

Collegio Carlo Alberto

Carlo Alberto Lecture 2007

**Discrimination:
Theory, Evidence, and Legal Issues**

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Roadmap

- Today's talk: the **law and economics of discrimination**
 - how economics can help us think through the law
- Relevant topic for Europe (immigrants, women, etc)
- Start with a specific case: **racial discrimination in policing**
 - Illustrate how economists approach a problem
 - Develop a set of ideas
- Later, enlarge our purview to broad principles of anti-discrimination law

Discrimination in Policing: Background

- Numerous lawsuits against U.S. city police departments alleging racially biased law enforcement practices
- **Common finding:** Blacks and Hispanics are overrepresented in police stops and searches relative to their population shares
- Two possible explanations
 - **Racism:** officers have a preference for searching cars of African American motorists
(Legally: **Discriminatory Intent**)
 - “**Statistical Discrimination**”: race helps to predict criminality, and officers use race in their efforts to fight crime
(Legally: only **Disparate Impact**)
- US law requires plaintiff to prove **discriminatory intent**, not merely **disparate impact** (14th amendment, Title VI)

Tests for Discrimination

- **“Benchmark” tests**
 - Regress search indicator on observable characteristics of driver
Does *Race* add explanatory power?
 - Drawbacks
 - *Require data on full set of characteristics, else subject to omitted variables bias*
 - *What are “valid” conditioning variables?*
 - Small consulting industry develops “benchmark ratios”
- **Outcomes-based test**
 - Gary Becker (1957, 1971) suggested examining profitability of discriminators
 - Knowles, Persico and Todd (*JPE* 2001) “hit rates” test:
use success rate of police searches as measure of profitability
 - *If success rate lower for African Americans, then conclude racism*
 - *If success rate equal across races, then statistical discrimination*

Toy Model

(Knowles, Persico and Todd, JPE 2001, abridged)

Players & Actions

- **Many police officers:** choose which groups of motorists to search. Each officer has 1 search.
- **Many motorists:** choose whether or not to carry drugs.

Heterogeneous in their propensity to carry drugs, but outwardly distinguishable only by race, A-A and W.

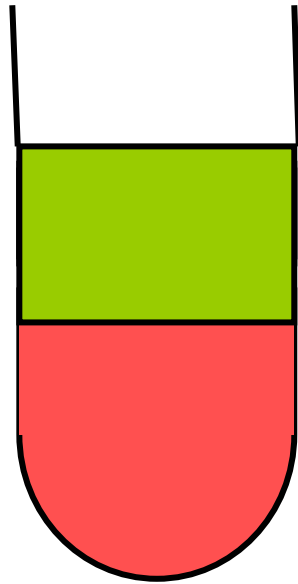
Payoffs

- **Officers**

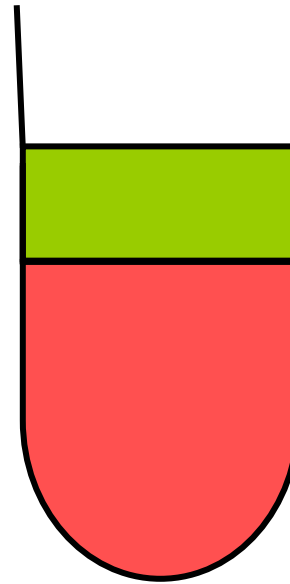
$$\begin{aligned} & \max \{ \text{expected return from search} \} \\ = & \max \{ \text{prob. of finding drugs} + \text{“bias factor”} \} \end{aligned}$$

- **Motorists:** some may want to carry drugs, if probability of being searched not too high
These “potential criminals” may be more frequent among A-A or W

