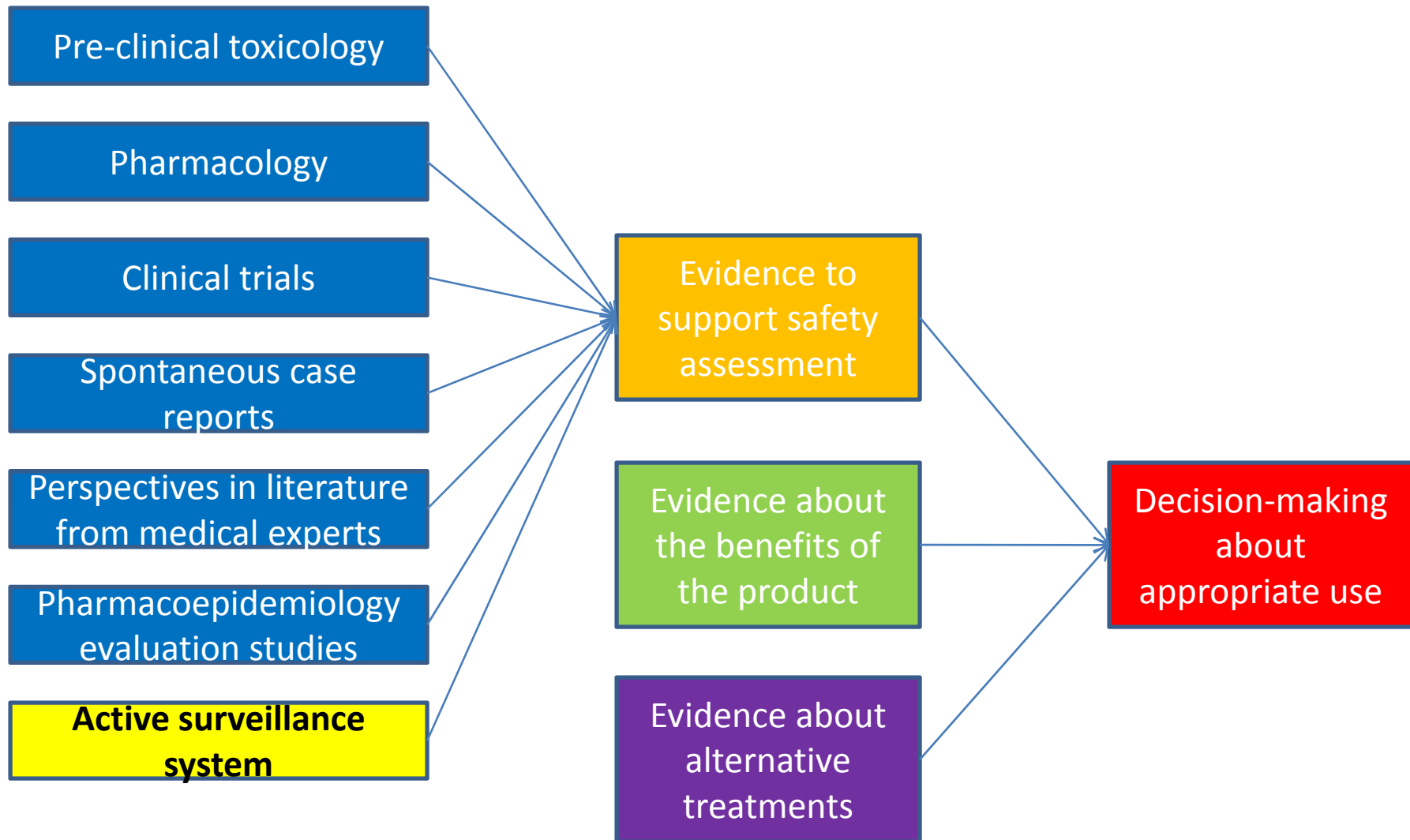


**OBSERVATIONAL
MEDICAL
OUTCOMES
PARTNERSHIP**

**Active Surveillance Methods
Performance and Challenges:
Lessons from the Observational
Medical Outcomes Partnership**

Patrick Ryan, on behalf of OMOP research team
March 14, 2011

Active surveillance: One additional piece of evidence to inform medical decision-making



Methodological challenges for active surveillance

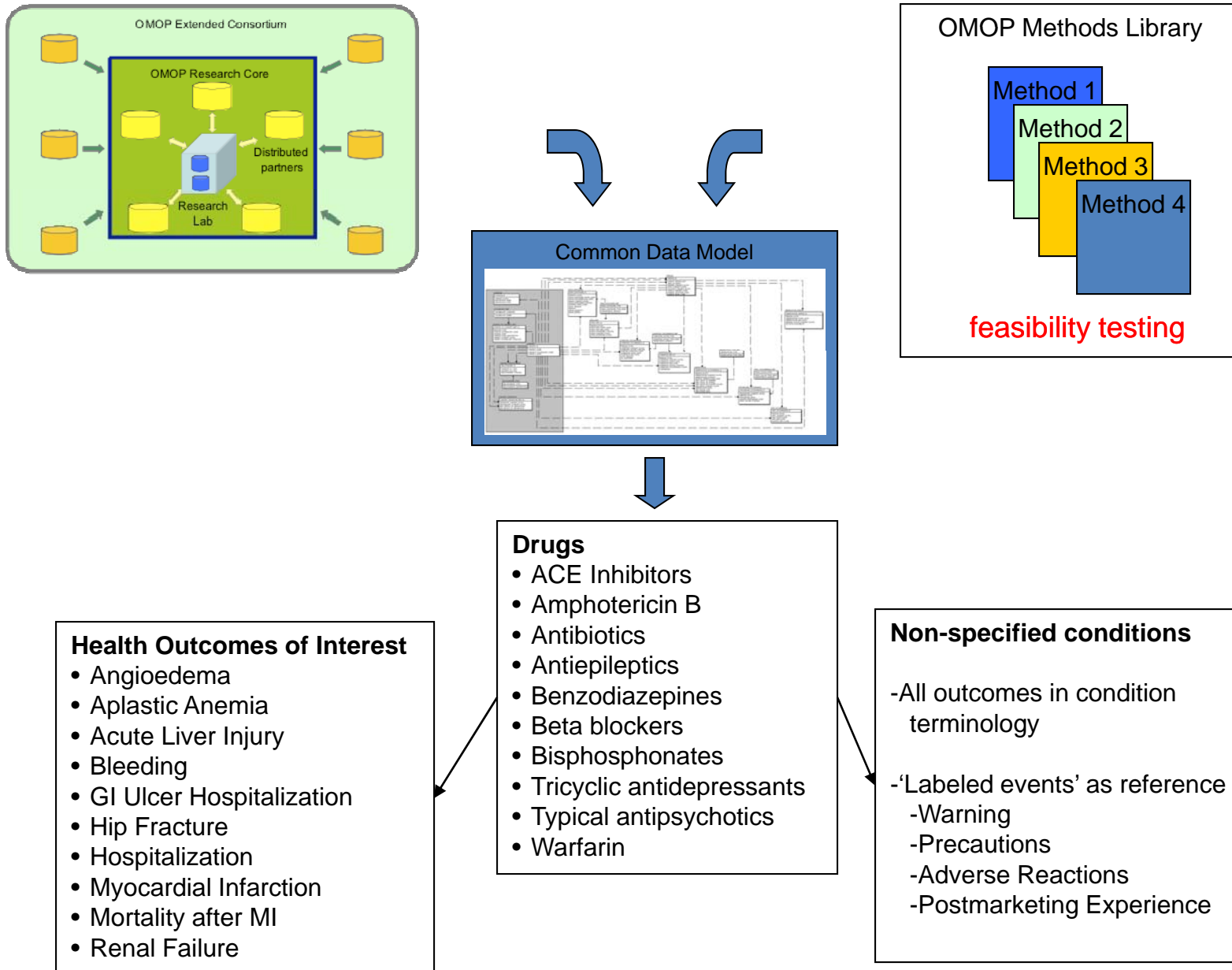
- A traditional pharmacoepidemiology study may conduct an analysis to estimate association of ONE drug and ONE outcome in ONE database at ONE point in time
- A national active surveillance system is envisioned to enable ONGOING monitoring of ANY medical product and ANY health outcome of interest across ALL databases in the network
- Methodological issues to be evaluated:
 - Precision
 - Accuracy
 - Value of information

