

# Opportunities and challenges for using networks of observational healthcare data for medical product safety surveillance

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BASS Conference XIX  
Savannah, GA  
6 November 2012

**With many thanks to:**

Patrick Ryan, Martijn Schuemie, and David Madigan  
on behalf of the OMOP research team

- ***Public-Private Research Partnership established to inform the appropriate use of observational healthcare databases for studying the effects of medical products:***
  - Conducting methodological research to empirically evaluate the performance of various analytical methods on their ability to identify true associations and avoid false findings
  - Developing tools and capabilities for transforming, characterizing, and analyzing disparate data sources across the health care delivery spectrum
  - Establishing a shared resource so that the broader research community can collaboratively advance the science

## A shared journey to learning about medical products

We still have a long way to go, and the future directions are not certain, but it is clear we can only continue to make progress if we work together as a research community toward our common goals

### Common goal:

Improved understanding of the effects of medical products so that the healthcare community can more accurately identify and evaluate risks and opportunities to improve patient care.

### 2012: Third OMOP Symposium:

- Expanded experiments have yielded more promising results
- Started to develop practical insights for how to build a risk identification system and how to interpret individual study results



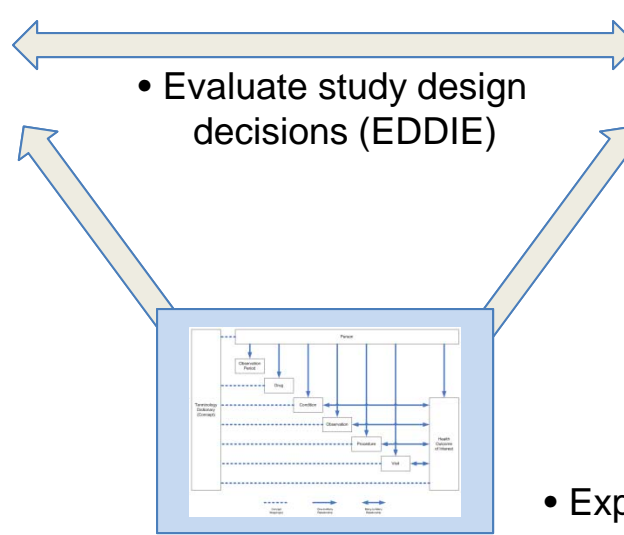
# OMOP 2011/2012 Research Agenda

## Drug-outcome pairs

	Positives	Negatives
<b>Total</b>	165	234
Myocardial Infarction	36	66
Upper GI Bleed	24	67
Acute Liver Injury	81	37
Acute Renal Failure	24	64

+ EU-ADR replication

- Improve HOI definitions
- Explore false positives



## Methods development

- Methods enhancements
- *Multivariate self-controlled case series*
- Increased parameterization
- *Case-control, new user cohort designs*
- Application of existing tools
- *ICTPD, OS, LGPS, DP*

- Expand CDM for additional use cases

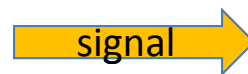
## Observational data

Real-world performance:



+ OMOP Distributed Partners  
+ EU-ADR network

Simulated data:



- Strength (RR)
- Type (timing)

# Ground truth for OMOP 2011/2012 experiments

	Positive controls	Negative controls	Total
<b>Acute Liver Injury</b>	81	37	118
<b>Acute Myocardial Infarction</b>	36	66	102
<b>Acute Renal Failure</b>	24	64	88
<b>Upper Gastrointestinal Bleeding</b>	24	67	91
<b>Total</b>	165	234	399

isoniazid

fluticasone

indomethacin

clindamycin

ibuprofen

loratadine

sertraline

pioglitazone

Criteria for positive controls:

- Event listed in Boxed Warning or Warnings/Precautions section of active FDA structured product label
- Drug listed as 'causative agent' in Tisdale et al, 2010: "Drug-Induced Diseases"
- Literature review identified no powered studies with refuting evidence of effect

Criteria for negative controls:

- Event not listed anywhere in any section of active FDA structured product label
- Drug not listed as 'causative agent' in Tisdale et al, 2010: "Drug-Induced Diseases"
- Literature review identified no powered studies with evidence of potential positive association

## Takeaways from insights about risk identification

- Performance of different methods
  - Self-controlled designs appear to consistently perform well
- Evaluating alternative HOI definitions
  - Broader definitions have better coverage and comparable performance to more specific definitions
- Performance across different signal sizes
  - A risk identification system should confidently discriminate positive effects with  $RR > 2$  from negative controls
- Data source heterogeneity
  - Substantial variation in estimates across sources suggest replication has value but may result in conflicting results
- Method parameter sensitivity
  - Each method has parameters that are expected to be more sensitive than others, but all parameters can substantially shift some drug-outcome estimates

