Search Distaste at the Highway Stop Level

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Highway Search

“Benchmarking” Papers: Compare Search Prob Using Covariate Adjustment


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Becker Model
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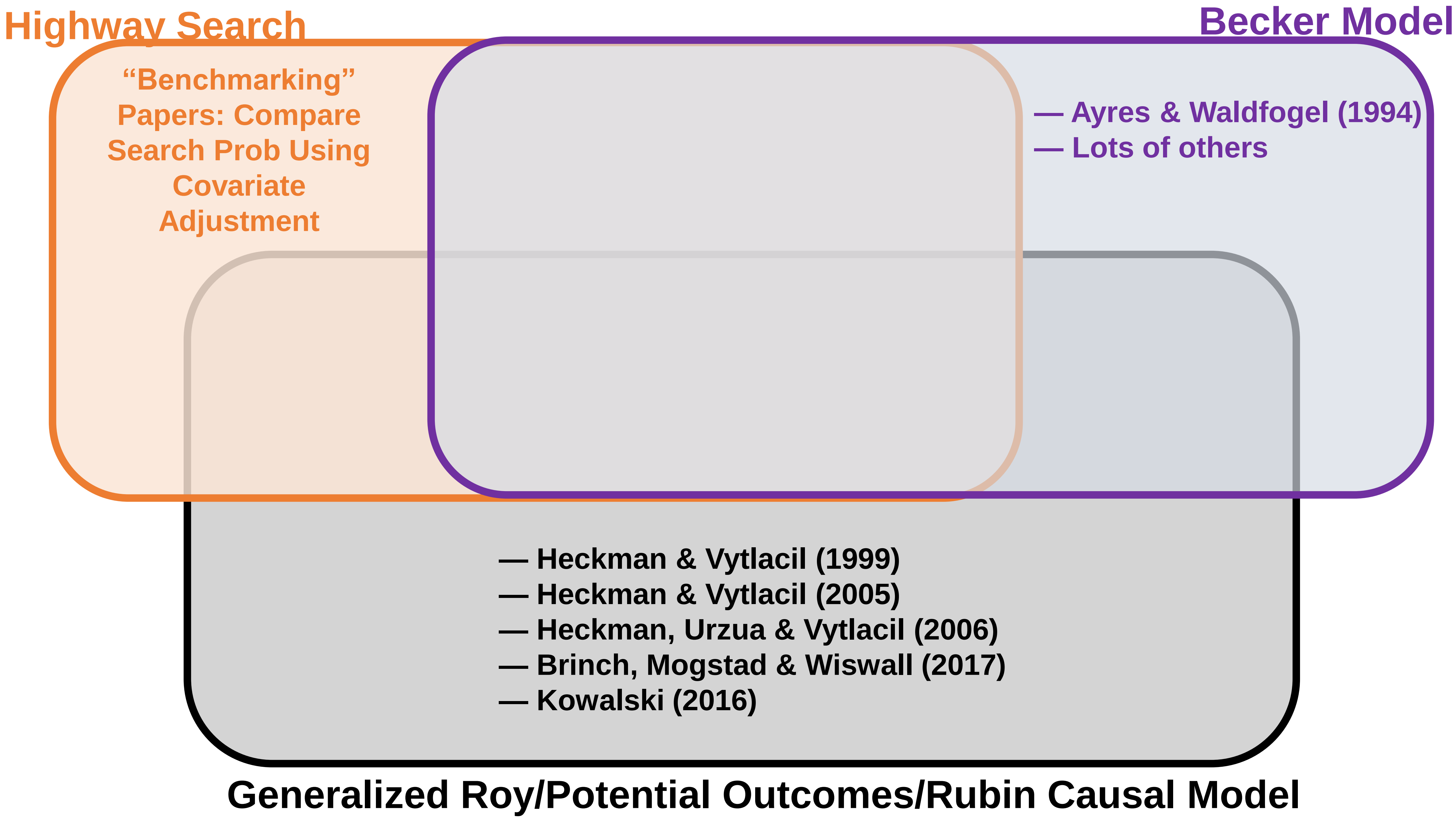
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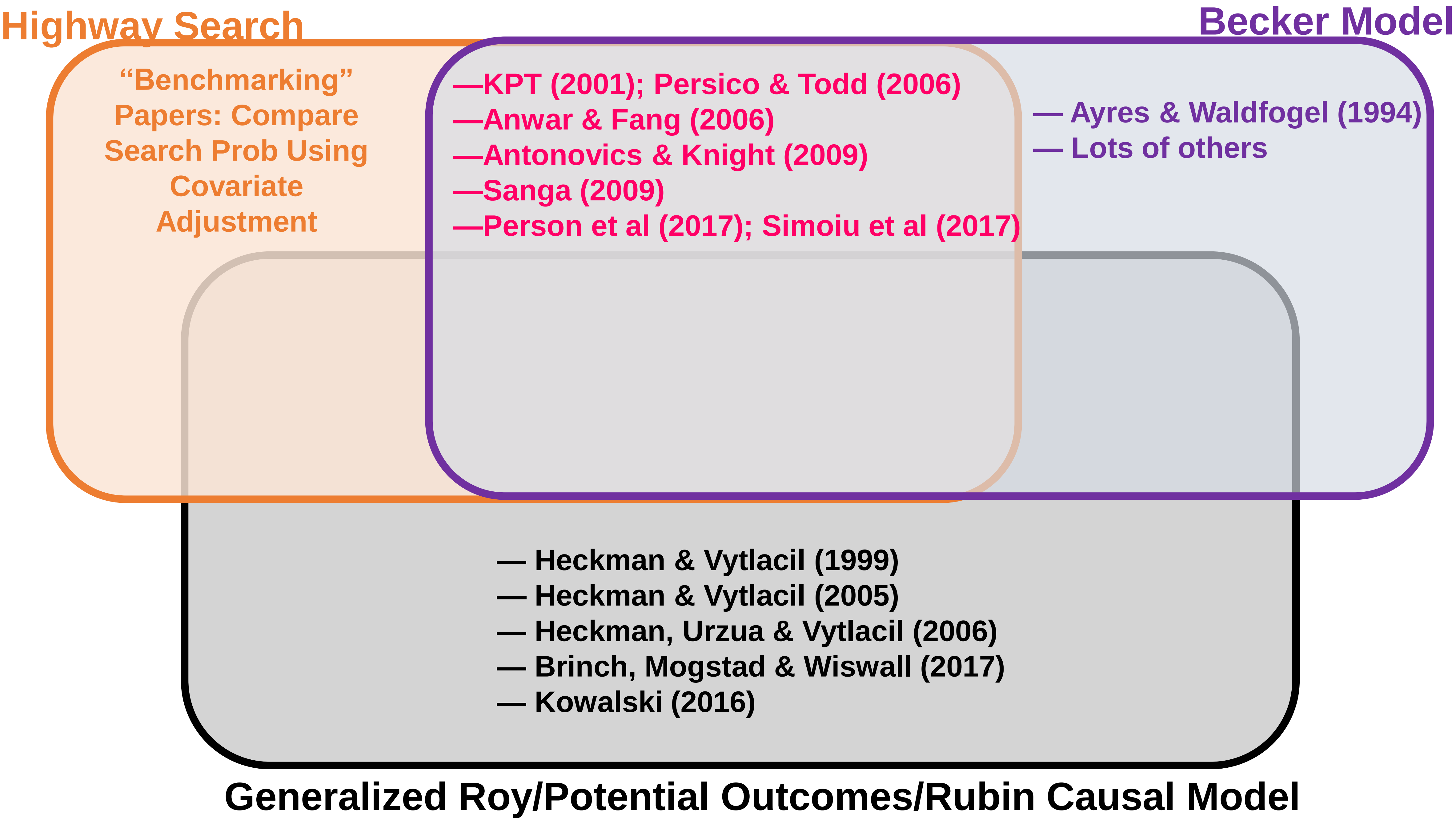
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