Observational Medical Outcomes Partnership

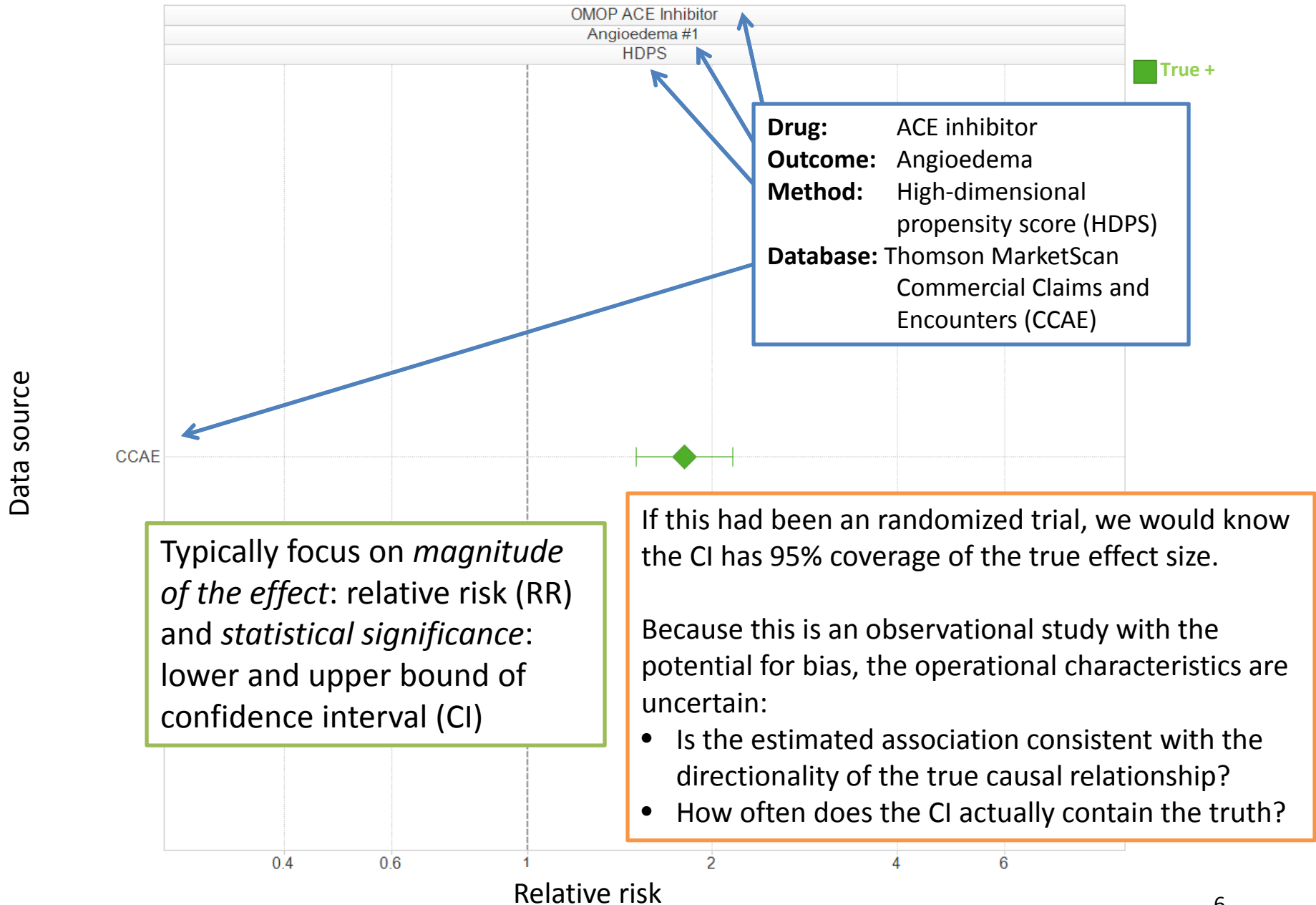
Established to inform the appropriate use of observational healthcare databases for active surveillance by:

- **Conducting methodological research** to empirically evaluate the performance of alternative methods on their ability to identify true drug safety issues
- **Developing tools and capabilities** for transforming, characterizing, and analyzing disparate data sources
- **Establishing a shared resource** so that the broader research community can collaboratively advance the science