Searching for drugs = sampling from urns



A-A urn



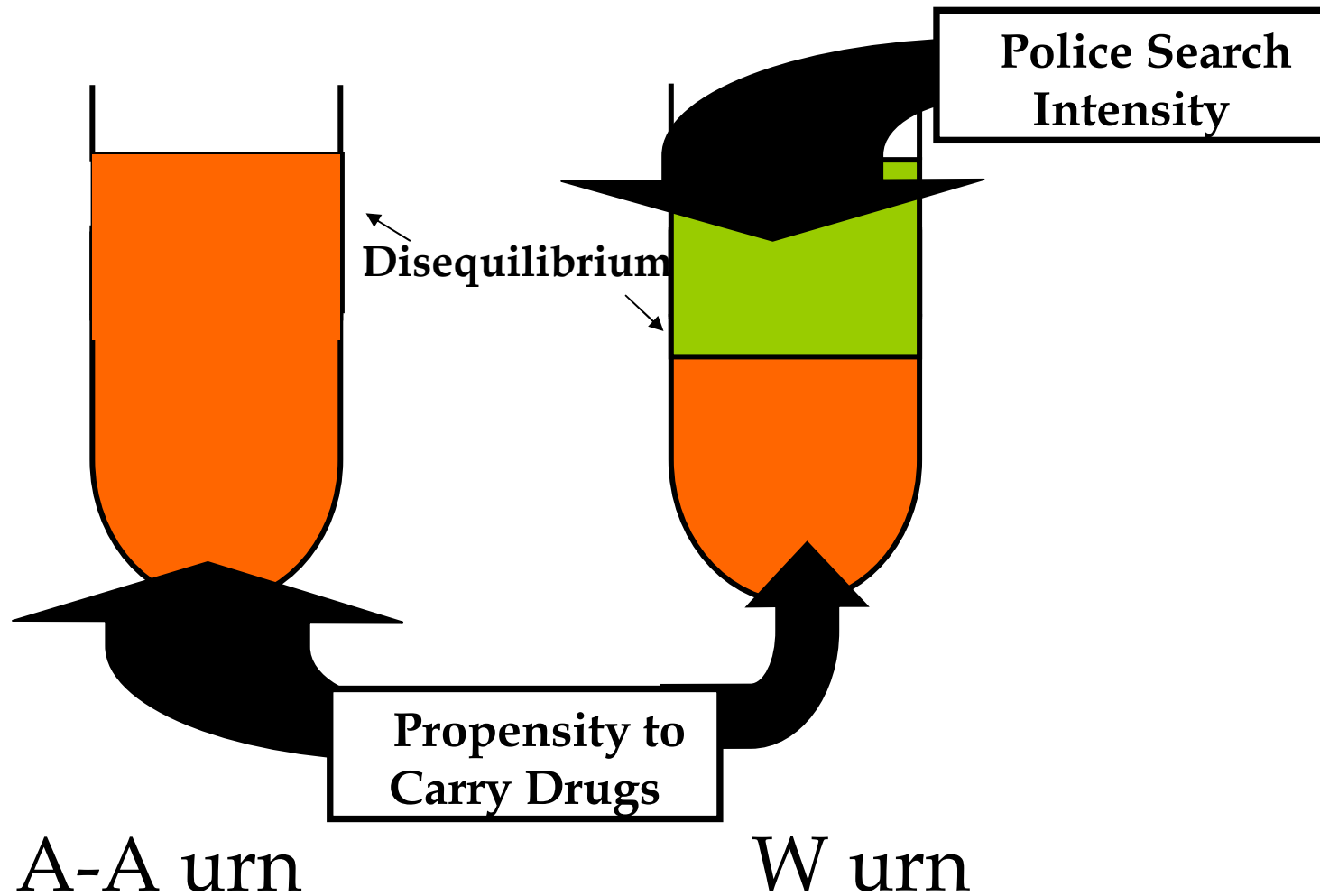