# **An empirical approach to null hypothesis testing**



## Revisiting clopidogrel & GI bleed (Opatrny, 2008)

Agent	Cases (n = 4028)	Controls (n = 40 171)	Crude rate ratio	Adjusted rate ratio*	95% confidence interval
<b>Antidepressants</b>					
SSRI	335 (8.3%)	1780 (4.4%)	1.97	1.33	1.09, 1.62
TCA	262 (6.5%)	1764 (4.4%)	1.52	1.04	0.83, 1.30
Venlafaxine	56 (1.4%)	229 (0.6%)	2.48	1.85	1.34, 2.55
<b>Anticoagulant</b>					
Warfarin	281 (7.0%)	1130 (2.8%)	2.64	2.17	1.82, 2.59
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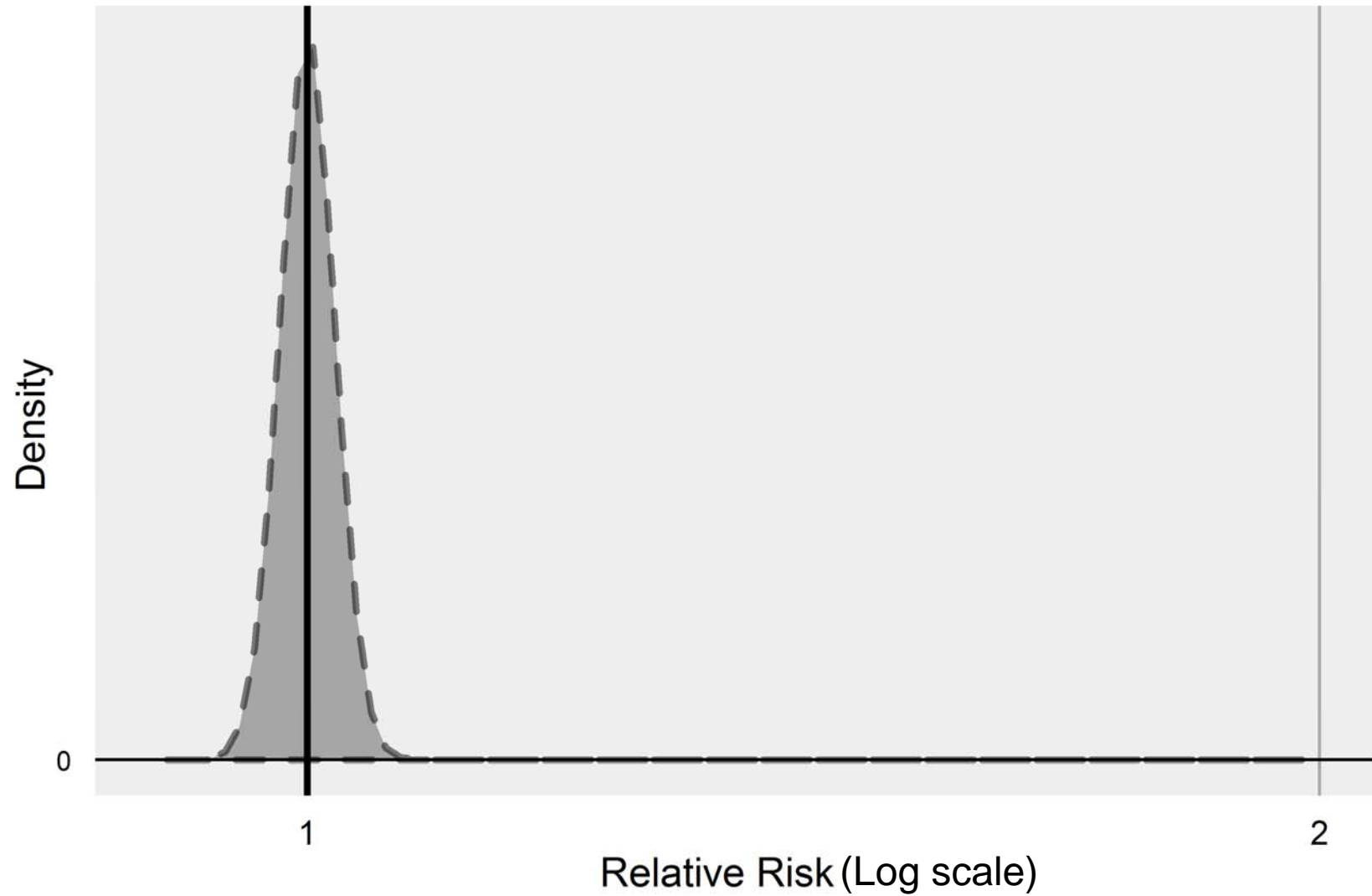
OMOP, 2012 (CC: 2000314, CCAE, GI Bleed)