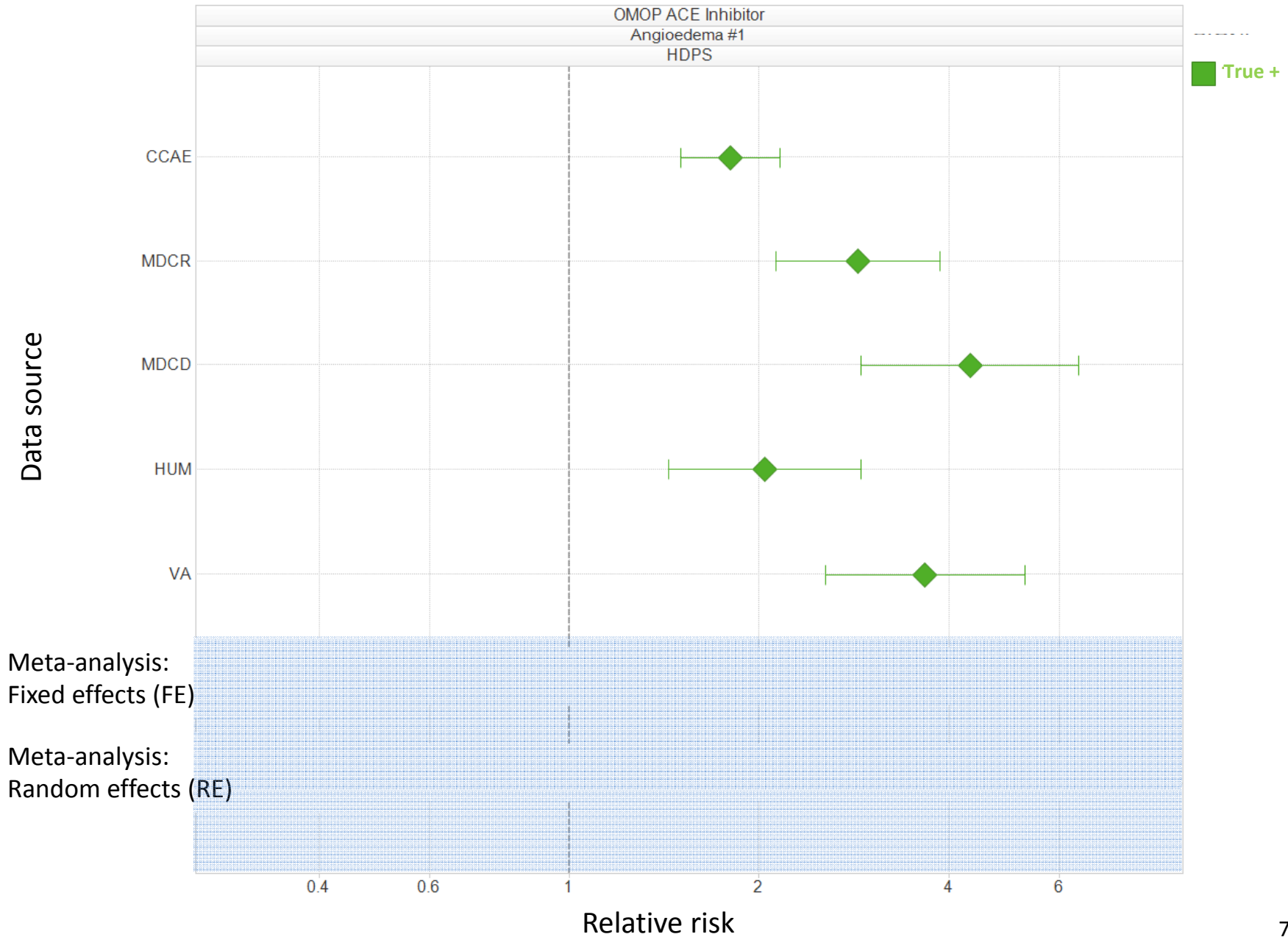
OMOP research experiment workflow



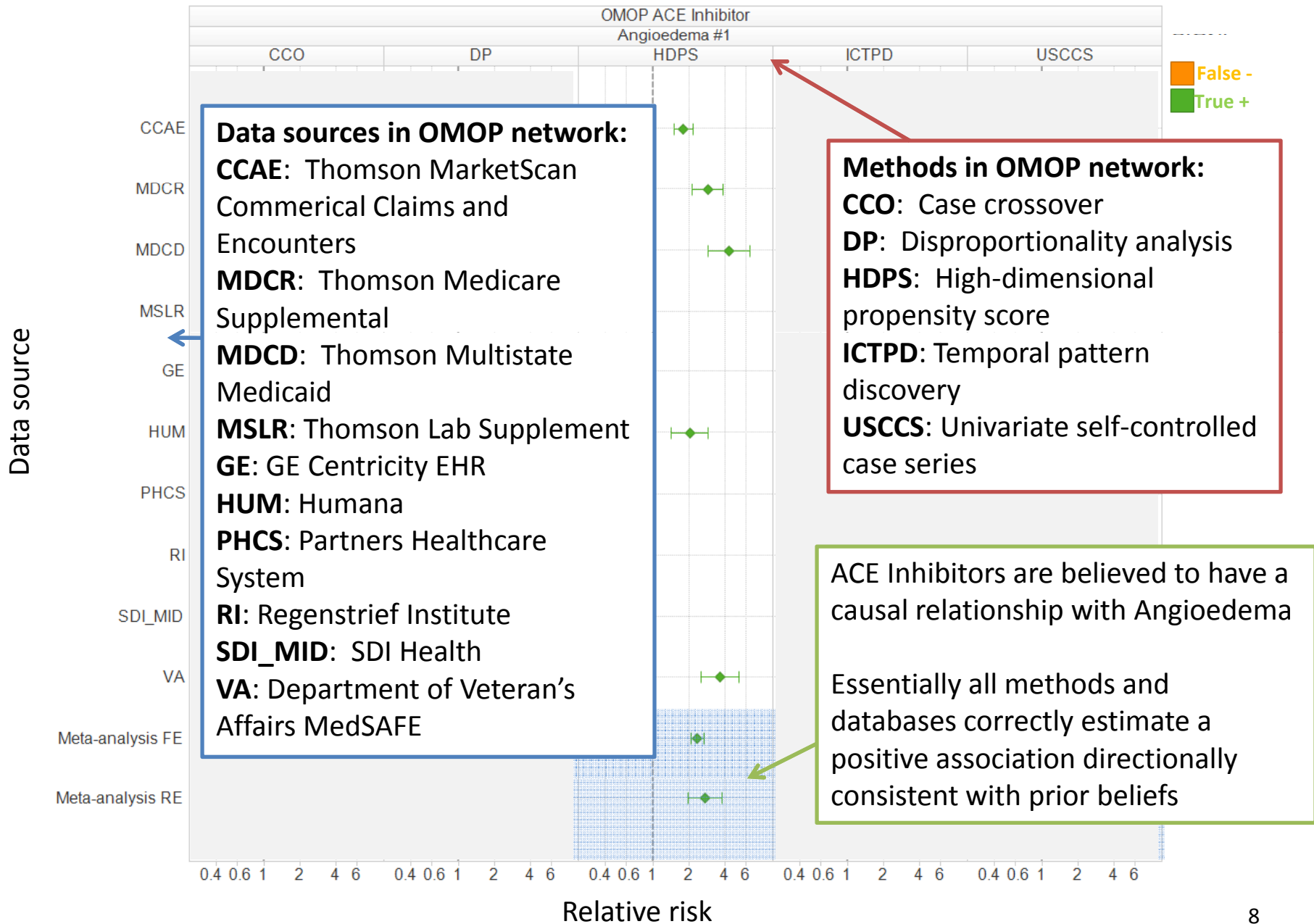
Typical scenario: Estimate the effect of one drug on one outcome using one method against one database



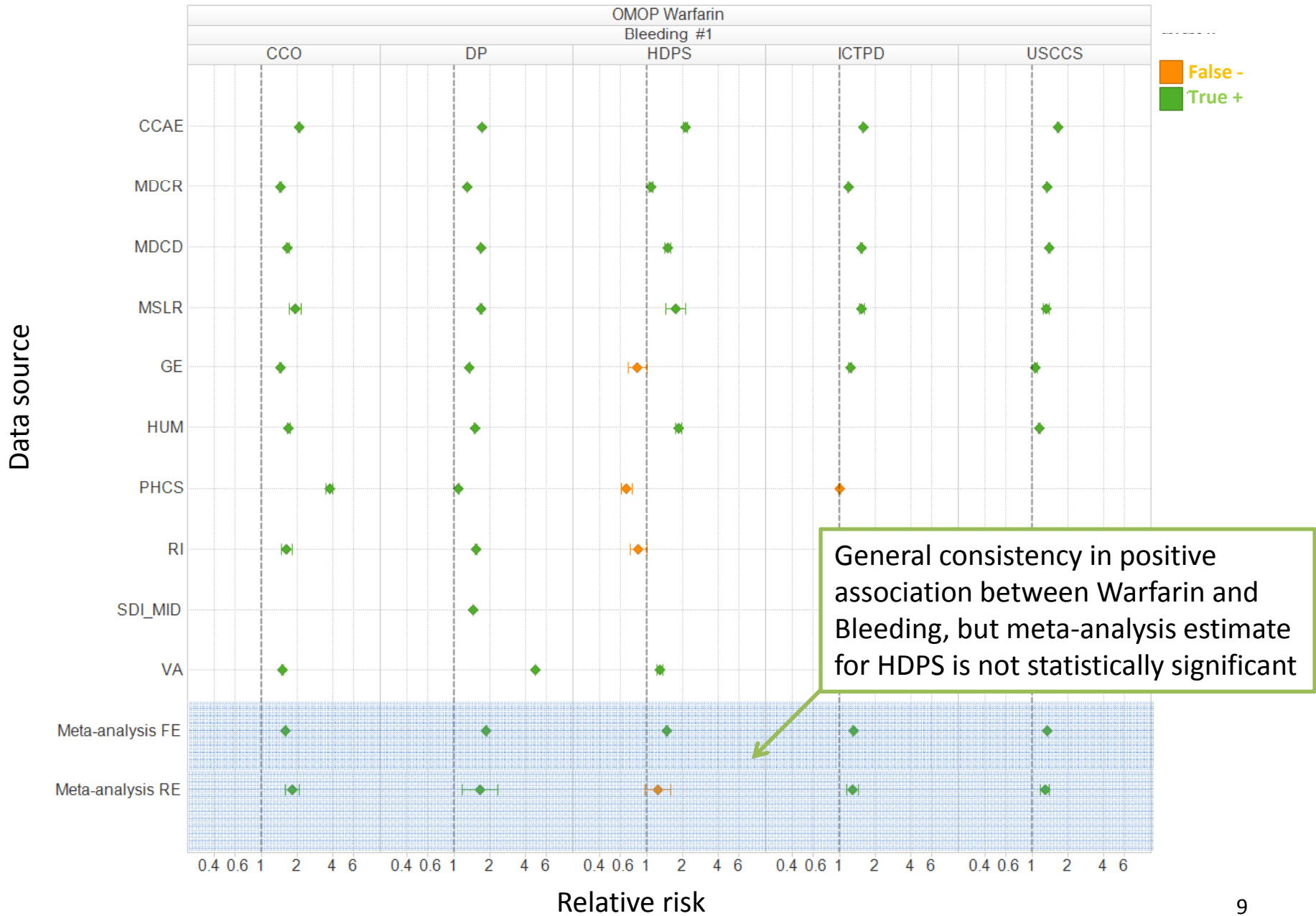
Opportunity for an active surveillance system: Pooling estimates across a network of disparate data sources



