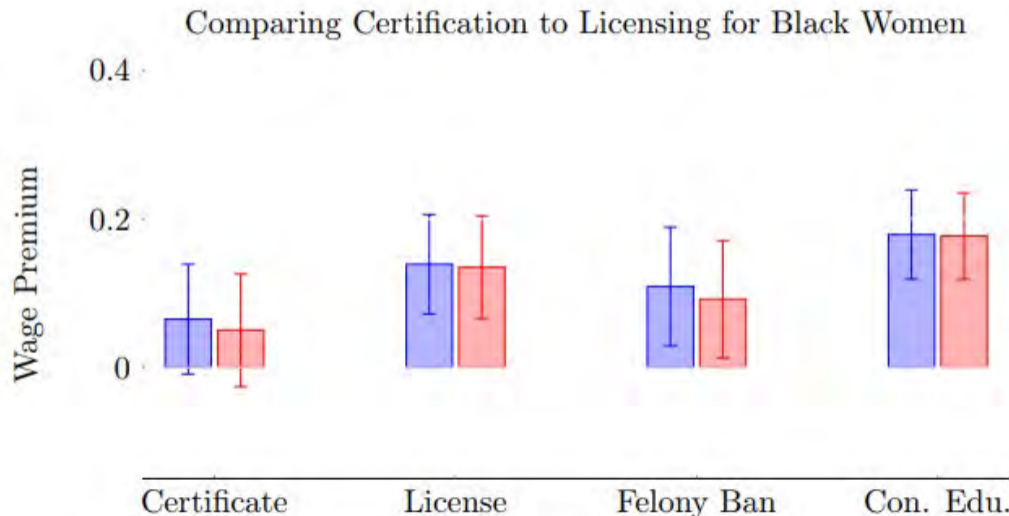


# White Women: License > Certification, Especially Informative License

License Premium Compared to Certification (White Women)

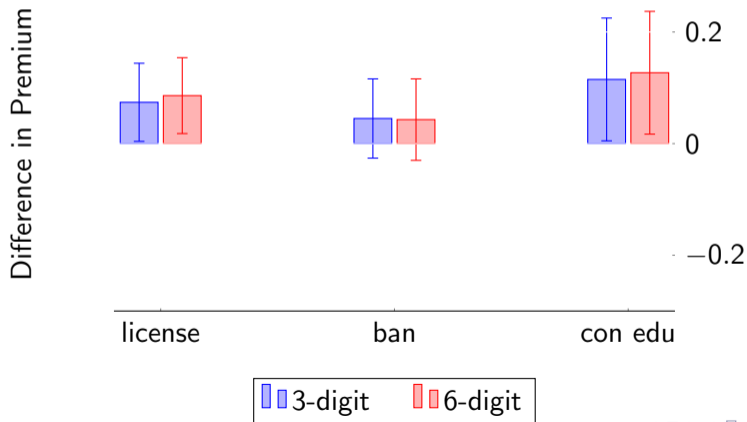


# License and Certificate Premiums for Black Women



# Black Women: Largest Premium in Licenses w/ Con. Ed.

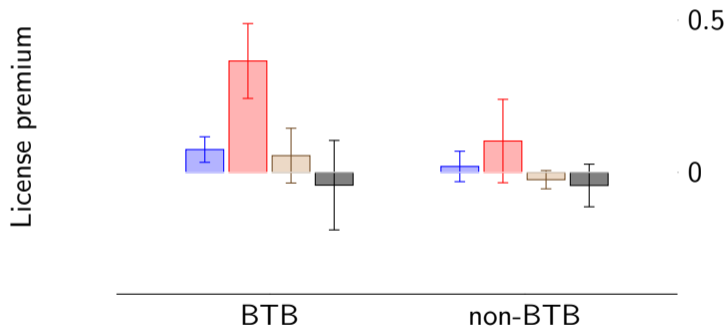
License Premium Compared to Certification (Black Women)





# ↑ Licensing Premium in Ban-the-Box States for Black Men

## Premiums in Occupations with Felony Restrictions on Licensing



■ White men   
 ■ Black men   
 ■ White women   
 ■ Black women

## ↑ Licensing Premium in Ban-the-Box States for Black Men

	Base Model	Ability (Linear)	Ability (Non-linear)
boxban	0.0802*** (0.0225)	0.0761*** (0.0219)	0.0751*** (0.0216)
boxban_blackmen	0.290*** (0.0644)	0.292*** (0.0607)	0.291*** (0.0634)
boxban_whitewomen	-0.0296 (0.0550)	-0.0223 (0.0542)	-0.0197 (0.0537)
boxban_blackwomen	-0.117 (0.0799)	-0.117 (0.0776)	-0.117 (0.0775)
noboxban	0.0201 (0.0273)	0.0216 (0.0267)	0.0195 (0.0265)
noboxban_blackmen	0.0726 (0.0689)	0.0839 (0.0716)	0.0839 (0.0725)
noboxban_whitewomen	-0.0480 (0.0316)	-0.0480 (0.0310)	-0.0437 (0.0313)
noboxban_blackwomen	-0.0573 (0.0407)	-0.0615 (0.0413)	-0.0623 (0.0412)
Observations	262,166	262,166	262,166