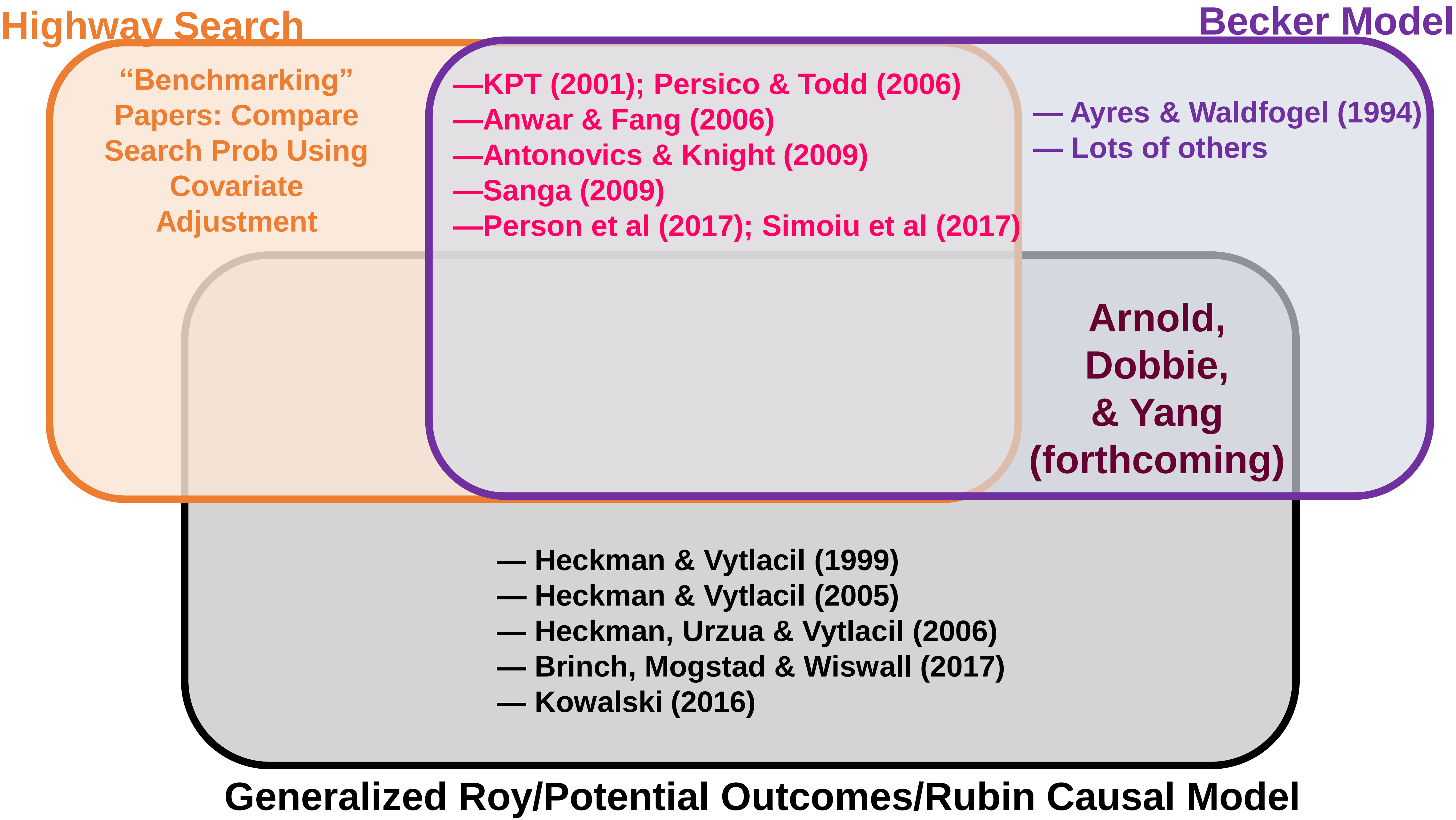
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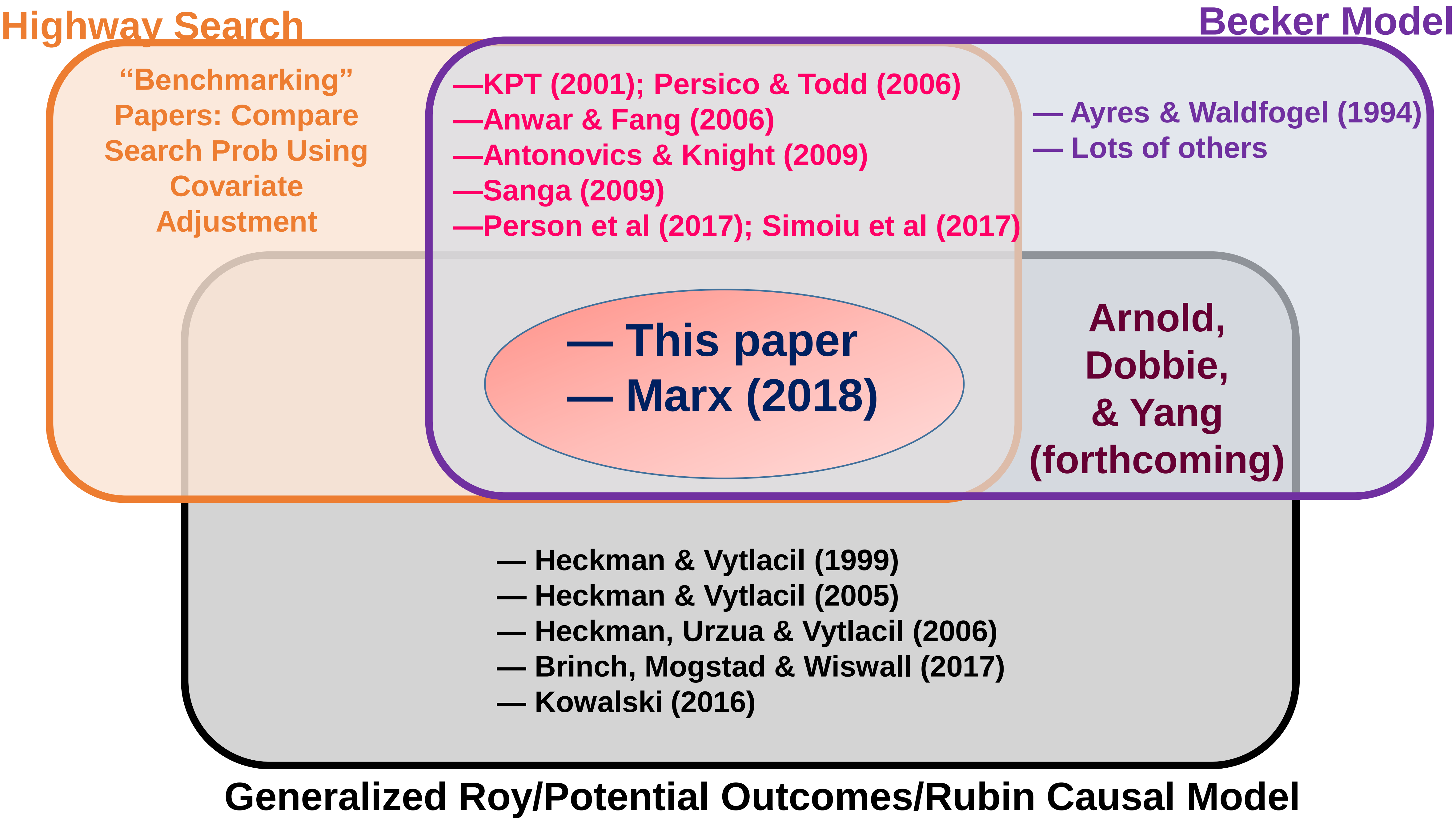
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Generalized Roy/Potential Outcomes/Rubin Causal Model