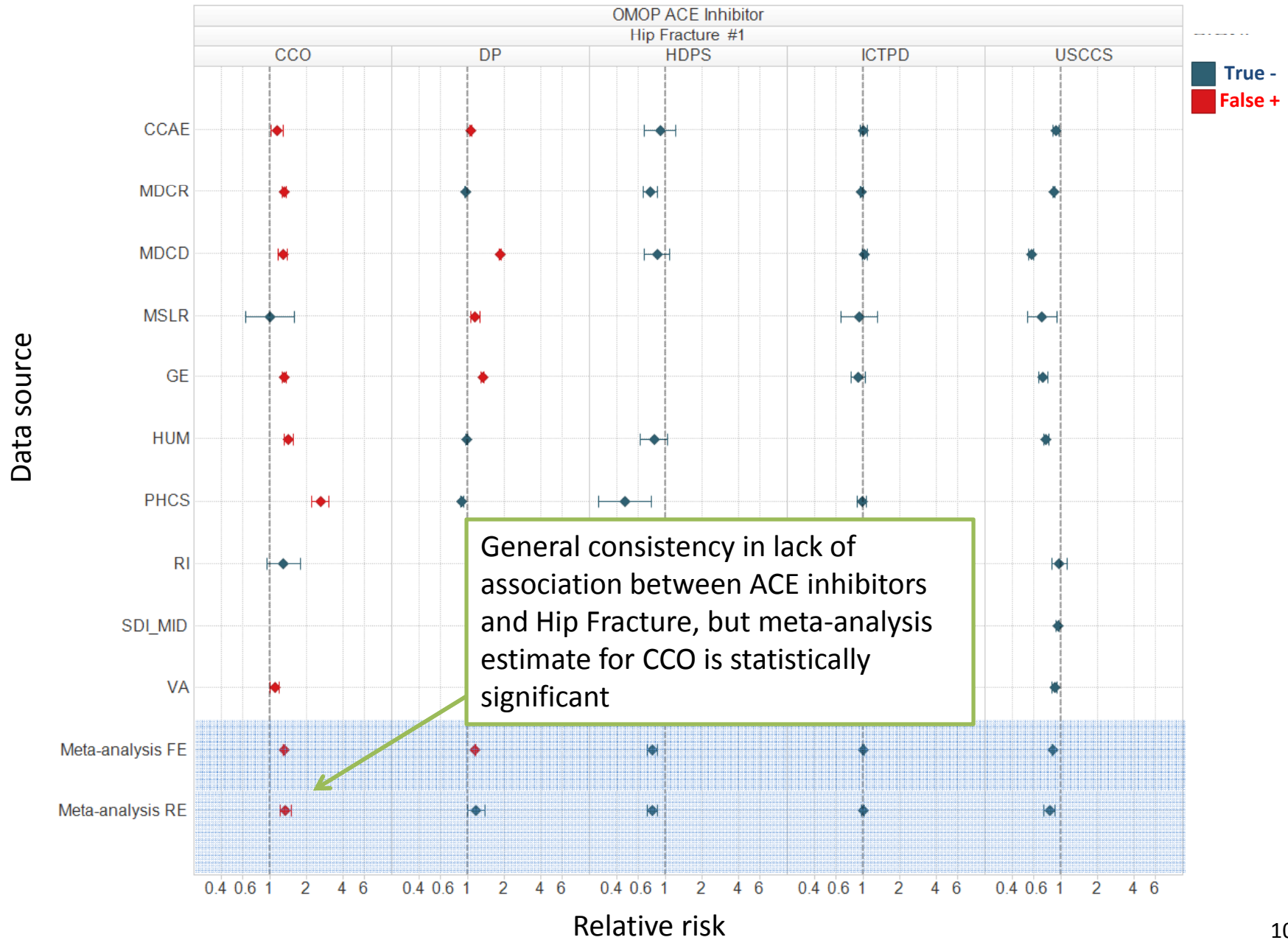
Systematic sensitivity analysis: Estimate the effect using multiple methods across the network of databases



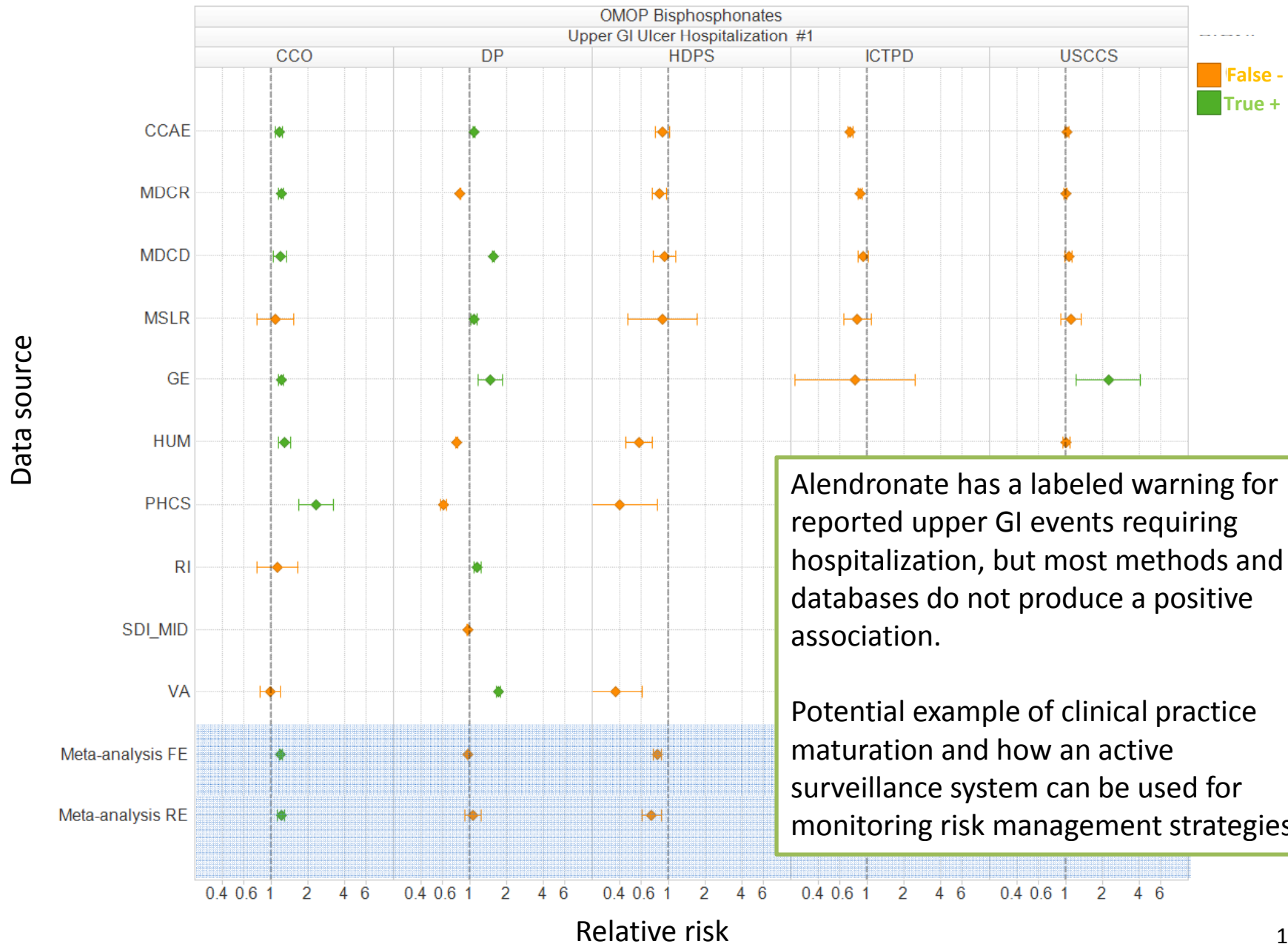
Evaluating the association between Warfarin and Bleeding