## Ban Premium ↓ in Firm Size for Black Men

	Firm size			
	>100	>200	>500	>1000
ban	0.00720 (0.0102)	0.0122 (0.0122)	0.0387** (0.0154)	0.0317* (0.0183)
ban_blackmen	0.218*** (0.0449)	0.221*** (0.0558)	0.164** (0.0719)	0.132 (0.0808)
ban_whitewomen	-0.00457 (0.0133)	0.00338 (0.0159)	-0.0172 (0.0198)	-0.0310 (0.0236)
ban_blackwomen	0.00353 (0.0252)	-0.0640** (0.0307)	-0.101*** (0.0370)	-0.117*** (0.0436)
Observations	102,860	74,967	49,020	35,724
R-squared	0.540	0.545	0.550	0.552

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

# Results Robust to Alternative Explanations

Felony Ban Premium not due:

- 1 Unobserved ability and taste [Results](#)
- 2 Measurement Error I: partial licensing and match quality of felony restrictions. [Results](#)
- 3 Measurement Error II: misreporting by individuals [Results](#)
- 4 Differences in return to education by license type [Results](#)
- 5 Differences in: state arrests disparity, fraction white in occupation, government employment, union status [Results](#)
- 6 Time-specific shock: run each wave of data separately [Results](#)
- 7 Occupational selection [Results](#)

## Summary of Findings

- Women and minorities earn higher licensing premia than white men
- Mechanisms: signalling non-felony status (black men), women: higher returns to education bundled with license + other labor market signalling.
- Certifications deliver equivalent premia to licenses for white men.
- Licenses deliver larger premia than certifications for women and black men.
- Absence of felony signally could lead to market unravelling for black men: lower probability of employment and lower wages.
- Efforts to reform licensing should consider the effect of this state-issued credential in reducing wage inequality.

# Discussion of Policy Options

- 1 Eliminate Licensing & replace with certification.
- 2 Promote Reciprocal Licensing Across States.
- 3 Permit relevant experience to substitute for licensing.
- 4 Make state licenses non-binding.
- 5 Certificate of Qualification of Employment for felons (effective in jobs and housing).

# Future Work on Occupational Licensing

- 1 Forthcoming paper on employment effects of licensing (joint w/ Bobby Chung)
- 2 Pending NSF application to collect time-series on ex-offender restrictions (joint w/ Morris Kleiner and Jason Hicks, Minnesota)

# Back-up Slides



## Former FTC Commissioner Maureen K. Ohlhausen

### FTC Report: Options to Enhance Occupational License Portability

“Most occupations are licensed state-by-state, meaning that a valid license in one state often will not easily transfer to a new state. This can create real hardships for those who cannot easily bear the costs of being relicensed, and can also reduce public access to trained professionals in rural areas who might otherwise be served by telehealth services or multistate practitioners. Today's FTC staff report provides important, useful guidance to help state policymakers find ways of reducing these burdens.” [Back](#)

# Assumptions on Ability, Taste and Licensing Cost

- Each worker is defined by:
  - ① Ability ( $a_i$ ):  $a_i \sim U[\mu_a - \sigma_a, \mu_a + \sigma_a]$
  - ② Relative taste for unlicensed sector ( $\epsilon_i$ ):  $\epsilon_i \sim U[\mu_\epsilon - \sigma_\epsilon, \mu_\epsilon + \sigma_\epsilon]$
- Licensing a costly function of ability:

$$c(a_i) = c_0 - \theta(a_i - \mu_a) \quad (2)$$

- $c_0$ : unconditional average cost of licensing
- $\mu_a$ : unconditional average worker ability.
- $\theta$ : marginal benefit of ability