Relative risk: 1.86, 95% CI: 1.79 – 1.93

Standard error: 0.02, p-value: <.001

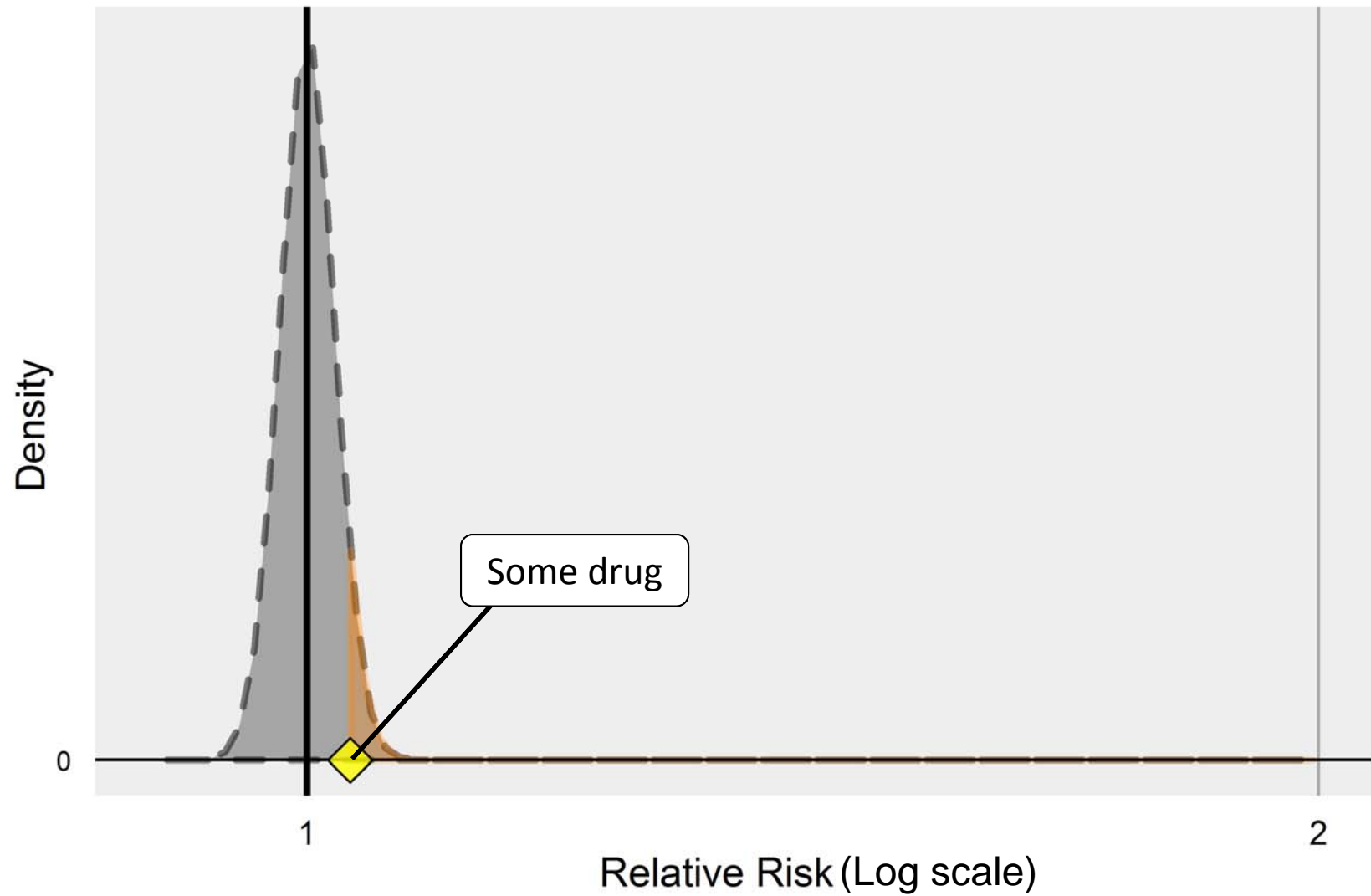
# Null distribution

CC: 2000314, CCAE, GI Bleed



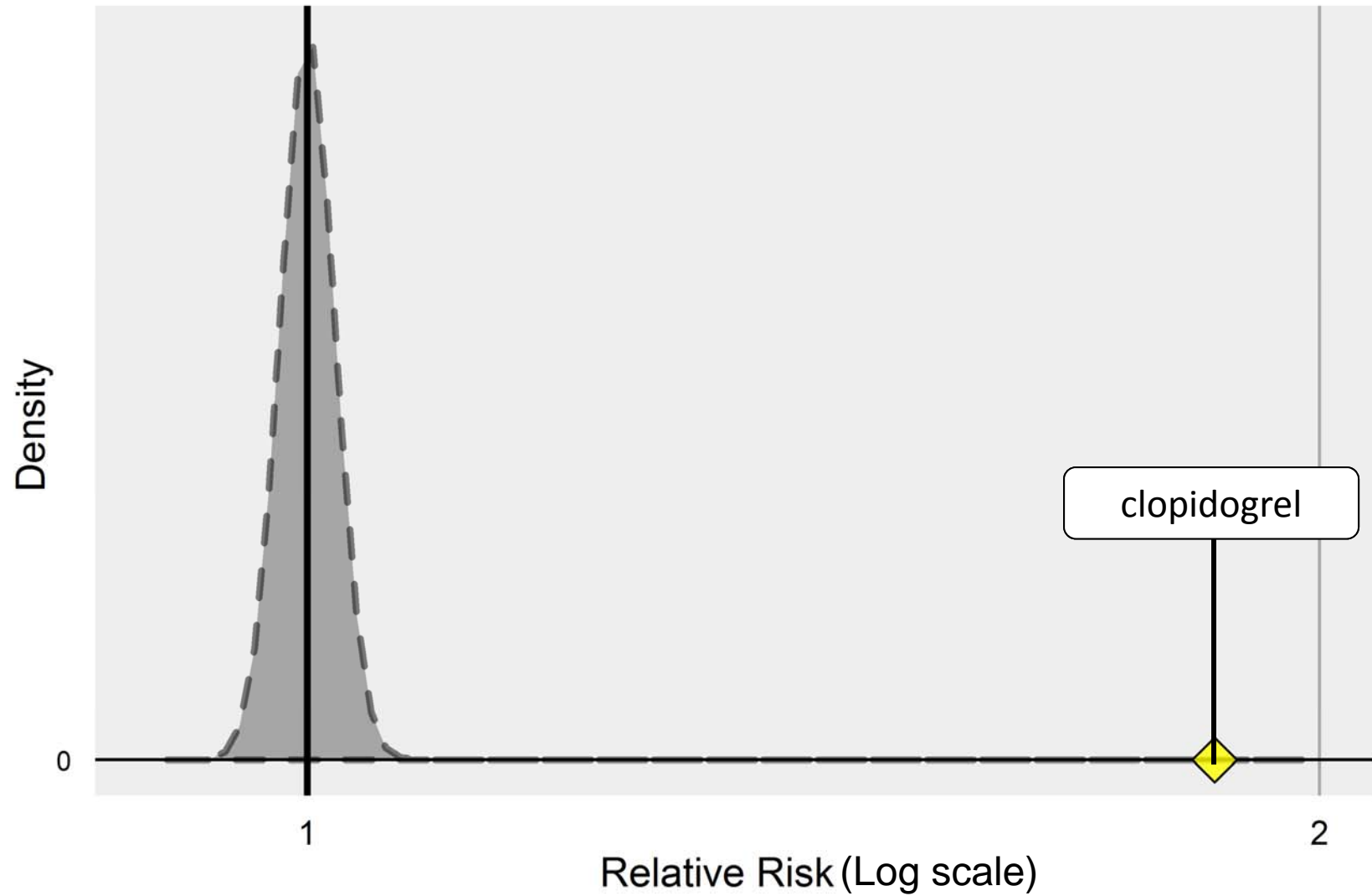
# Null distribution

CC: 2000314, CCAE, GI Bleed



# Null distribution

CC: 2000314, CCAE, GI Bleed



## Evaluating the null distribution?

- Current p-value calculation assumes that you have an unbiased estimator (which means confounding either doesn't exist or has been fully corrected for)
- Traditionally, we reject the null hypothesis at  $p < .05$  and we assume this threshold will incorrectly reject the null hypothesis 5% of time. Does this hold true in observational studies?
- We can test this using our negative controls