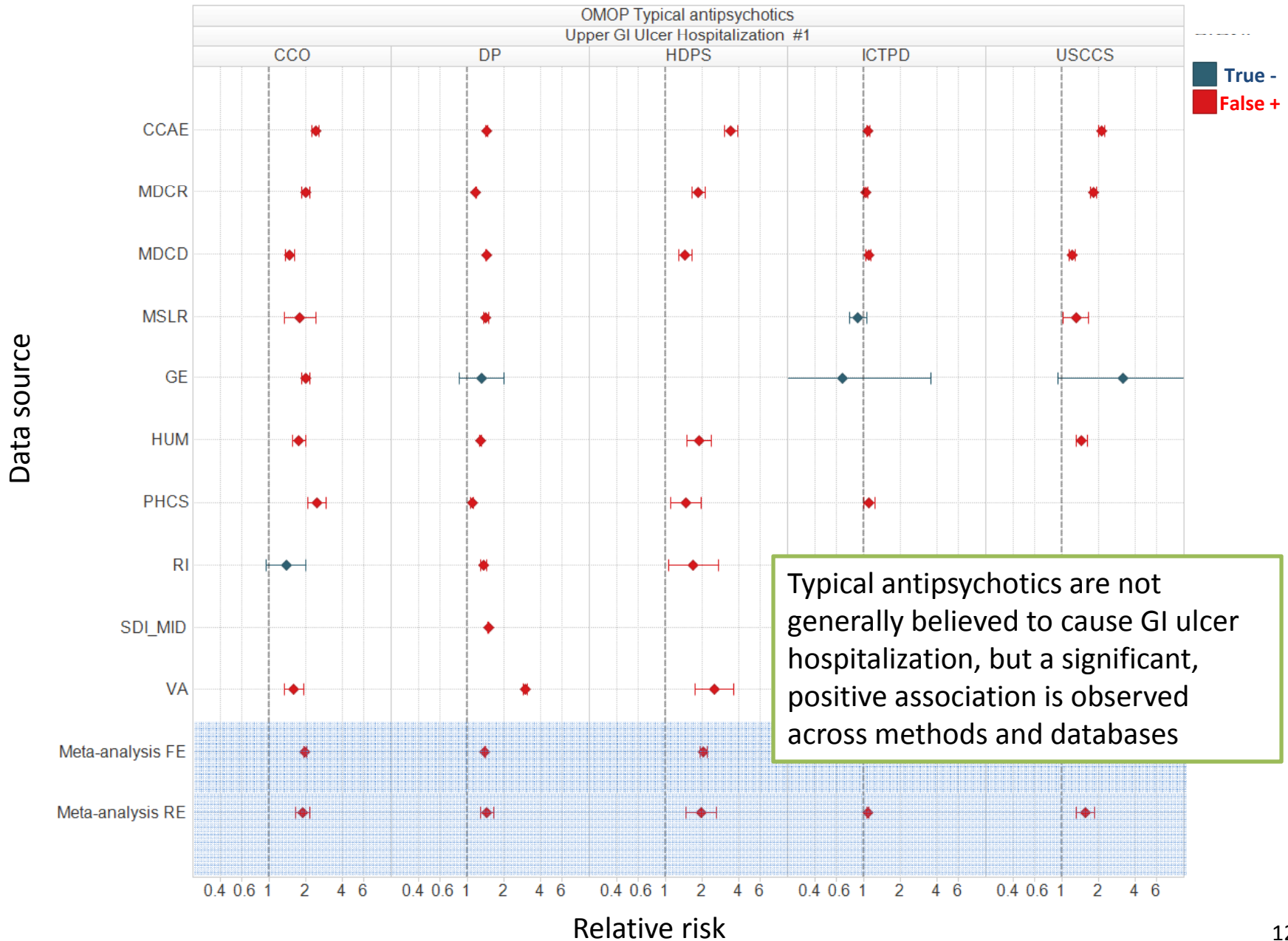
'True negative' observed for 'negative control' of ACE Inhibitors and Hip Fracture



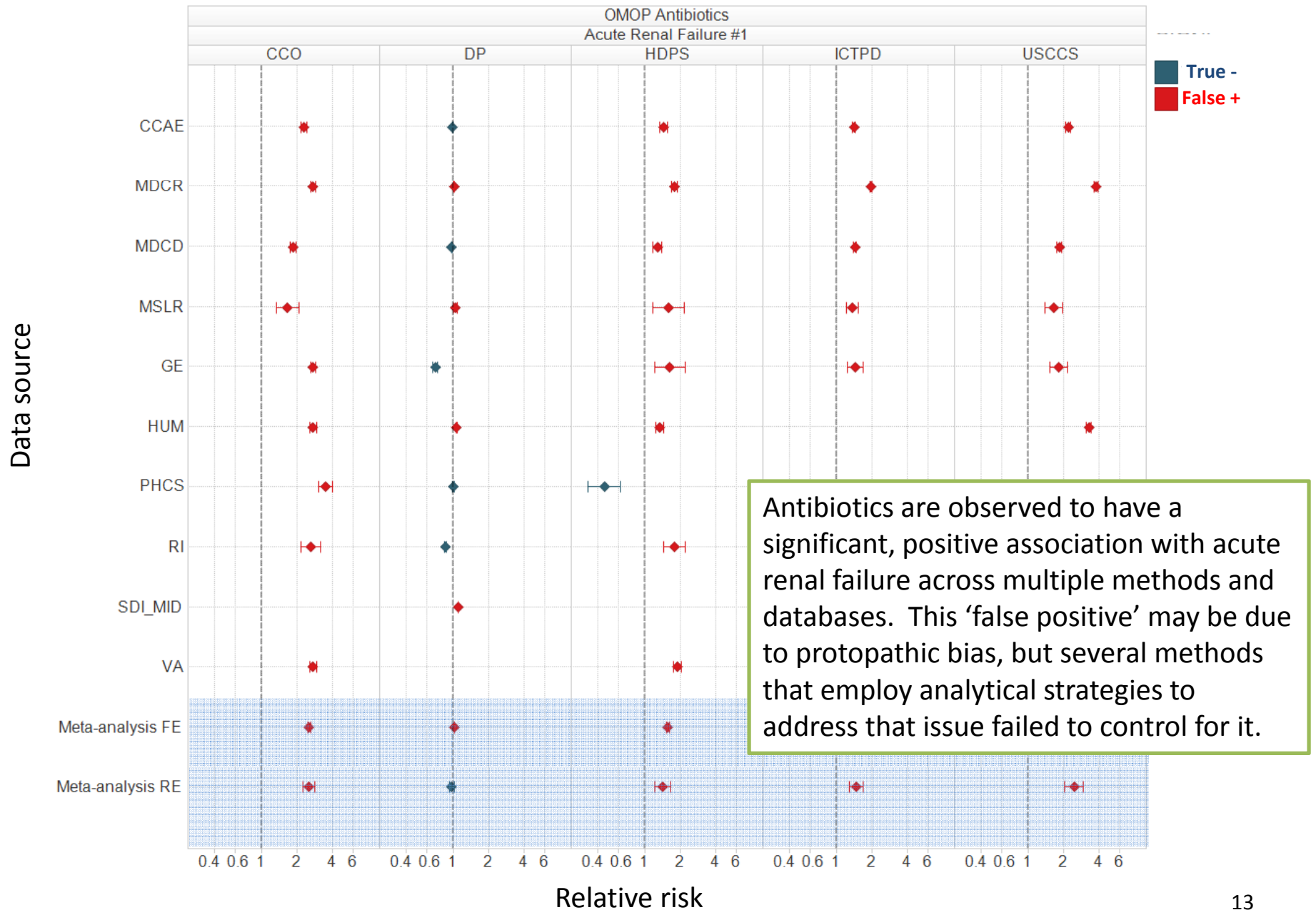
Consistent 'false negative' observed for 'true' association between Bisphosphonates and GI Ulcer Hospitalization