# Worker Utility & Probability of Obtaining a License

Workers sort into sector delivering highest utility

- 1 Worker utility in unlicensed sector given by:

$$V_{U,i} = \omega_U + \epsilon_i$$

- 2 Worker utility in licensed sector:

$$V_{L,i} = \omega_L - [c_0 - \theta(a_i - \mu_a)]$$

- 3 Probability of obtaining a license conditional on ability:

$$P(L_i = 1|a_i) = \text{Prob}(V_{L,i} > V_{U,i})$$

# Firms Profit Maximizing Talent Agencies

- 1 Each firm is a talent agency: receives  $\bar{\omega}$  per worker ability unit
- 2 Human capital augments per worker ability unit return by factor  $(1 + h)$
- 3 Firm set sector wages  $\omega_L$  (licensed) and  $(\omega_U)$  (unlicensed) to maximize expected profits:

$$E[\pi_L] = \underbrace{\overbrace{\bar{\omega}(1+h) \times E[a_i|L_i=1]}^{\text{Avg. Output per Worker}} \times \overbrace{E[P(L_i=1|a_i)]}^{\text{No. of Workers}}}_{\text{Expected Revenue}} - \underbrace{\omega_L E[P(L_i=1|a_i)]}_{\text{Expected Labor Cost}},$$

$$E[\pi_U] = \underbrace{\bar{\omega} \times E[a_i|L_i=0] \times E[P(L_i=0|a_i)]}_{\text{Expected Revenue}} - \underbrace{\omega_U E[P(L_i=0|a_i)]}_{\text{Expected Labor Cost}},$$

[Return to Model Outline](#)

## Equilibrium Wages and Fraction of Licensed Workers

If the average cost of licensing  $c_0 \in (\underline{c}, \bar{c})$ , where  $\underline{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon - 3\sigma_\epsilon$  and  $\bar{c} \equiv h\bar{\omega}\mu_a - \mu_\epsilon + 3\sigma_\epsilon$ , there is a unique Sub-game Perfect Nash Equilibrium in which the wages are given by:

$$\omega_U^* = \bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c}), \quad (3)$$

$$\omega_L^* = \underbrace{\bar{\omega}\mu_a - \frac{1}{3}(c_0 - \underline{c})}_{\omega_U^*} + \underbrace{\frac{1}{3}h\bar{\omega}\mu_a + \frac{2}{3}(c_0 + \mu_\epsilon)}_{\text{Wage Benefit of Licensing}}, \quad (4)$$

and fraction of workers with an occupational license,  $0 < f^* < 1$ , is an interior solution:

$$f^* \equiv E[P(L_i = 1|a_i)] = \left( \frac{\bar{c} - c_0}{6\sigma_\epsilon} \right). \quad (5)$$

# What is the Efficient Average Cost of Licensing?

## Definition

**Industry surplus:** the sum of expected firm profits and worker wages net of the expected licensing cost.

If  $\bar{c} > 0$ , then there exists a unique  $c_0^* > 0$  that maximizes the industry surplus:

$$c_0^* = \frac{1}{2} (\bar{c} + h\bar{\omega}\mu_a),$$

Caveat: This result is partial equilibrium result because it does not account for workers as consumers who face price changes under licensing. Model Predictions

## Premia for Licenses Barring Felons Smallest for White Men

Unconditional License premia in occupations precluding felons: white men (15%), black men (24 %), white women (32 %), black women (38 %) [Back](#)

	mean	sd	min	max	N
<i>Unlicensed</i>					
White men	23.73	15.60	5.00	100.00	80,492
Black men	18.63	12.40	5.00	100.00	9,152
White women	18.33	12.02	5.00	98.00	72,644
Black women	15.92	10.31	5.00	100.00	11,738
Other	22.70	16.20	5.00	100.00	15,599
Subtotal	20.84	14.22	5.00	100.00	189,625
<i>Licensed (with felony bans)</i>					
White men	29.90	16.18	5.00	100.00	4,714
Black men	25.46	14.33	6.00	88.00	332
White women	27.14	14.22	5.00	100.00	9,419
Black women	21.49	13.23	5.00	71.00	1,184
Other	34.83	21.55	6.00	100.00	1,146
Subtotal	28.00	15.58	5.00	100.00	16,795
Total	22.30	14.62	5.00	100.00	262,166

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

## Examples of Licensing Requirements in Rhode Island

- 1 Ordinary license: upholsterers (pay \$180 and fill out a form); animal breeder (pay \$100 and fill out a form)
- 2 Felony ban: actuaries; fish and game wardens (also includes a training requirement)
- 3 Continuous Education Requirement: real estate brokers; elementary and middle school teachers

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# Ban Premium for Black Men not Due to Heterogeneous Greater Returns to Education