W urn

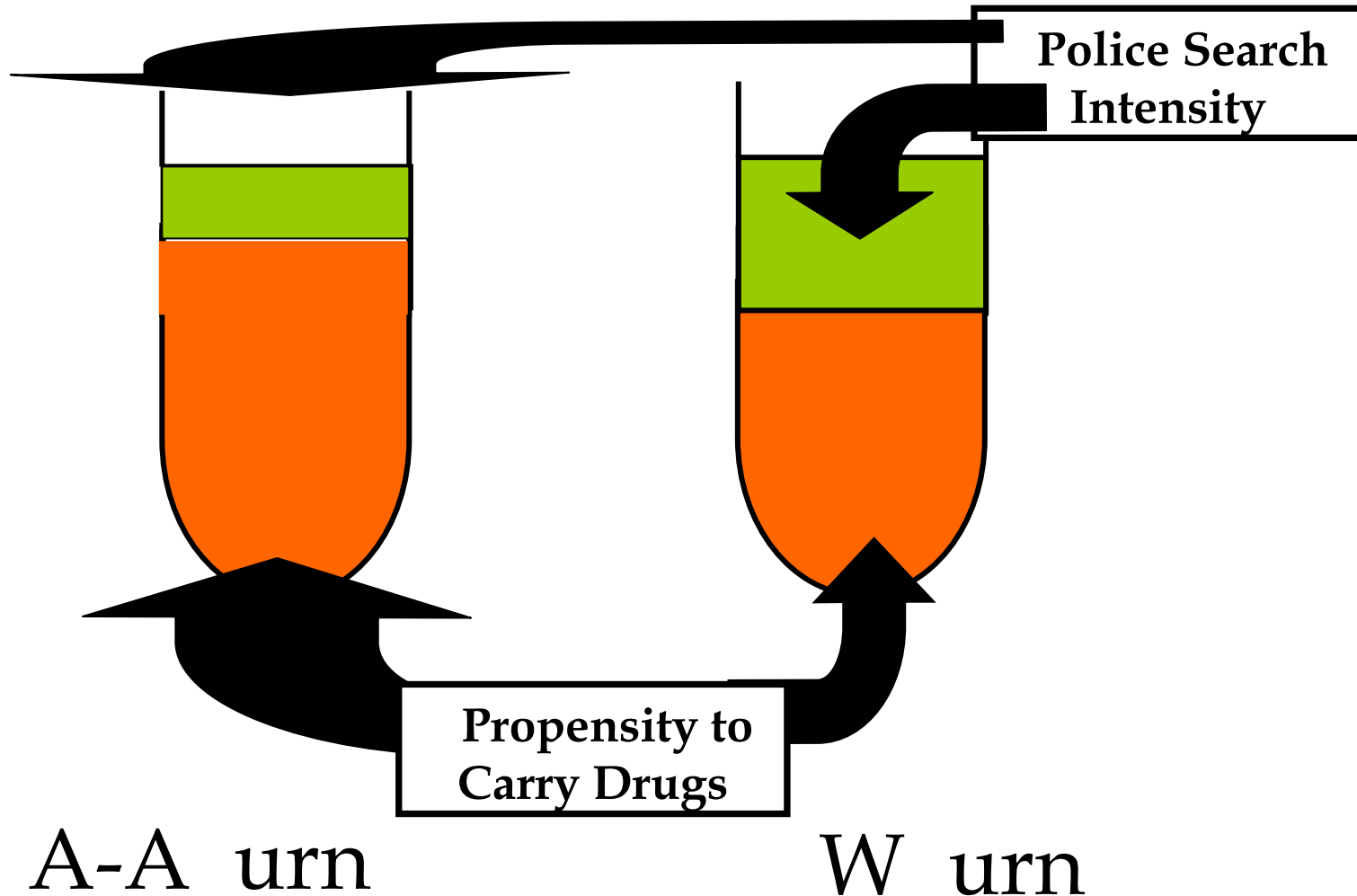
Green = honest

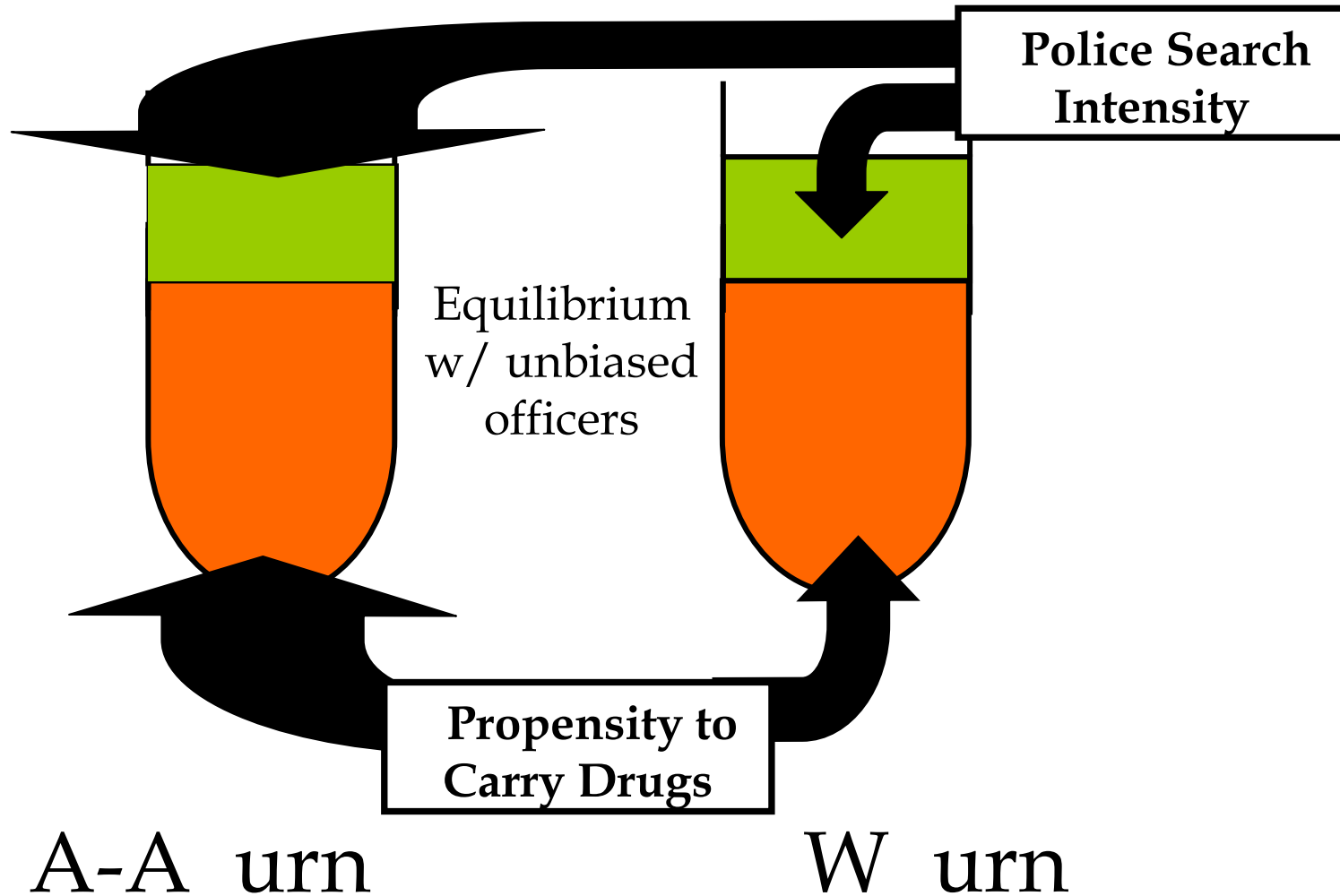