## Ground truth for OMOP 2011/2012 experiments

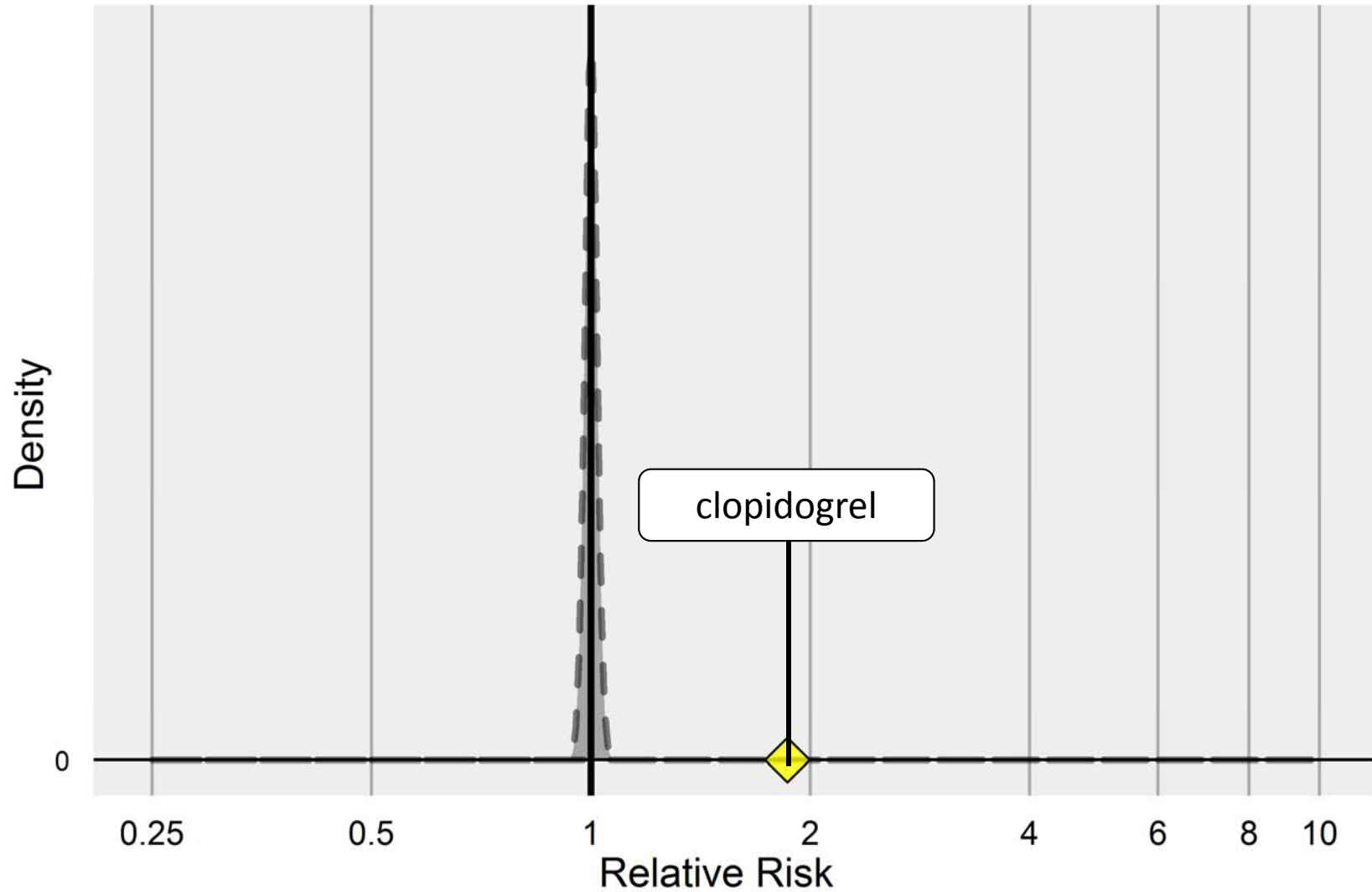
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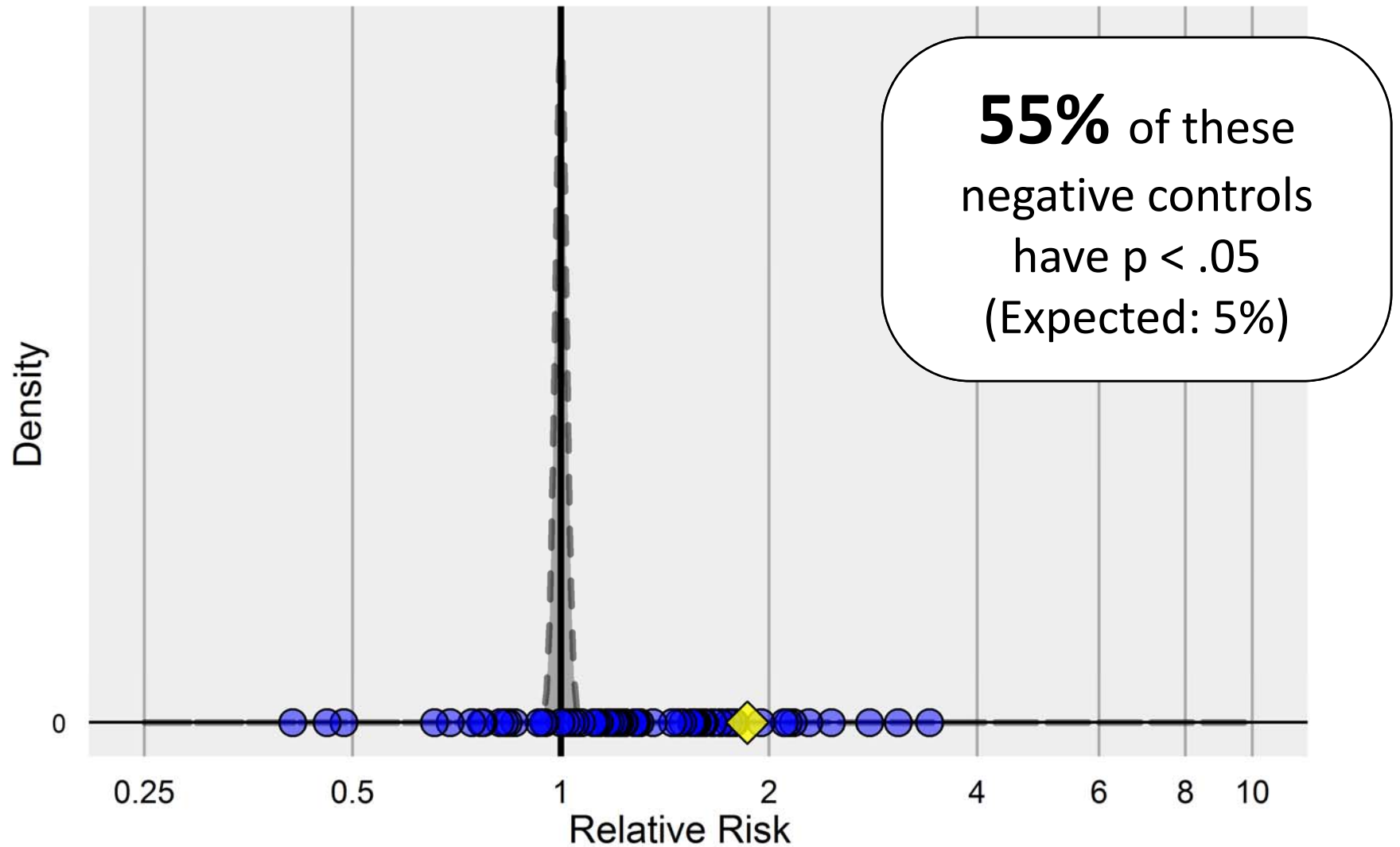
# Negative controls & the null distribution