	(1) Licensed (with felony bans)	(2) Licensed (no felony bans)	(3) Unlicensed
blackman	0.0702 (0.0901)	-0.170** (0.0795)	-0.105*** (0.0195)
postHS	0.0477 (0.0622)	0.103*** (0.0276)	0.0943*** (0.00885)
postHS_blackman	-0.00362 (0.129)	0.0798 (0.109)	-0.0152 (0.0297)
postHS_whitewoman	0.0747 (0.0982)	0.0566 (0.0491)	-0.0191 (0.0130)
postHS_blackwoman	0.0808 (0.0967)	0.156 (0.135)	-0.0178 (0.0237)
Observations	14,878	28,065	198,412
R-squared	0.511	0.446	0.534

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

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## Ban Premium for Black Men Robust

	(1) Racial Disparity in Arrest	(2) Frac. White in Occupation	(3) Government Employment	(4) Union Status
ban	0.0335 (0.0234)	0.0407* (0.0237)	0.0325 (0.0233)	0.0305 (0.0233)
ban_blackmen	0.139** (0.0634)	0.133** (0.0649)	0.156** (0.0707)	0.154** (0.0685)
ban_whitewomen	-0.0388 (0.0274)	-0.0422 (0.0271)	-0.0375 (0.0278)	-0.0344 (0.0282)
ban_blackwomen	-0.0460 (0.0394)	-0.0683* (0.0396)	-0.0456 (0.0390)	-0.0447 (0.0394)
Observations	261,617	262,166	262,166	262,166
R-squared	0.526	0.531	0.526	0.526

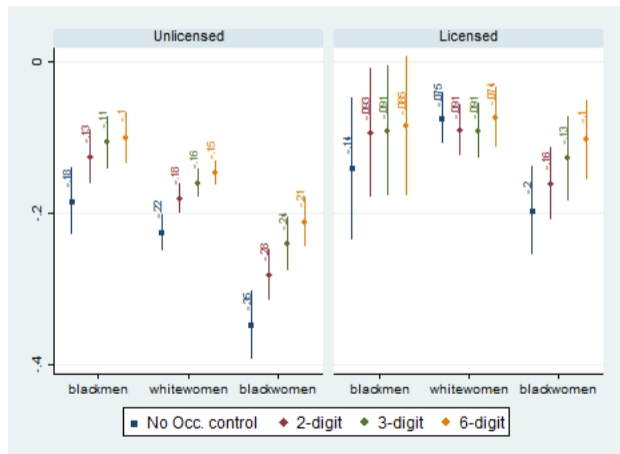
Data Source: Wave 13 to Wave 16 of SIPP Panel 2008.

## Running each waves separately: Sample Attrition Bias $\implies$ Estimate Lower Bound on Ban Premium

	(1) Wave 13	(2) Wave 14	(3) Wave 15	(4) Wave 16
ban	0.0226 (0.0288)	0.0188 (0.0312)	0.0340 (0.0283)	0.00603 (0.0402)
ban_blackmen	0.202*** (0.0737)	0.202** (0.100)	0.195* (0.100)	0.0254 (0.126)
ban_whitewomen	-0.0123 (0.0365)	-0.00619 (0.0448)	-0.0355 (0.0385)	-0.0172 (0.0530)
ban_blackwomen	-0.00804 (0.0496)	-0.0338 (0.0525)	-0.0389 (0.0554)	-0.0930 (0.0761)
Observations	75,843	69,881	68,497	47,945
R-squared	0.527	0.523	0.529	0.532

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# Occupational Selection Does Not Explain Positive Effect of Licenses in Closing Wage Gaps

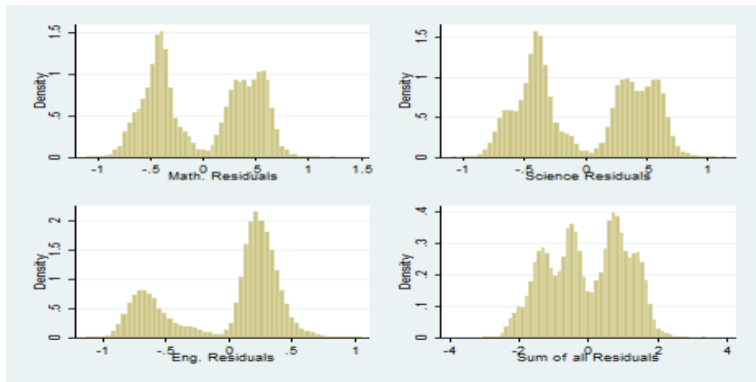


# Controlling for Unobserved Ability & Unobserved Taste for Licensing

- 1 In the data we observe the workers answers to the following question:
  - *“Did [he/she] get this certificate or license mainly for work-related or mainly for personal interest.”*
  - Control for this as measure of taste for licensing.
- 2 In the data, we observe whether an individual chose to pursue advanced math, advanced science and advanced English classes in high school.
  - Separately regress each choice on observable (excluding licensing decision).
  - Regression residuals generates 3 continuous measures of unobserved ability in: science, math and English.