Consistent 'false positive' observed for 'negative control' of Typical antipsychotics and GI Ulcer Hospitalization



Consistent 'false positive' observed for 'negative control' of Antibiotics and Acute Renal Failure



Measuring method performance: Classifying the illustrative examples

Drug-condition association status

Y – ‘true association’,

N – ‘negative control’

Y

N

Method prediction:
Drug-condition pair met a specific threshold:
(LB 95% CI > 1)

Y

N

<p>True positives: ACE Inhibitors- Angioedema Warfarin- Bleeding</p>	<p>False positives: Typical antipsychotic- GI Ulcer hospitalization Antibiotics- Acute renal failure</p>
<p>False negatives: Bisphosphonates- GI Ulcer hospitalization</p>	<p>True negatives: ACE Inhibitors- Hip fracture</p>

Measuring method performance

Drug-condition association status

Y – ‘true association’,

N – ‘negative control’

Y

N

Method prediction:
Drug-condition
pair met a
specific
threshold

Y

True positives

False positives

N

False negatives

True negatives

Question: For any method applied to any data source, what are the expected operating characteristics?

'Ground truth' assumed for Monitoring Health Outcomes of Interest

Outcome	ACE Inhibitors	Amphotericin B	Antibiotics: erythromycins, sulfonamides, tetracyclines	Anti epileptics: carbamazepine, phenytoin	Benzodiazepines	Beta blockers	Bisphosphonates: alendronate	Tricyclic antidepressants	Typical antipsychotics	Warfarin
Angioedema	True positive risk	Negative control		Negative control	Negative control	Negative control				Negative control
Aplastic Anemia	Negative control	Negative control	Negative control	True positive risk	Negative control	Negative control	Negative control	Negative control		Negative control
Acute Liver Injury		Negative control	True positive risk		Negative control	Negative control	Negative control			
Bleeding			Negative control				Negative control			True positive risk
Hip Fracture	Negative control	Negative control			True positive risk	Negative control				Negative control
Hospitalization	True positive benefit									
Myocardial Infarction			Negative control		Negative control		Negative control	True positive risk	True positive risk	
Mortality after MI		Negative control		Negative control		True positive benefit				Negative control
Renal Failure		True positive risk	Negative control	Negative control	Negative control	Negative control	Negative control	Negative control	Negative control	Negative control
GI Ulcer Hospitalization	Negative control			Negative control		Negative control	True positive risk		Negative control	

Legend	Total
True positive benefit	2
True positive risk	9
Negative control	44

Measuring method performance example: Random-effect meta-analysis of estimates from High-dimensional propensity score

Drug-condition association status

Y – ‘true association’,

N – ‘negative control’

Y

N

Method prediction:
Drug-condition pair met a specific threshold:
(LB 95% CI > 1)

Y

N

True positives: 5	False positives: 8
False negatives: 4	True negatives: 36

Positive predictive value
= precision
= $TP / (TP+FP)$
= $5 / (5+8) = 0.38$

Negative predictive value
= $TN / (FN+TN)$
= $36 / (4+36) = 0.90$

Sensitivity
= Recall
= $TP / (TP+FN)$
= $5 / (5+4) = 0.56$

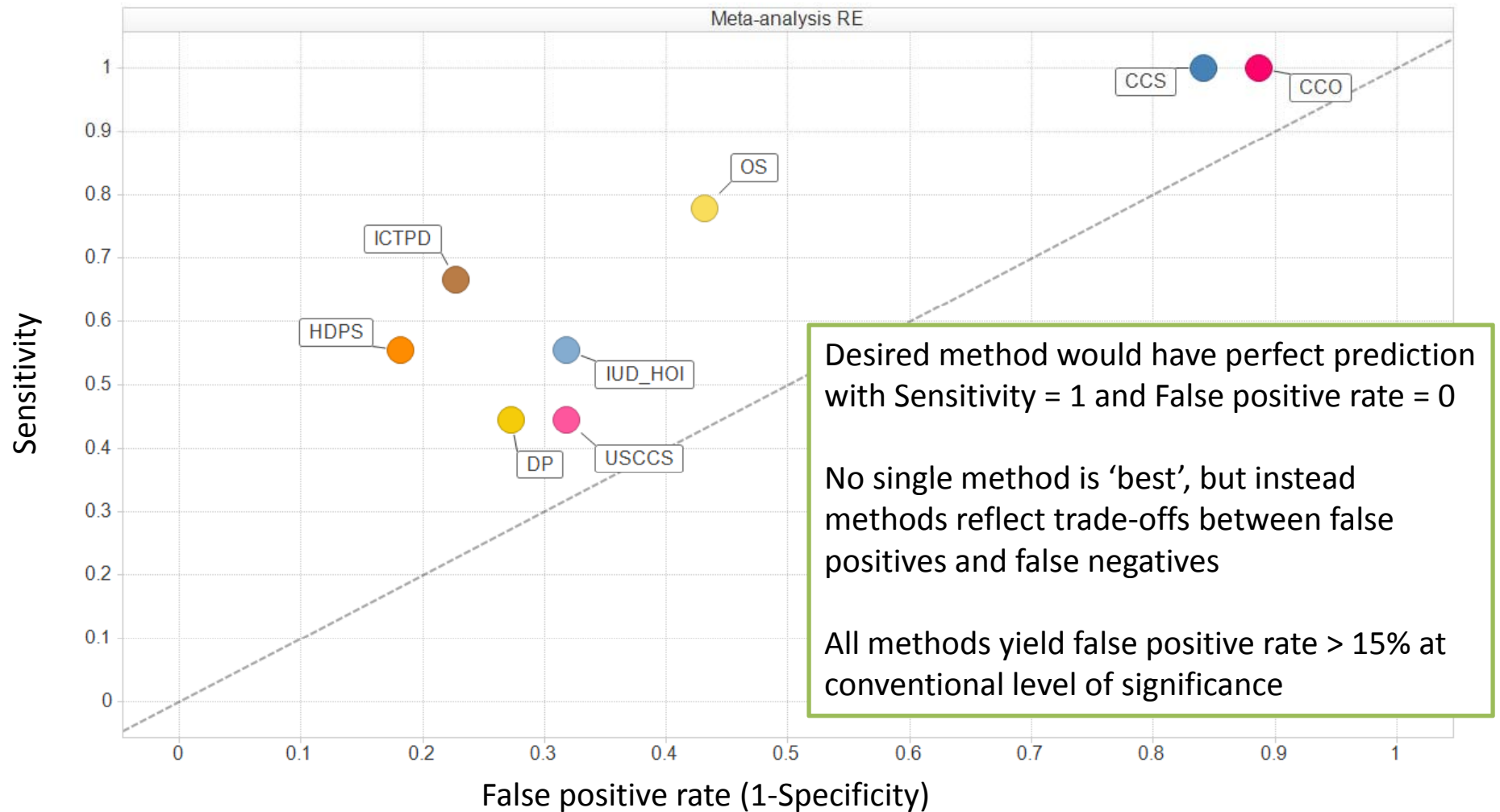
Specificity
= $TN / (FP+TN)$
= $36 / (8+36) = 0.82$
False positive rate
= $1 - 0.82 = 0.18$