The Model

Highway stops by officer *j* occur exogenously

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Produce driver with misconduct probability M

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Officer has search distaste δ

Search occurs if $M > \delta$

Highway stops by officer j occur exogenously

Produce driver with misconduct probability M

If race is r & driver/stop characteristics $X = x$:

Search occurs if $M > \delta_{r,j}(x)$

Measure of stop-level discrimination:

$$\Delta_j(\ r_2, r_1) \equiv \delta_{r_2,j} - \delta_{r_1,j}$$

Same officer

Measure of stop-level discrimination:

Same driver/stop characteristics

$$\Delta_j(x; r_2, r_1) \equiv \delta_{r_2,j}(x) - \delta_{r_1,j}(x)$$

Same officer

Measure of stop-level discrimination:

$$\Delta_j(x; r_2, r_1) \equiv \delta_{r_2,j}(x) - \delta_{r_1,j}(x)$$

We can average this over X, over j, or both

So the ideal object of estimation is

$$\delta_{r,j}(x)$$

Assume

$$\boldsymbol{\delta_{r,j}(x) = \delta_r(x, \tilde{z}_j)},$$

where $\tilde{z}_j$ is an instrumental variable.

Assume

$$\delta_{r,j}(x) = \delta_r\left(x, \tilde{z}_j\right),$$

For stop i, use

$$\tilde{z}_j \equiv \frac{1}{N_j - 1} \sum_{k \neq i} D_k$$

Driver misconduct probability distribution

$$\boldsymbol{P(M \leq m) \quad = \quad F_M(m)}$$

Driver misconduct probability distribution

Allowing differences by r and X:

Driver misconduct probability distribution

Allowing differences by r and X:

$$P(M \leq m | r, X = x) = F_{M|X,r}(m | r, X = x)$$

Driver misconduct probability distribution

I will often drop the r subscript and focus on

$$P(M \leq m|X = x) = \boxed{F_{M|X}(m|X = x)}$$

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1. Notice that $\tilde{z}$ does not appear.

Driver misconduct probability distribution

I will often drop the r subscript and focus on

$$P(M \leq m|X = x) = \boxed{F_{M|X}(m|X = x)}$$

2. KPT: This is degenerate—all mass at $\mathbf{m} = \bar{h}$

Driver misconduct probability distribution

I will often drop the r subscript and focus on

$$P(M \leq m|X = x) = \boxed{F_{M|X}(m|X = x)}$$

Time to define search & hit rates…

The search rate

$$s(\delta) = 1 - F_M(\delta)$$

The search rate and the hit rate

$$s(\delta) = 1 - F_M(\delta)$$

$$h(\delta) = \frac{\int_{\delta}^{1} m f_m(m)\,dm}{s(\delta)}$$

The unconditional hit rate

$$\int_{\delta}^{1} m f_m(m)\,dm$$

$$v(\delta) \quad = \quad s(\delta)h(\delta)$$

Two key facts

1. The hit rate and search rate are negatively related
2. The slope of the unconditional hit rate identifies δ

$$\frac{dw}{d\delta} = -\delta f(\delta), \quad \frac{ds}{d\delta} = -f(\delta) \Rightarrow \frac{dw}{ds} = \delta$$