CC: 2000314, CCAE, GI Bleed



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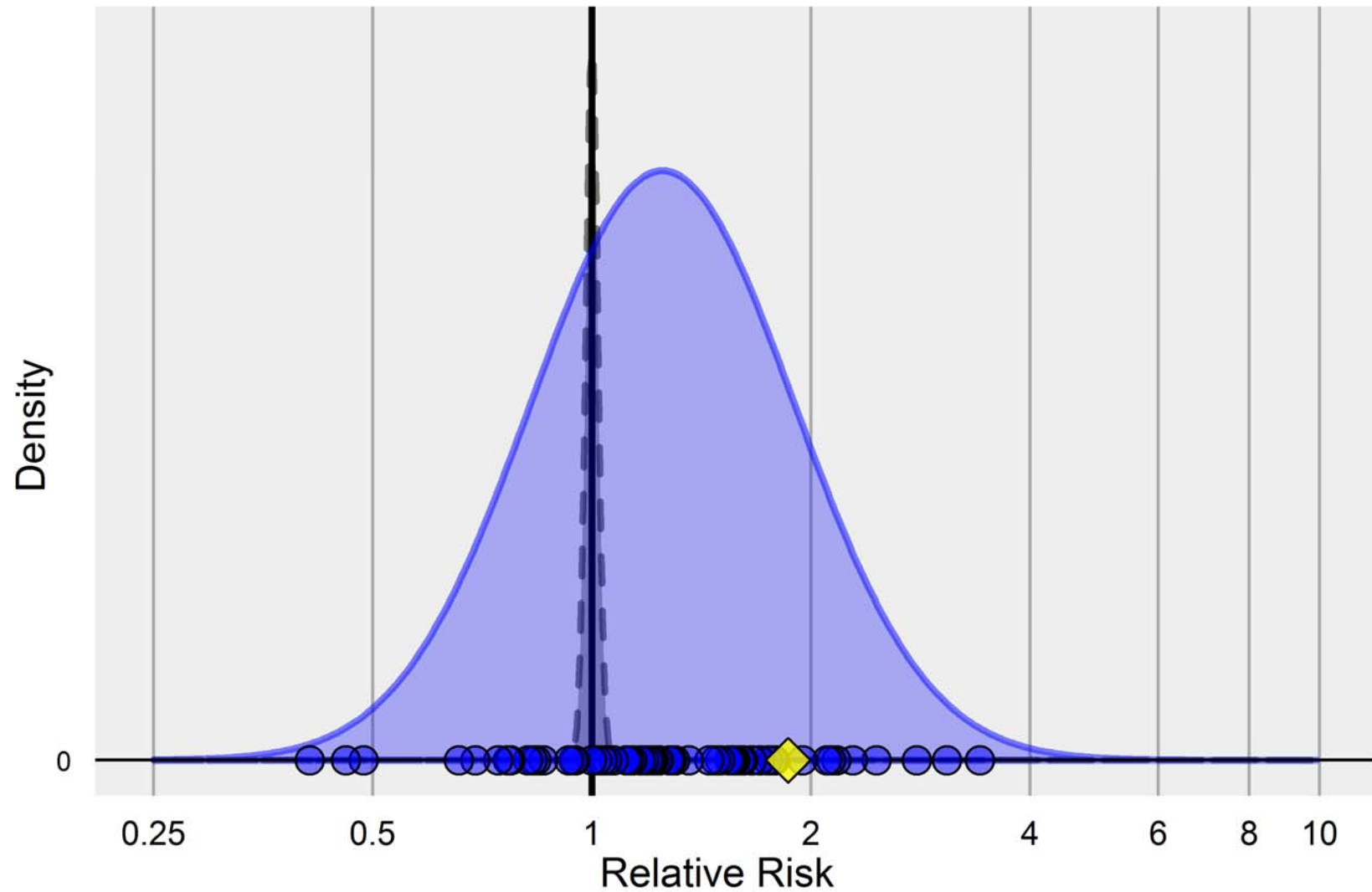