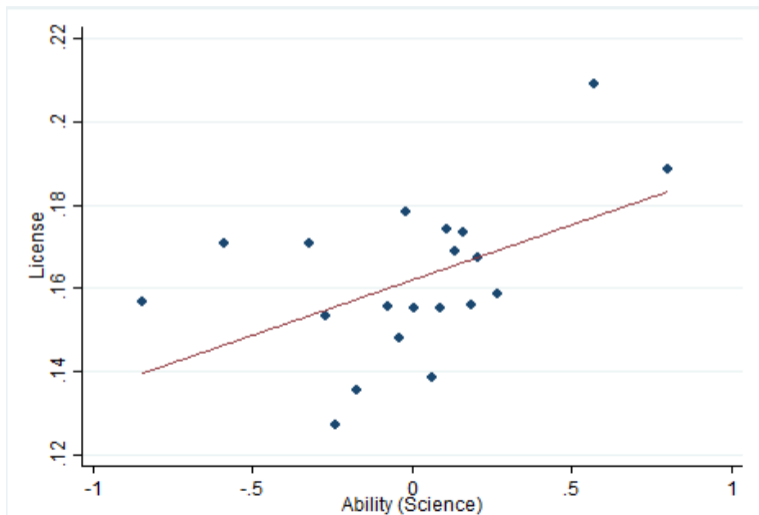
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# Distribution of Unobserved Science, Math & English Ability

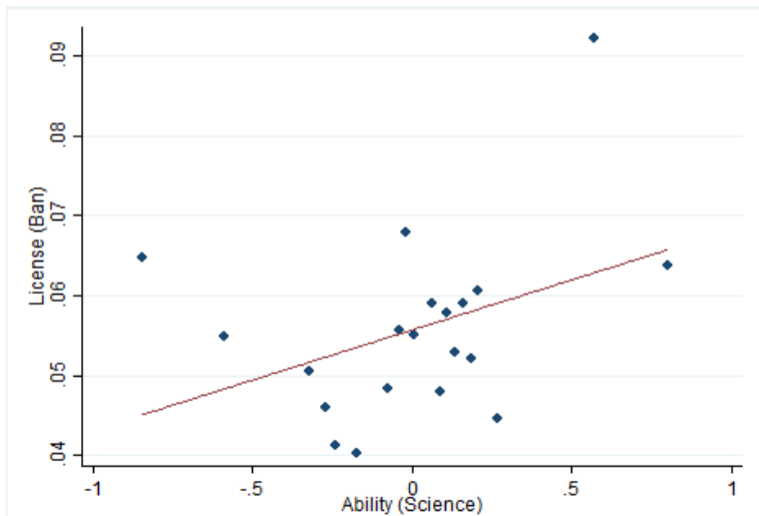


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## License Predicted by Science Ability