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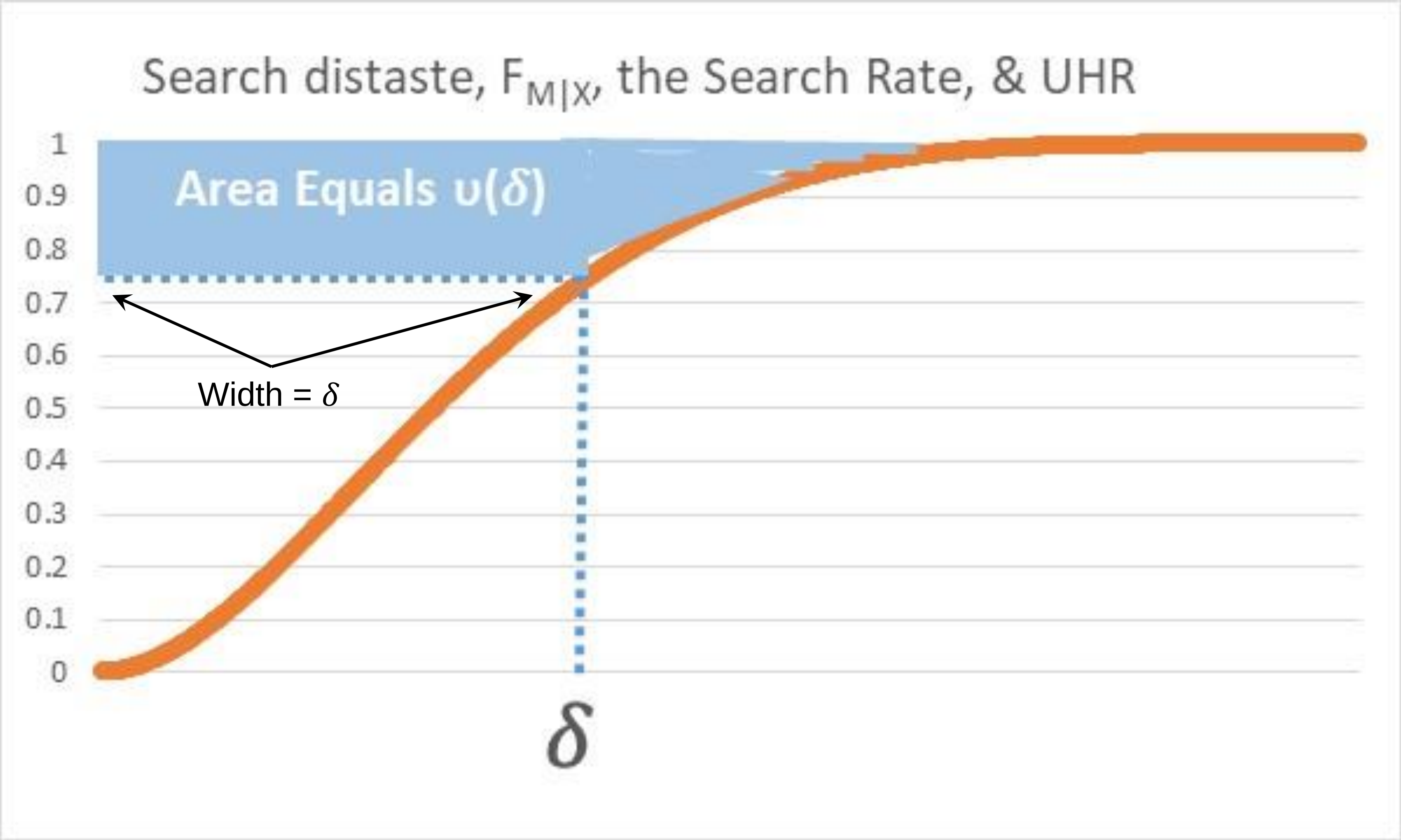

Search distaste, $F_{M|X}$, the Search Rate, & UHR
Area Equals υ(δ)
Width = δ
δ
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0

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This is empirically useful: $v(s)$ is E[Y|s]

Data

Florida data — From Anwar & Fang (2006)

— 906k stops from 2001

— 9k searches

— Data include lots of covariates

* Driver gender; time of day; location*
* Officer race & gender
* Out-of-state tags, number of passengers

Harris County data

— **From Stanford Open Policing Project**

— **600k stops from 2006-2015**

— **Also about 9k searches**

— **Fewer covariates available**

* **Driver gender; time of day; f.g. location**

Specification test: Are h & s negatively related?