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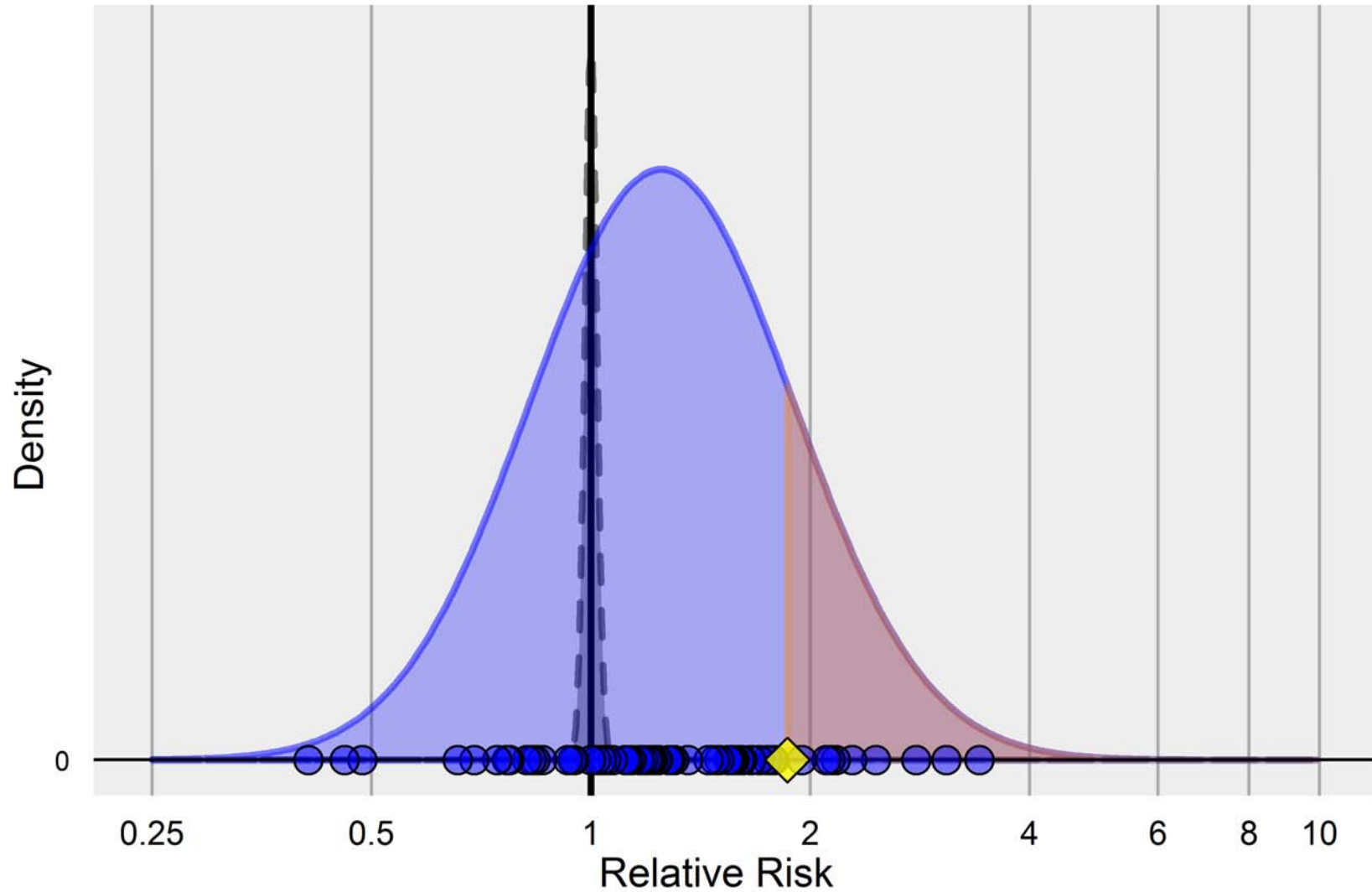
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