Accuracy
= $(TP+TN) / (TP+TN+FP+FN)$
= $(5+36) / (9+44) = 0.77$

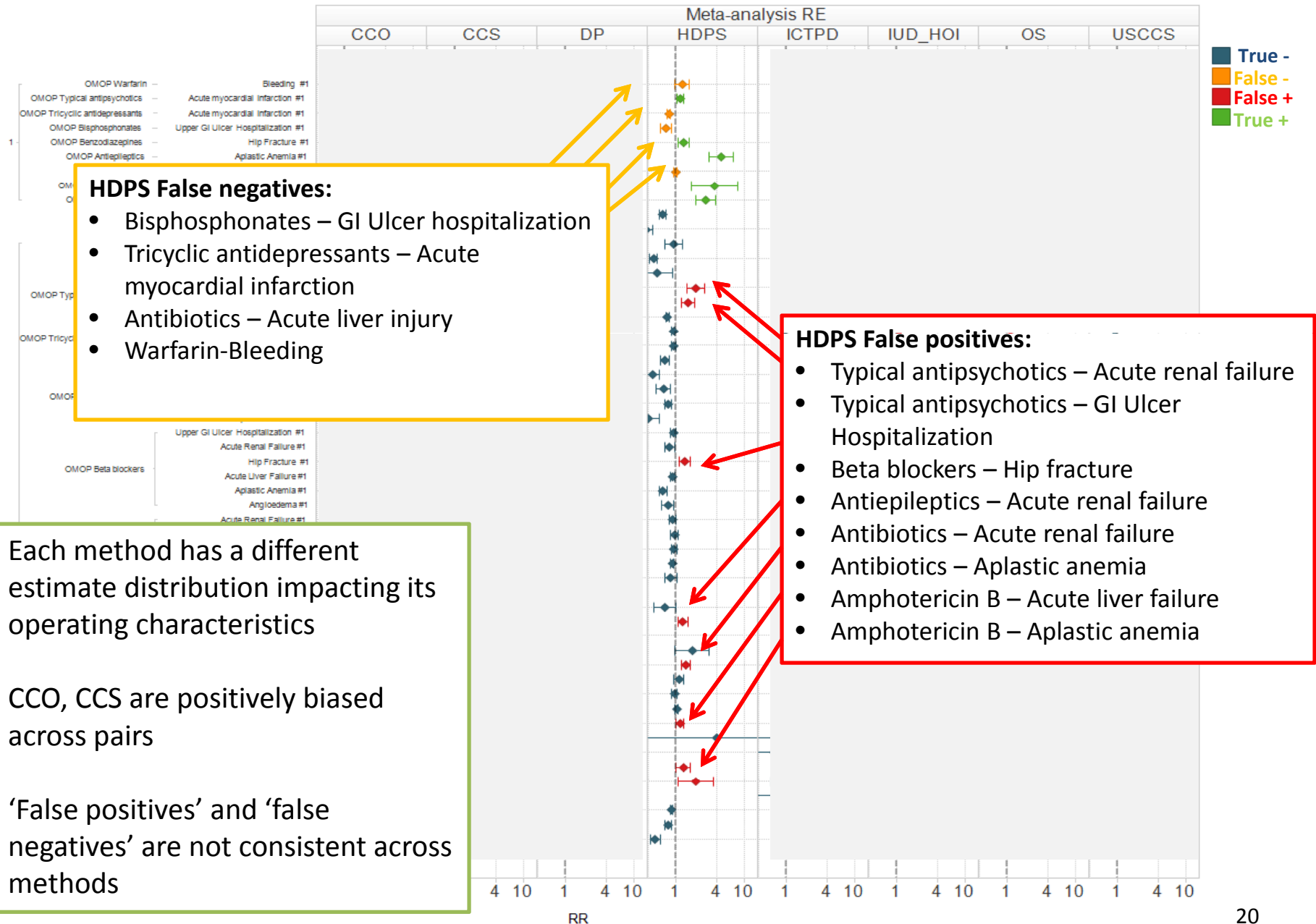
Active surveillance methods under evaluation in OMOP experiment

Method name	Contributor	Release date
Disproportionality analysis		
Disproportionality analysis (DP)	Columbia / Merck	15-Mar-10
IC Temporal Pattern Discovery (ICTPD)	Uppsala Monitoring Centre	23-May-10
HSIU cohort method (HSIU)	Regenstrief / Indiana University	8-Jun-10
Case-based methods		
Univariate self-controlled case series (USCCS)	Columbia	2-Apr-10
Multi-set case control estimation (MSCCE)	Columbia / GlaxoSmithKline	16-Apr-10
Bayesian logistic regression (BLR)	Rutgers / Columbia	21-Apr-10
Case-control surveillance (CCS)	Lilly	2-May-10
Case-crossover (CCO)	University of Utah	1-Jun-10
Exposure-based methods		
Observational screening (OS)	ProSanos / GlaxoSmithKline	8-Apr-10
High-dimensional propensity score (HDPS)	Harvard Medical School / Columbia	6-Aug-10
Incident user design (IUD-HOI)	University of North Carolina	26-Oct-10
Sequential testing methods		
Maximized Sequential Probability Ratio Test (MSPRT)	Harvard Pilgrim / Group Health	25-Jul-10
Conditional sequential sampling procedure (CSSP)	Harvard Pilgrim / Group Health	30-Aug-10