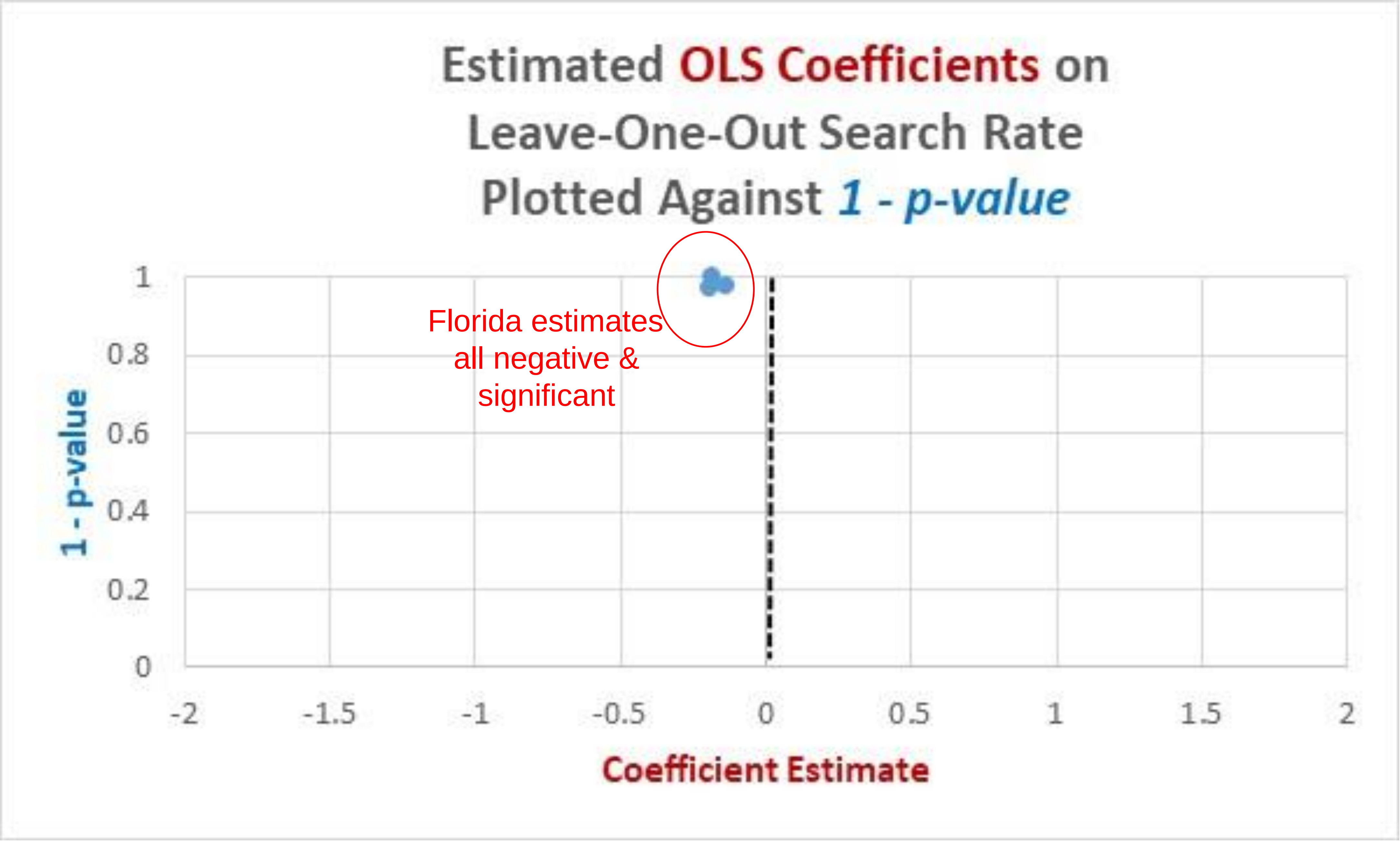
— Dependent variable is conditional hit dummy

— OLS coefficient on officer search rate

* Calculated using leave-one-out approach
* Search rate among others stopped by j

(other covariates included, too)

Specification Test Results


Estimated OLS Coefficients on
Leave-One-Out Search Rate
Plotted Against 1 - p-value
Florida estimates
all negative &
significant
1 - p-value
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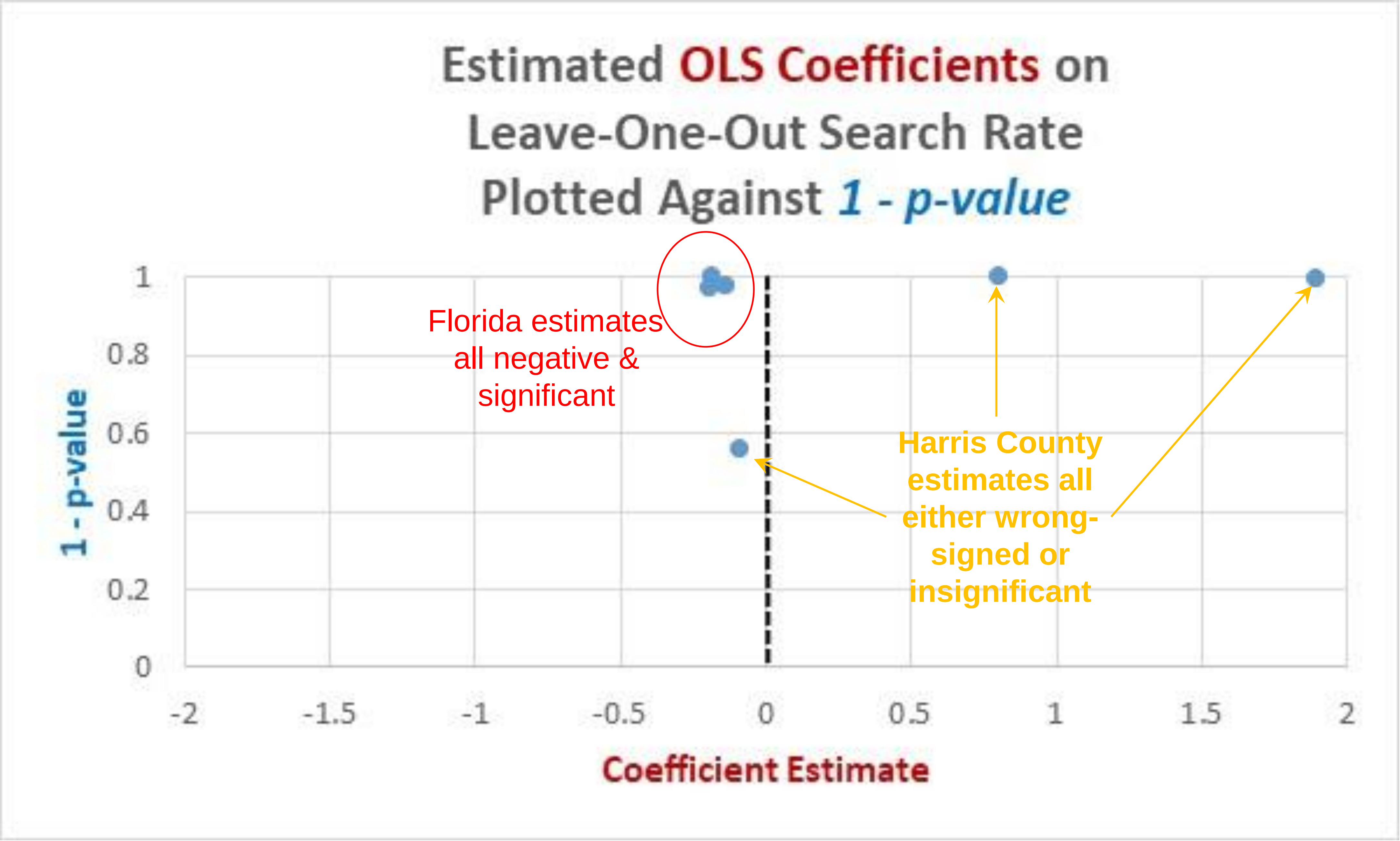
0.8
0.6
0.4
0.2
0
-2
-1.5
-1
-0.5
0
0.5
1
1.5
2
Coefficient Estimate