Red = criminal

Equilibrium

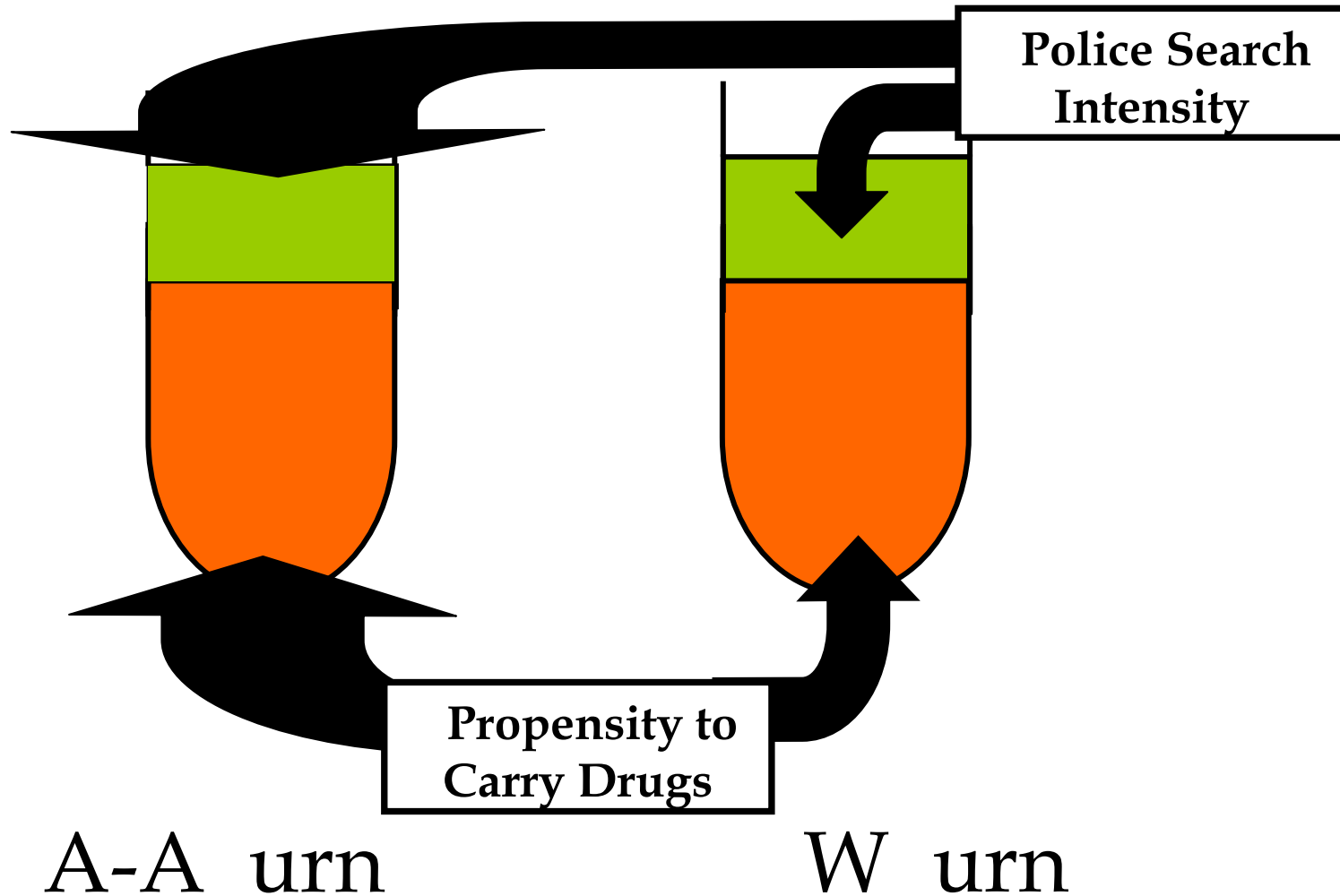
Let's follow notional adjustment process toward equilibrium, starting from a disequilibrium point (only W searched)