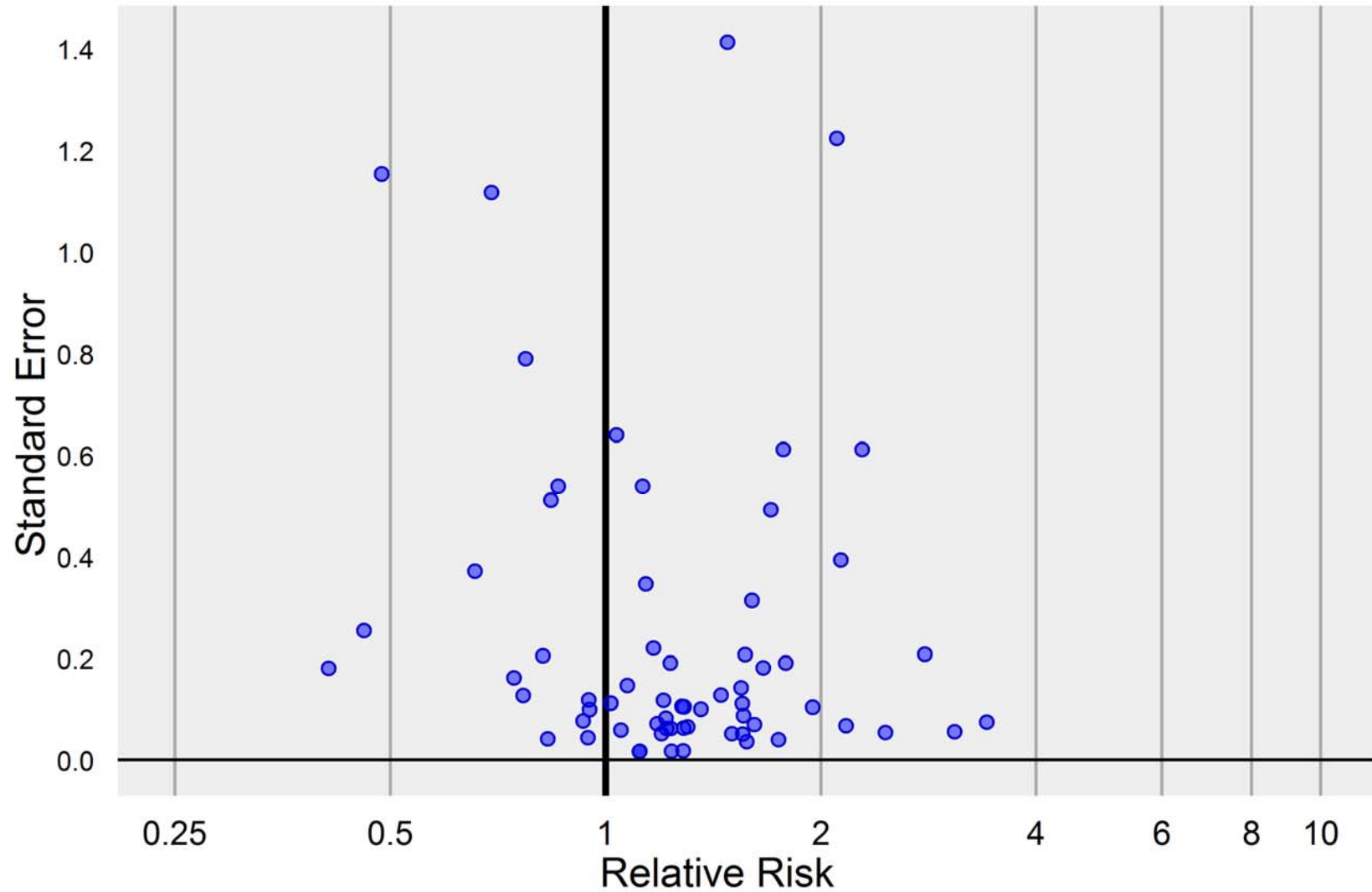
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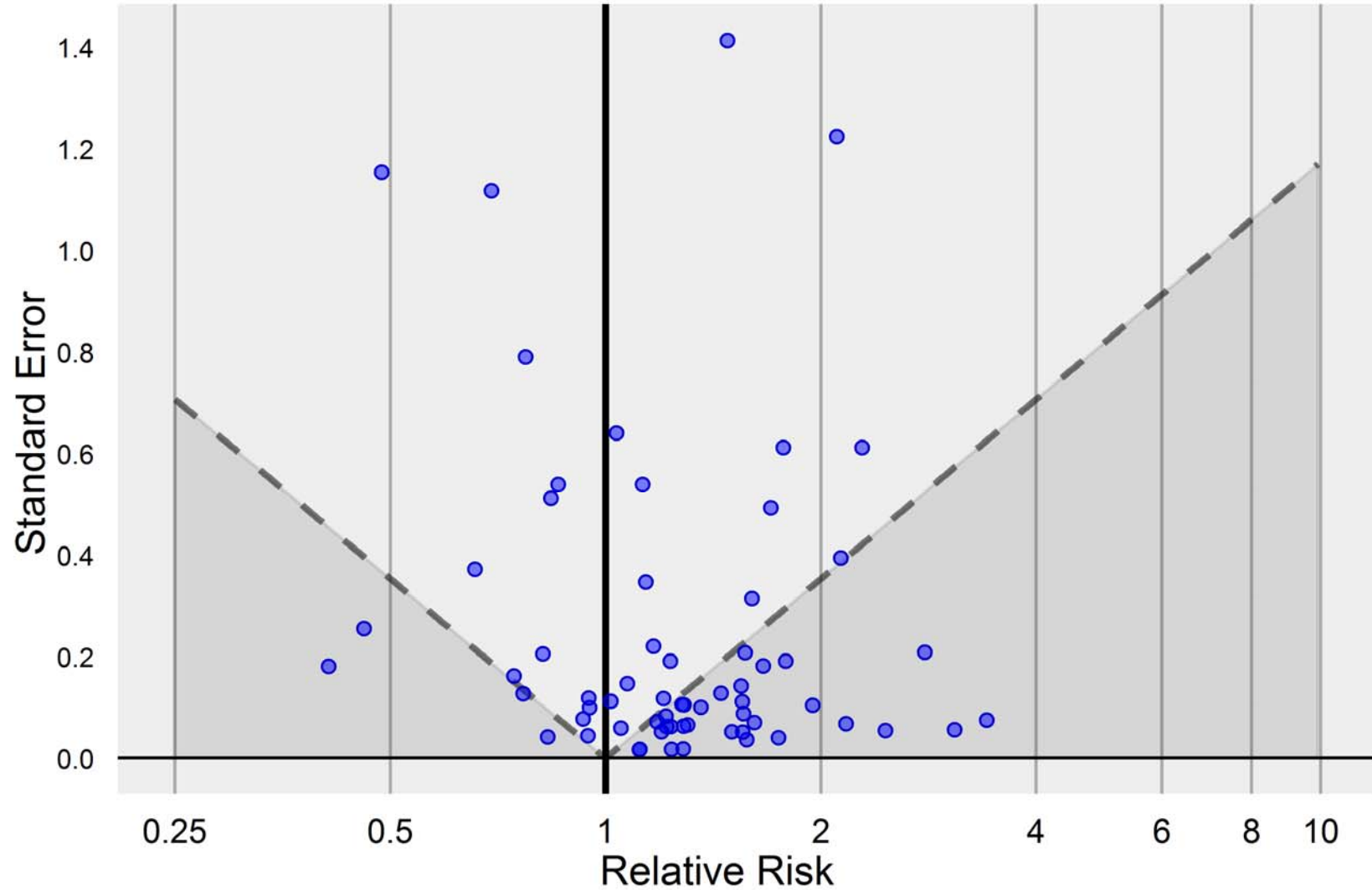
# p-value calibration plot