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Coefficient Estimate
Florida estimates all negative & significant
Harris County estimates all either wrong-signed or insignificant

Take-home points

1. **Florida data support non-degenerate $F_{M|X}$**

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2. Harris County data do <u>not</u>

   —But KPT model also not supported
   —T5 reports several significant coefficients
   —Maybe I lack enough X for Harris County?

Take-home points

1. Florida data support non-degenerate $F_{M|X}$

2. Harris County data do <u>not</u>

   —But KPT model also not supported
   —T5 reports several significant coefficients
   —Maybe I lack enough X for Harris County?

3. No support for estimating my model in Harris

Identification & Estimation

Identification of δ involves two key equations

$$P(D = 1 | x, \tilde{z}_j) \quad = \quad 1 - F_{M|X}\left(\delta\left(x, \tilde{z}_j\right)\right)$$

Propensity-score equation: At least identifies s

Identification of δ involves two key equations

$$P(D = 1|x, \tilde{z}_j) = 1 - F_{M|X}\left(\delta(x, \tilde{z}_j)\right)$$

$$\frac{dv}{ds} = \delta(x, \tilde{z}_j)$$

Slope of UHR

Object of interest

Identification of δ involves two key equations

$$P(D = 1|x, \tilde{z}_j) = 1 - F_{M|X}\left(\delta(x, \tilde{z}_j)\right)$$

$$\frac{dv}{ds} = \frac{dE[Y = 1|x, P = s]}{ds} = \delta(x, \tilde{z}_j)$$

Slope of UHR

Heckman & Vytlacil's Local IV Parameter

Object of interest

Two Examples In Which δ is Identified

Strategy #1: Identification via nonlinearity

Suppose the probability of search and δ satisfy

$$F_{M|X}(\delta|X = x) = F_0($$

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Suppose the probability of search and δ satisfy

$$F_{M|X}(\delta|X = x) = F_0(F_0^{-1}(\delta))$$

δ-quantile of x-normalized misconduct distribution

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Suppose the probability of search and δ satisfy

$$F_{M|X}(\delta|X=x) = F_0\left(F_0^{-1}(\delta) - x\alpha_0\right)$$

δ-quantile of x-normalized misconduct distribution

Location shift

Strategy #1: Identification via nonlinearity

Suppose the probability of search and δ satisfy

$$F_{M|X}(\delta|X = x) = F_0(F_0^{-1}(\delta) - x\alpha_0)$$

$$\delta(x, \tilde{z}) = g(x\alpha_1 + \tilde{z}\gamma).$$

Strategy #1: Identification via nonlinearity

Now suppose $F_0 = \Lambda$ (logistic) and $g = \Phi$

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Propensity score equation:

$$P(D = 1|x, \tilde{z}) = 1 - \Lambda\left(\ln\left(\frac{\Phi(\mathrm{x}\alpha_1+\tilde{z}\gamma)}{1-\Phi(\mathrm{x}\alpha_1+\tilde{z}\gamma)}\right) - x\alpha_0\right)$$

$$\overbrace{1 - \Lambda\left(\qquad\qquad\qquad\qquad \right)}^{F_{M|X}(\qquad |X=x)}$$

$$1 - \Lambda\left(\overbrace{\qquad\qquad\qquad\qquad\qquad\qquad}^{F_{M|X}(\delta(x,\tilde{z})|X=x)}\right)$$