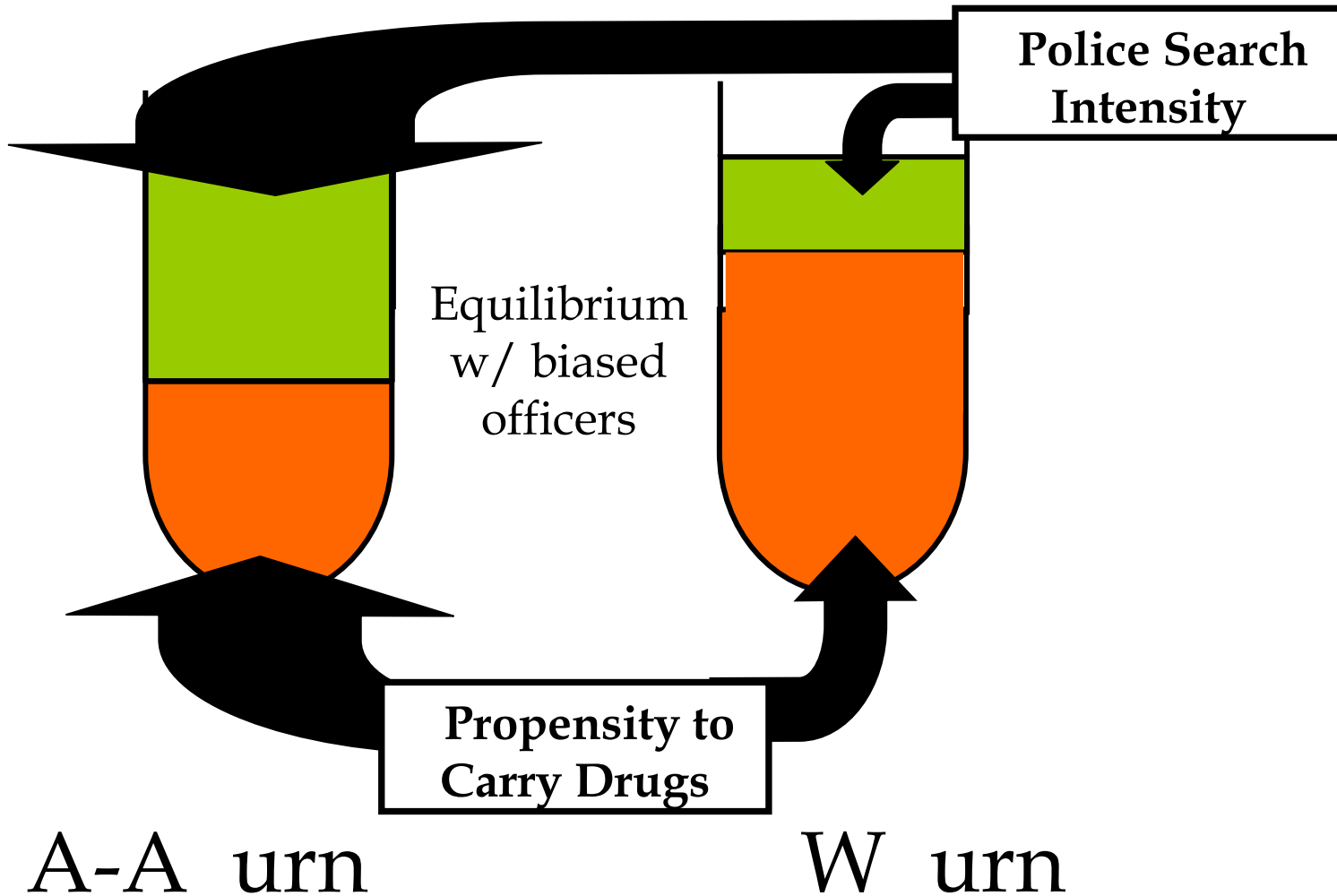






- If officers are biased against A-A, this is not equilibrium
- Biased officers will over-search A-A, owing to bias





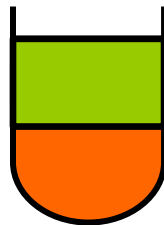
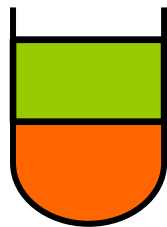
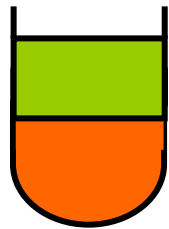
Summing up (I)

- Police bias (intent to discriminate) reflected in likelihood that a police search is successful (hit rate). Lower hit rate on A-A indicates bias (**outcome test**)
- Search intensities not informative on police bias
- In particular, different search intensities together with equal hit rates not indicative of bias, but rather of different propensities to commit crime

Extending outcome-based test to simultaneously ...