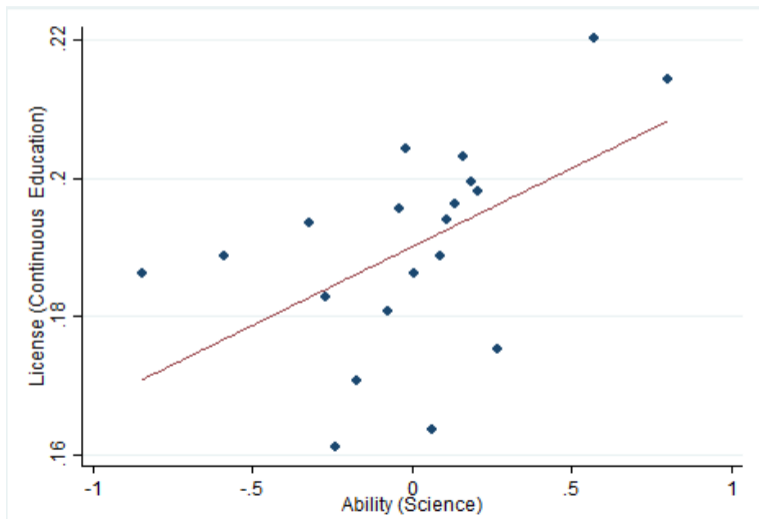


# Felony Ban License Predicted By Science Ability

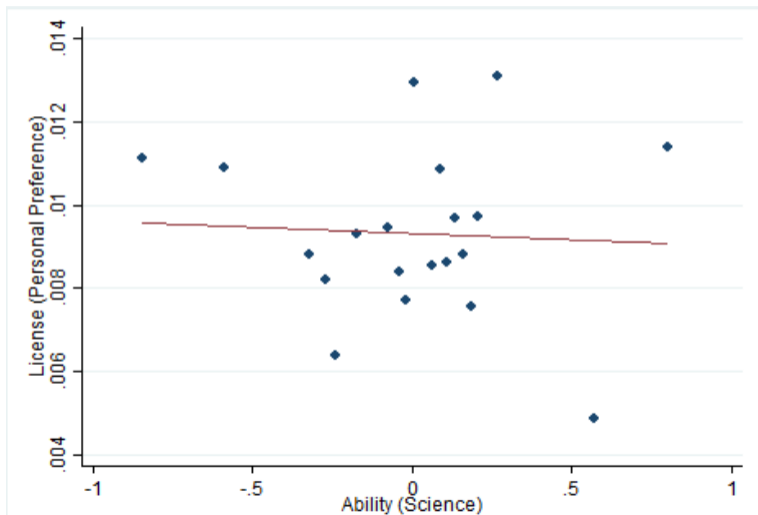




## License w/ Human Capital Requirement Predicted By Science Ability



## Taste for Licensing Uncorrelated with Science Ability



# Ability Correlated w/ Licensing, but Independent of Taste

Regress License decision on measures of ability:

- 1  $\uparrow$  ability from min to median  $\implies$  1.3 p.p.- 2.65 p.p.  $\uparrow$  in the prob. of license
- 2 Science ability positively correlated with all license types
- 3 Math ability negatively correlated w/ felony restriction license
- 4 English: positively correlated w/ human capital license

	(1) license	(2) con_edu	(3) ban	(4) person
Ability (sci)	0.0265*** (0.00834)	0.0227** (0.00980)	0.0126*** (0.00465)	-0.000299 (0.00202)
Ability (math)	-0.0157* (0.00903)	-0.00271 (0.00910)	-0.0130** (0.00545)	-0.000630 (0.00217)
Ability (eng)	0.0103 (0.0102)	0.0192* (0.00967)	0.00488 (0.00470)	0.000475 (0.00128)
Observations	18,881	18,881	18,881	18,881
R-squared	0.058	0.068	0.045	0.004
control	X	X	X	X

Robust standard errors in parentheses; \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Data Source: *Wave 13 to Wave 16 of SIPP Panel 2008.*

# Main Results Robust to Controlling for Ability and Tastes

- 1  $\uparrow$  ability from min to median  $\implies$  1.3%-2.8%  $\uparrow$  in wages.
- 2 Comparable to returns to licensing for a white male in an occupation with no human capital component and no felony restriction.
- 3 Including linear ability and taste controls to wage regression yields similar results:
  - Licensing premia for white men unaffected.
  - Felony ban effect for black men goes *up* by 0.5 p.p.
  - Licensing premia for women change by 0.1 - 0.3 p.p. (magnitude).
- 4 Results hold using higher (5th) order ability controls. [Results](#)

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# Result Robust to Partial Licensing & Controlling for Match Quality of Felony Data

## ① Partial licensing of occupations:

- Include indicator for partially licensed occupations: results similar
- Drop all partially licensed workers:
  - ① black male premium in felony occupations similar.
  - ② returns to education component of license  $\uparrow$  for white men and  $\downarrow$  for women and black men. [Partial Licensing Results](#)

## ② Imperfect matching of legal felony bans to occupations:

- SOC-autocoder yields match quality for occupations
- Binary Control for above median quality level: results similar to OLS
- Continuous Control log (101-quality): results similar to OLS
- [Match Quality Results](#)

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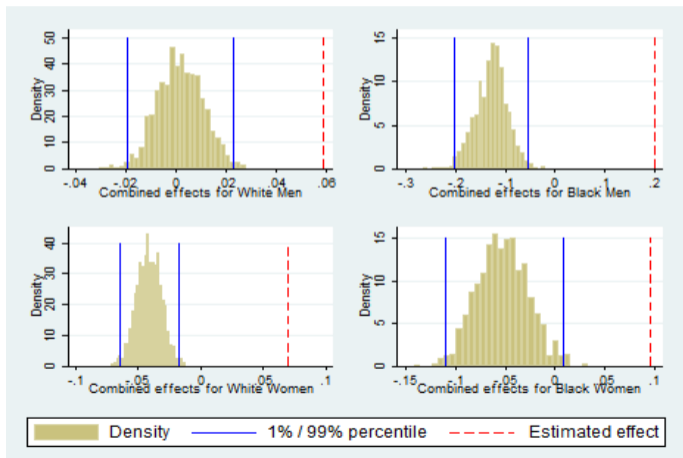
## Result Robust to Measurement Error Placebo Tests