Comparing methods by sensitivity and specificity at alpha=0.05



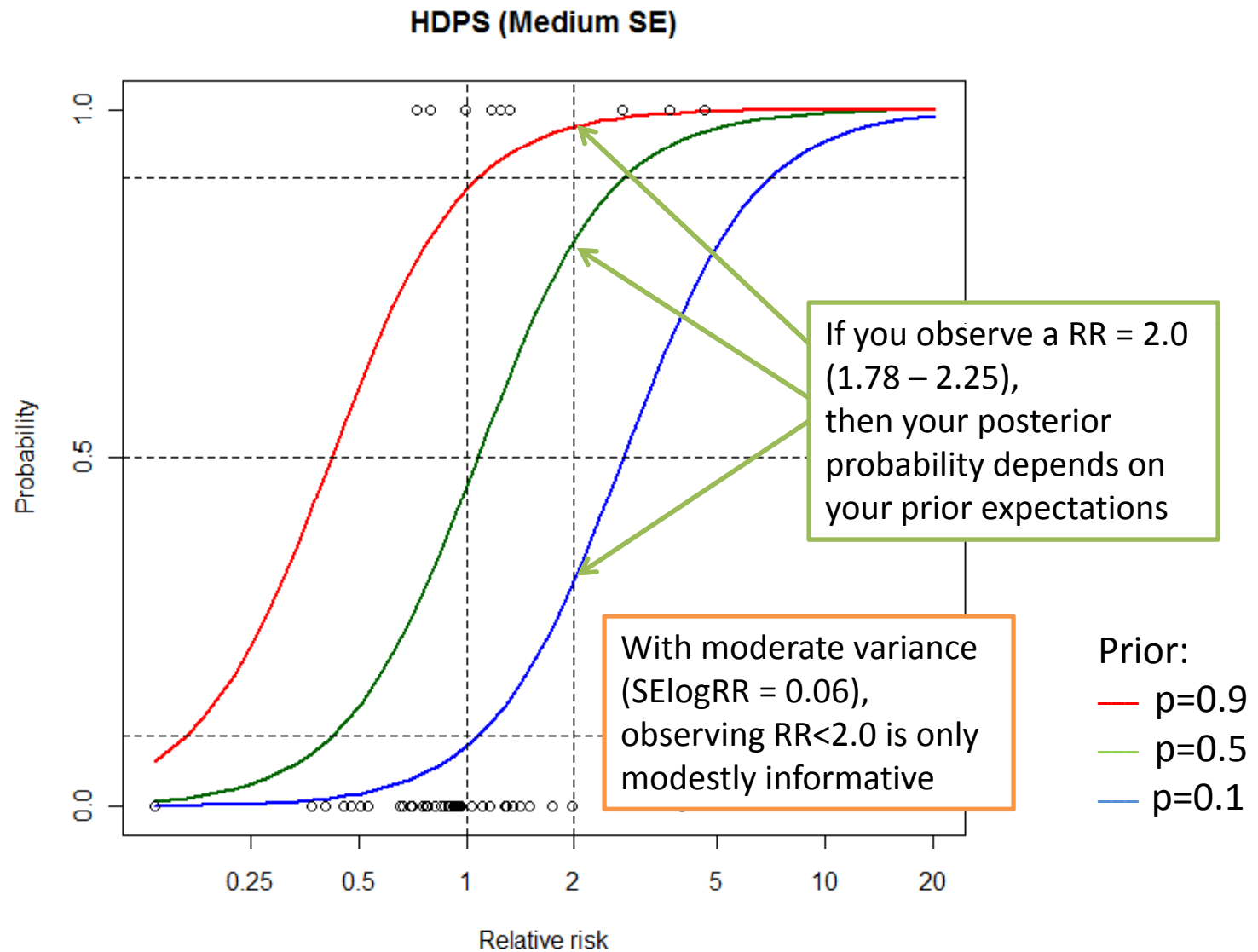
Distribution of estimates across all drug-outcome pairs



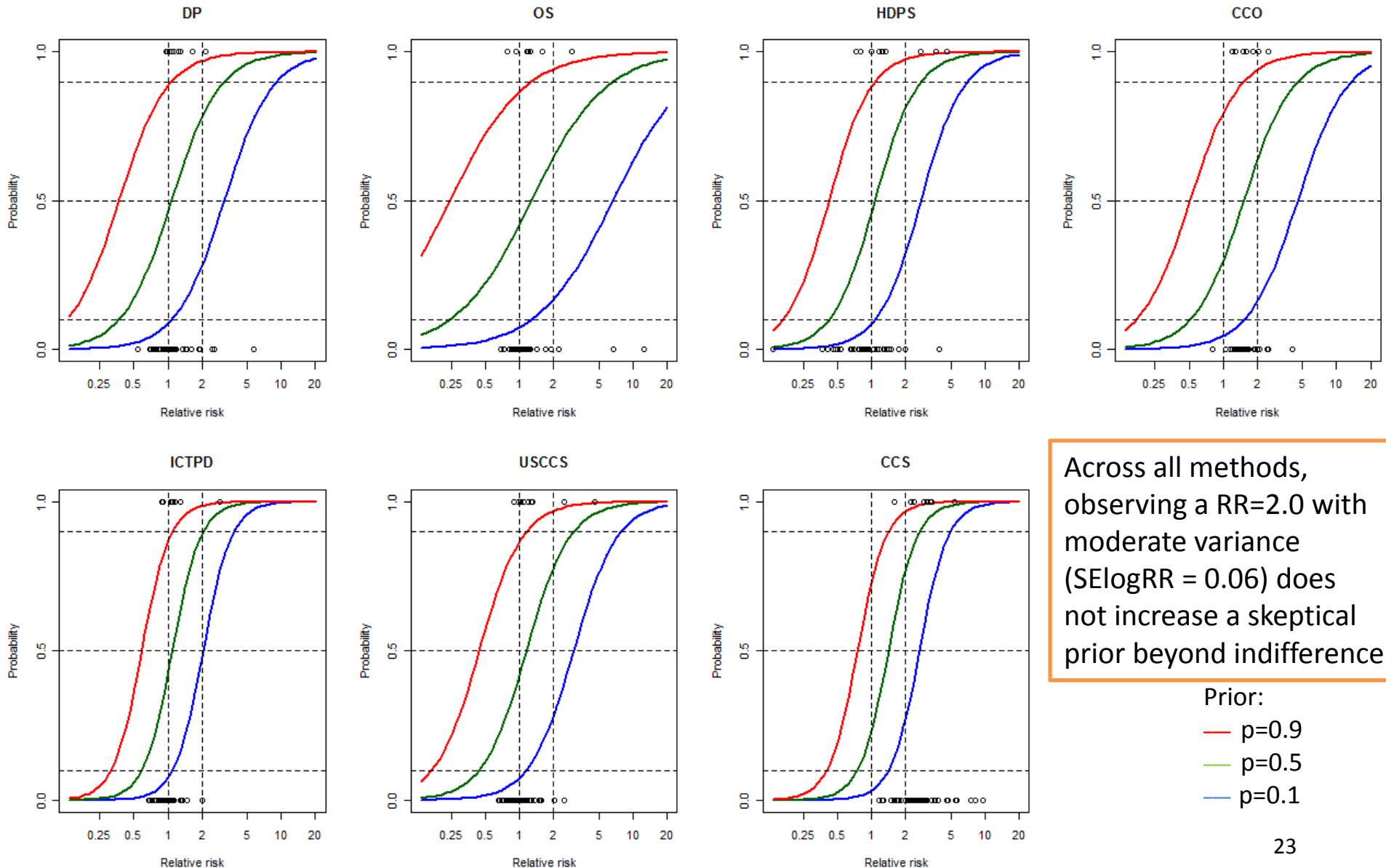
So given these operating characteristics, what can we expect to do in practice....

- Use case: An emerging safety concern is raised for a new medical product. The association between the drug and outcome could be estimated by running an OMOP active surveillance method across the network of observational databases
 - The method will produce a relative risk and standard error from each participating data source, which can then be pooled together in a meta-analytic framework
 - Hypothetical scenario: The random-effects meta-analysis yields an RR=2.0 with SE=0.06.
 - Question: what is the probability that there is a true causal relationship given this observed association?
- Bayes rule enables such calculation...
 - $p(\text{true} | \text{RR}, \text{SE}) \sim p(\text{RR}, \text{SE} | \text{true}) * p(\text{true})$
 - $p(\text{true})$ is the prior probability of true association; consider a family of priors: skeptical (0.1), indifferent (0.5), enthusiastic (0.9)
 - $p(\text{RR}, \text{SE} | \text{true})$ can be estimated from empirical data (OMOP experimental results)

Revising prior expectations in light of new evidence from an active surveillance system



Revising prior expectations in light of new evidence from an active surveillance system: Impact of using estimates from different methods



Concluding thoughts

- An active surveillance system can complement current practice by providing evidence to support a comprehensive safety assessment
- No one clear 'best' method, as it depends on tolerance for false positives vs. false negatives
- Systematic pharmacoepidemiology can achieve:
 - At 50% sensitivity, false positive rate ranges 16%-30%
 - At 10% false positive rate, sensitivity ranges 9%-33%
- Need to be cautious in interpreting results from single method in single database
 - Replication does not necessarily provide complete confidence
- You need a relative risk > 2 to have confidence in result
....detecting effects smaller than 2 will incur higher risk of false positives

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