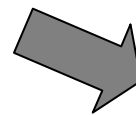
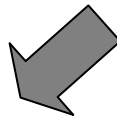
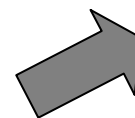
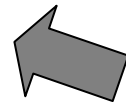
- **More observable characteristics**, complex types
- **Allowing for unobservables**
(police observe more motorist characteristics
than econometrician)

Multidimensional (and Potentially Unobservable) Driver Types



A-A
urns

Search Everybody



W urns

Outcome-based test is also robust to ...

- Some dimensions of heterogeneity within police force (PT 2005)
- To motorist masquerading (some motorists change skin color, at a cost) (PT 2005)

Evidence from Maryland State Police

(Knowles, Persico, Todd 2001)

- **Data:** 1590 observations on all motor vehicle searches (no stops) on a stretch of I-95 in Maryland from 1995 through 1999
- Collected as part of the settlement of a lawsuit filed in February 1993 by ACLU

Table 1
Means and Standard Deviations of Variables used in Analysis
(standard error of the mean shown in parentheses)

African-American	0.63 (0.01)
White	0.29 (0.01)
Hispanic	0.06 (0.01)
Female	0.07 (0.01)
Cocaine	0.08 (0.01)
Marijuana	0.23 (0.01)
Crack Cocaine	0.04 (0.01)
Heroin	0.02 (.004)
Morphine	0.001 (.001)
Other Drugs	0.01 (.003)
Paraphernalia	0.01 (.002)
Number of Observations	1590

Table 2a
Proportion of Vehicles Searched Found to be Carrying Drugs
by Race/Ethnicity

African American	0.34
White	0.32
Hispanic	0.11
Other	0.30

Table 2b
Proportion of Vehicles Searched Found to be Carrying Drugs
by Sex

Male	0.32
Female	0.36

Table 2c
Proportion of Vehicles Searched Found to be Carrying Drugs
by Time of Day

Day	.32
Night	.33

Table 2d
Proportion of Vehicles Searched Found to be Carrying Drugs
by Type of Car

Luxury	.25
Not Luxury	.33
Older Car (>= 10 years old)	.32
Newer Car (< 10 years old)	.33
Third party vehicle	.29
Own vehicle	.33

Table 3
P-values from Pearson Chi-Squared Tests on
Hypothesis that Proportion Guilty is Equal
Across Various Groupings

Race (African American, Hispanic and white)	<0.001
Race (African American, White)	0.33
Race (African American, White, males only)	0.75
Race (African American, White, females only)	0.02
Sex (male, female)	0.37
Sex and race (African American, Hispanic, white and male, female)	<0.001
Sex and race (African American, white and male or female)	0.10
Luxury model	.06
Older vehicle	.67
Third party vehicle	0.28
Time of day (day/night)	.69

Summing Up (II)

- Large **disparate impact** in MSP searches, BUT
...
- No **intent to discriminate**
- Wichita data (PT 2005): other data set, same message (not shown here)
- Carry out your own analysis on these and other jurisdictions! (My web page)

The Hit Rates Test More Broadly

Summary of Hit Rate Findings for Racial Profiling Studies

	Hit Rates for Whites	Hit Rates for Blacks	Hit Rates For Hispanics
Wichita, KS (this study)	22.7	22.03	18.9
Maryland++	32	34	11
Florida§§	25.1	20.9	11.5
Tennessee§	20.1	19.2	10.3
New Jersey**	10.5	13.5	nr
Rhode Island+	23.5	17.8‡	17.8‡
New York (pedestrian)*	13	11	nr
Charlotte, NC¶	30.9	24.2	nr
Lansing, MI ¶¶	6.8	8.7	nr
Missouri †	23.2	17.5	14.7
San Antonio, TX††	17.2	14.6	14.9
Denver, CO#	16.5	19.7	11.3
Denver, CO (pedestrian)#	18.7	20.6	14.6
Los Angeles, CA ##	23.8	18.2	17.2
Sacramento, CA***	26.5	22.4	28
San Diego, CA§§§	11	12	5
Washington State†††	32	21	nr