One additional source of measurement error is misreporting of license attainment. To generate the empirical distribution of our results in the face of this type of measurement error we:

- 1 Generate  $N = 1000$  *placebo tests* in which we randomize license attainment for all workers, matching fraction of licensed workers (separately) at:
  - national level
  - state level
  - state-by-occupation levels.
- 2 Compare the estimated coefficients from *placebo tests* to licensing premia from the true data to their empirical distribution from randomized data using z-scores and p-values.
  - There are twelve (12) race-by-gender-by-license premia for each level of aggregation (36 overall).

# Ban Premium Not Due to Measurement Error

Placebo Tests that keep fraction licensed the same at *national level*:



## Results of All Placebo Tests at the National Level

At national level 11/12 premia z-score  $> 2$  and p-value  $< 1\%$ . All except white men in licenses with no human capital or felony information.

		License	Con. Edu	Felony Ban
whitemen	p-value	0.187	0.001	0.001
	z score	-1.000	4.920	6.228
blackmen	p-value	0.001	0.001	0.001
	z score	7.450	5.437	10.195
whitewomen	p-value	0.001	0.001	0.001
	z score	15.406	11.288	11.076
blackwomen	p-value	0.001	0.001	0.001
	z score	10.477	9.729	5.778



# Summary of Placebos

Overall 34/36 premia z-score  $> 2$  and p-value  $< 1\%$ :

- 1 National level: all license premium significant except for white men (no ban, no human capital) [Figure](#) [t-statistics](#)
- 2 At state-level: all license premium significant at 1% level. [Figure](#) [t-statistics](#)
- 3 State-by-occupation: all license premium significant at 1% level except black man with human capital. [Figure](#) [t-statistics](#)

Key take-away: license premium with felony bans for black men and license premium with human capital for women are positive and robust to measurement error. [Back to Main](#)

# No ability Bias in Results

	Base model	Ability (Linear)	Ability (Polynomial)
ban	0.0354 (0.0235)	0.0354 (0.0228)	0.0336 (0.0228)
ban_blackmen	0.131* (0.0725)	0.140* (0.0735)	0.139* (0.0743)
ban_whitewomen	-0.0475* (0.0271)	-0.0456* (0.0269)	-0.0417 (0.0270)
ban_blackwomen	-0.0728* (0.0388)	-0.0756* (0.0392)	-0.0765* (0.0393)
con_edu	0.0349** (0.0163)	0.0336** (0.0163)	0.0332** (0.0162)
con_edu_blackmen	0.0120 (0.0609)	0.0130 (0.0607)	0.0104 (0.0609)
con_edu_whitewomen	0.0369** (0.0176)	0.0364** (0.0178)	0.0379** (0.0174)
con_edu_blackwomen	0.00905 (0.0303)	0.0126 (0.0318)	0.00942 (0.0321)
Math Ability		0.0278*** (0.00679)	
Science Ability		0.0132 (0.00912)	
English Ability		0.0200*** (0.00619)	
Ability Polynomial			X
Observations	262,166	262,166	262,166
R-squared	0.565	0.566	0.567

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## Partially Licensing: $\uparrow$ Return to Human Cap. for Women

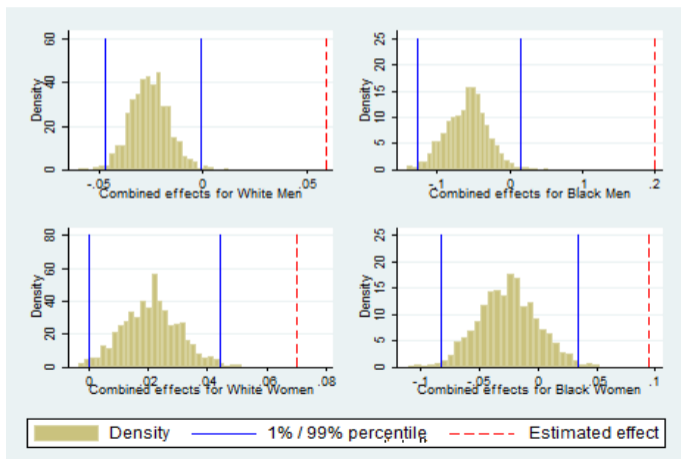
	Base model	Partial	Drop Partial
ban	0.0354 (0.0228)	0.0360 (0.0229)	0.0499 (0.0456)
ban_blackmen	0.140* (0.0735)	0.140* (0.0735)	0.145 (0.137)
ban_whitewomen	-0.0456* (0.0269)	-0.0459* (0.0269)	-0.0910 (0.0663)
ban_blackwomen	-0.0756* (0.0392)	-0.0757* (0.0392)	-0.179 (0.176)
con_edu	0.0336** (0.0163)	0.0336** (0.0163)	0.0520** (0.0245)
con_edu_blackmen	0.0130 (0.0607)	0.0132 (0.0608)	-0.0567 (0.0750)
con_edu_whitewomen	0.0364** (0.0178)	0.0364** (0.0178)	0.0131 (0.0286)
con_edu_blackwomen	0.0126 (0.0318)	0.0124 (0.0318)	-0.00624 (0.0590)
partial		0.00483	
Observations	262,166	262,166	179,417
R-squared	0.566	0.566	0.585