$$1-\Lambda\left(\underbrace{\ln\left(\frac{\delta(x,\tilde{z})}{1-\delta(x,\tilde{z})}\right)}_{\mathrm{logit}(\delta(x,\tilde{z}))}\right)$$

$$1 - \Lambda\left(\underbrace{\ln\left(\frac{\Phi(\mathbf{x}\alpha_1 + \tilde{\mathbf{z}}\gamma)}{1 - \Phi(\mathbf{x}\alpha_1 + \tilde{\mathbf{z}}\gamma)}\right)}_{\text{logit}(\delta(x,\tilde{z}))}\right)$$

$$1 - \Lambda\left(\underbrace{\ln\left(\frac{\Phi(\mathrm{x}\alpha_1 + \tilde{z}\gamma)}{1 - \Phi(\mathrm{x}\alpha_1 + \tilde{z}\gamma)}\right)}_{\text{logit}(\delta(x,\tilde{z}))} \underbrace{-x\alpha_0}_{\text{Location shift}}\right)$$

Strategy #1: Identification via nonlinearity

Now suppose $F_0 = \Lambda$ (logistic) and $g = \Phi$

Propensity score equation:

$$P(D = 1|x, \tilde{z}) = 1 - \Lambda\left(\ln\left(\frac{\Phi(x\alpha_1 + \tilde{z}\gamma)}{1 - \Phi(x\alpha_1 + \tilde{z}\gamma)}\right) - x\alpha_0\right)$$

Nonlinearity can be enough to identify α_1 & γ

Strategy #2: Identification/estimation via IV

Now suppose $F_0 = g$

Propensity score equation:

$$P(D = 1|x, \tilde{z}) = 1 - F_0(x(\alpha_1 - \alpha_0) + \tilde{z}\gamma)$$

Can't distinguish α_1 & α_0 using only P-score eq

Strategy #2: Identification/estimation via IV

Now suppose $F_0 = g$

Unconditional hit rate slope equation:

$$\frac{dE[Y|x,P(Z)=s]}{ds} = \mathbf{F_0}\left(\mathbf{x}\alpha_0 + \mathbf{F_0^{-1}}(\mathbf{1} - \mathbf{s})\right)$$

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Now suppose $F_0 = g$

Unconditional hit rate slope equation:

$$\frac{dE[Y|x, P(Z)=s]}{ds} = \mathbf{F_0}\left(\mathbf{x}\alpha_0 + \mathbf{F_0^{-1}}(\mathbf{1} - \mathbf{s})\right)$$

Now we integrate…

Strategy #2: Identification/estimation via IV

Now suppose $F_0 = g$

Unconditional hit rate slope equation:

$$E[Y|x, P = s] = \mathbf{x}\alpha_2 + \int F_0\left(\mathbf{x}\alpha_0 + \mathbf{F_0^{-1}}(\mathbf{1} - \mathbf{s})\right)\mathbf{ds}$$

Note the presence of both x and s inside the $\int$

Strategy #2: Identification/estimation via IV

Now suppose $F_0 = g$ is linear.

Then:

$$E[Y|x, P(Z) = s] = \mathrm{x}\alpha_2 + (s\mathrm{x})\alpha_0 + Q(1 - s)$$

Strategy #2: Identification/estimation via IV

Now suppose $F_0 = g$ is linear.

$$\boldsymbol{E[Y|x, P(Z) = s] = x\alpha_2 + (sx)\alpha_0 + Q(1 - s)}$$

We can do

—Local regression: HUV (2006)

—Global poly: Kowalski (2016); Brinch et al (2017)

Generalized Roy Model Representation

Connecting to the Generalized Roy Model

Let Y_d be "found with contraband" if $D = d$

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Let Y_d be "found with contraband" if $D = d$

Here is a GRM representation:

$$Y_0 = 0$$

$$Y_1 = 1[1 - U_1 \geq 0]$$

$$D = 1[U_D \leq \mu_D(Z)],\ U_D \sim \text{Unif}(0,1)$$

$$U_1 = F_{M|X}(U_1^*|X = x) + U_D,\ U_1^* \sim \text{Unif}(0,1)$$

$$\tilde{Z} \perp U_D|X,$$

2 More Specification Tests

(1) Leveraging the P-score equation

— $s = 1 - F_M(\delta) \Rightarrow ds = -f_M(\delta)d\delta < 0$

—So δ decreasing in search prob.

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—So δ decreasing in search prob.

(2) Leveraging inframarginality

—$E[Y|D = 1] \geq E[\delta]$

—So hit rate greater than average δ

Table 1: Means for variables used in analysis (Anwar & Fang Florida data)
(generating time: Mon Jul 23 11:49:05 2018 from file *summary-stats.ara*, table 1.)

	Full sample	Black	Hispanic	White
Search rate				
Search was conducted	0.010	0.013	0.013	0.008
Hit rates				
Among only those searched	0.210	0.209	0.115	0.251

What to Take Home

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