Discrimination Law: A Tale of Two Standards

- In **US law**, plaintiff must usually prove **intentional discrimination**
 - Though in several important areas of law plaintiff needs only to show **disparate impact**, the burden of proof shifts on defendant to show that disparity is a “business necessity”
- In **EU law**, it is enough for plaintiff to prove **disparate impact**
 - (referred to as **indirect discrimination**)
 - In EU, for example, the MSP might well lose their case
- EU system potentially more litigious

Philosophy of Discrimination Law

- **Intentional discrimination** standard focuses on procedural unfairness
- **Disparate impact** standard is about ?
 - reallocating resources across protected classes? OR ...
 - establishing a *prima facie* inference of procedural unfairness in asymmetric information environments?
- When the two views clash: kidney transplants

Concluding Remarks:

How economics can help shape discrimination law?

- Many lawyers view **disparate impact** standard as a second-best solution for getting at **intentional discrimination** in informationally asymmetric settings
- When economists can provide tests to detect **intentional discrimination**, then less need for second-best **disparate impact** standard
 - Laband and Piette 's test of sex discrimination in academic publishing
- This is good because **disparate impact** standard is intrusive and poses risk of excessive litigation.

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Carlo Alberto Medal 2007: thank you!



Table 1a
Comparison of Stop and Search Percentages Against Population Benchmark

	Percentage in Population*	Percentage of stops	Percentage of searches ⁺
Black	11.4	21.45	32.65
Asian	4.0	2.81	2.09
White (incl. Hispanic)	75.2	73.90	63.61
White - NonHispanic	65.6	64.37	50.81
White -Hispanic	9.6	9.53	12.80
Native American	1.2	0.17	0.48
Other	8.2	1.68	1.17

* Based on Withrow (2002), tabulated from Census 2000 data for Wichita.

+ Excludes searches that were incident to an arrest (where officers are required to search) and searches for which there was a warrant for the arrest of the driver.

Table 4a
Hit Rates by Race/Ethnicity
(Total Number of Observations in parenthesis)

	Percentage
Black	22.69 (811)
Hispanic	18.87 (318)
White	22.03 (1262)
P-values from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal	0.365

Table 4b
Hit Rates by Age
(Total Number of Observations in parenthesis)

	Percentage
Age < 18	28.64 (206)
Age 18-24	21.71 (866)
Age 25-34	19.93 (602)
Age 35-50	21.77 (611)
Age over 50	20.59 (102)
P-value from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal	0.137

Table 4c
Hit Rates by Age and Race
(Total Number of Observations in parenthesis)

	Black	Hispanic	White	p-value*
Age < 18	30.77 (65)	26.09 (23)	27.97 (118)	0.885
Age 18-24	20.00 (300)	17.12 (146)	24.58 (419)	0.113
Age 25-34	23.12 (199)	16.00 (100)	19.14 (303)	0.309
Age 35-50	24.09 (220)	20.09 (46)	19.77 (344)	0.367
Age over 50	20.0 (25)	50.0 (2)	20.0 (75)	0.5830

***P-value from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal Across Race Groups.**

Table 4d
Hit Rates by Gender
(number of observations in category in parenthesis)

	Percentage
Male	21.61 (1916)
Female	22.64 (477)
P-value from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal	0.625

Table 4e
Hit Rates by Gender and Race
(number of observations in category in parenthesis)

	Black	White	Hispanic	P-value
Male	22.71 (687)	18.86 (281)	21.67 (946)	0.418
Female	22.58 (124)	18.92 (37)	23.10 (316)	0.847

Table 4f
Hit Rates by Time of Day
(number of observations in category in parenthesis)

	Proportion
Daytime	17.11 (561)
Nighttime	23.38 (1835)
P-value from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal	0.002

* Daytime is in between the hours of 8am and 7pm.

Table 4g
Hit Rates by Time of Day and Race
(number of observations in category in parenthesis)

	Black	Hispanic	White	P-value*
Daytime	19.34 (181)	9.09 (55)	17.69 (294)	0.208
Nighttime	23.65 (630)	16.77 (155)	23.35 (968)	0.165

*P-value from Pearson Chi-Squared Tests of Hypothesis that Proportion Equal Across Race Categories.