## Results Robust to Controlling for Occ. Match Quality

	Base model	Binary control	Continuous control
ban	0.0354 (0.0228)	0.0313 (0.0256)	0.0181 (0.0280)
ban_blackmen	0.140* (0.0735)	0.139* (0.0733)	0.140* (0.0734)
ban_whitewomen	-0.0456* (0.0269)	-0.0452 (0.0270)	-0.0441 (0.0268)
ban_blackwomen	-0.0756* (0.0392)	-0.0746* (0.0395)	-0.0730* (0.0393)
con_edu	0.0336** (0.0163)	0.0336** (0.0163)	0.0335** (0.0163)
con_edu_blackmen	0.0130 (0.0607)	0.0132 (0.0606)	0.0142 (0.0606)
con_edu_whitewomen	0.0364** (0.0178)	0.0365** (0.0178)	0.0366** (0.0177)
con_edu_blackwomen	0.0126 (0.0318)	0.0124 (0.0319)	0.0130 (0.0318)
poormatch		0.0118 (0.0179)	
log(101-quality)			-0.0193 (0.0183)
Observations	262,166	262,166	262,166
R-squared	0.566	0.566	0.566

# Felony Ban Premium Not Due to Measurement Error

Placebo Tests that keep fraction licensed the same at *state level*:



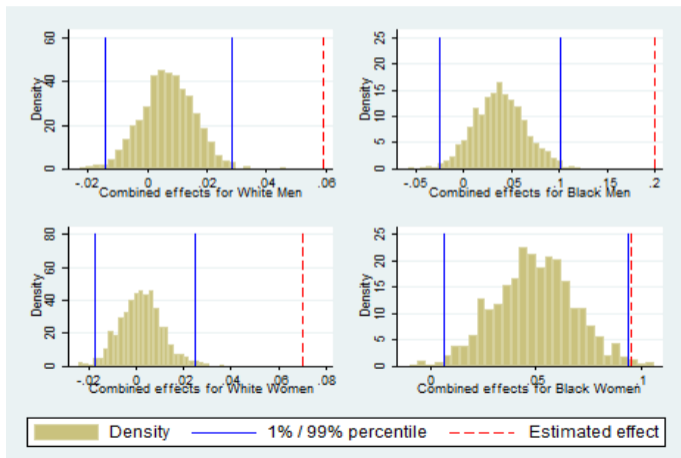
## Results of All State Level Placebo Tests

At national level 12/12 premia z-score  $> 2$  and p-value  $< 1\%$ .

		License	Con. Edu	Felony Ban
whitemen	p-value	0.005	0.001	0.001
	z score	2.66	5.31	8.95
blackmen	p-value	0.001	0.001	0.001
	z score	3.84	5.18	8.79
whitewomen	p-value	0.001	0.001	0.001
	z score	12.20	10.38	5.06
blackwomen	p-value	0.001	0.001	0.001
	z score	9.18	7.69	4.73

# Felony Ban Premium Not Due to Measurement Error

Placebo Tests that keep fraction licensed the same at *state-by-occupation level*:



## Results of All State-by-Occupation Placebo Tests

At state-by-occupation level 11/12 premia z-score  $> 2$  and p-value  $< 1\%$ . (Exception: Black men in licensed occupations with continuous education requirements.)

		License	Con. Edu	Felony Ban
whitemen	p-value	0.001	0.001	0.001
	z score	3.98	12.13	5.78
blackmen	p-value	0.001	0.085	0.001
	z score	-2.66	1.44	6.02
whitewomen	p-value	0.001	0.006	0.001
	z score	10.28	2.68	7.51
blackwomen	p-value	0.001	0.001	0.009
	z score	6.11	4.05	2.39