CC: 2000314, CCAE, GI Bleed



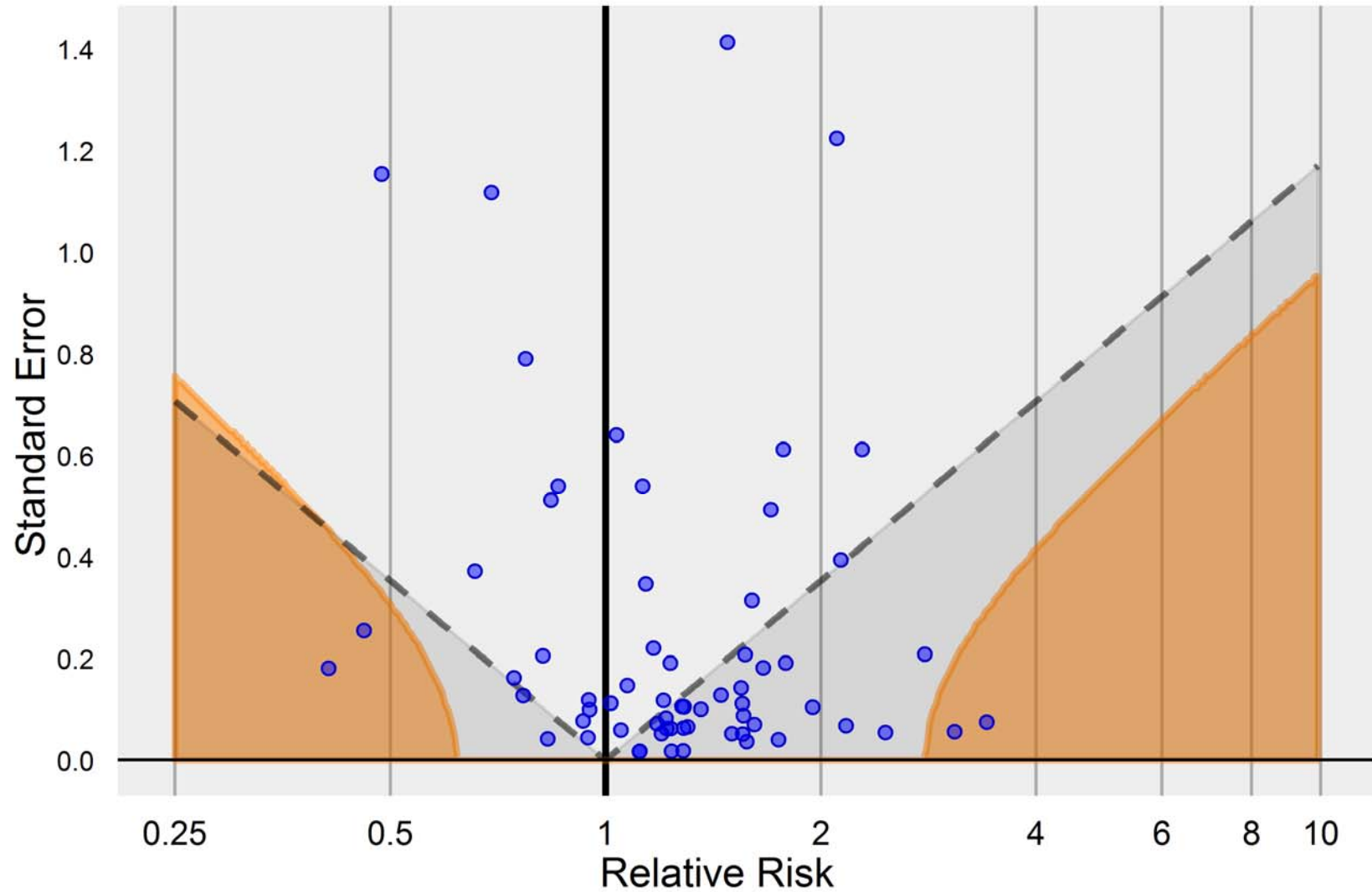
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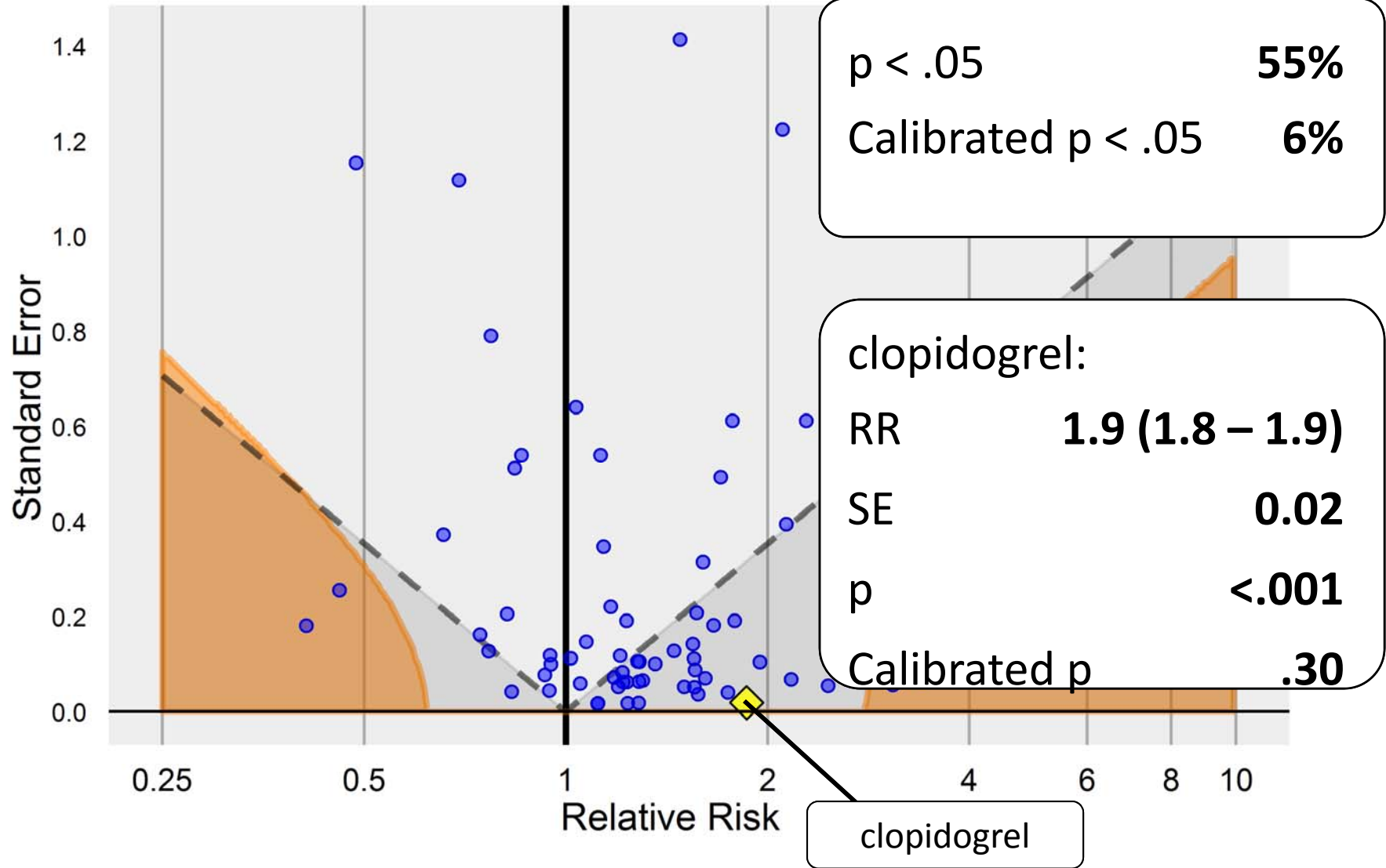
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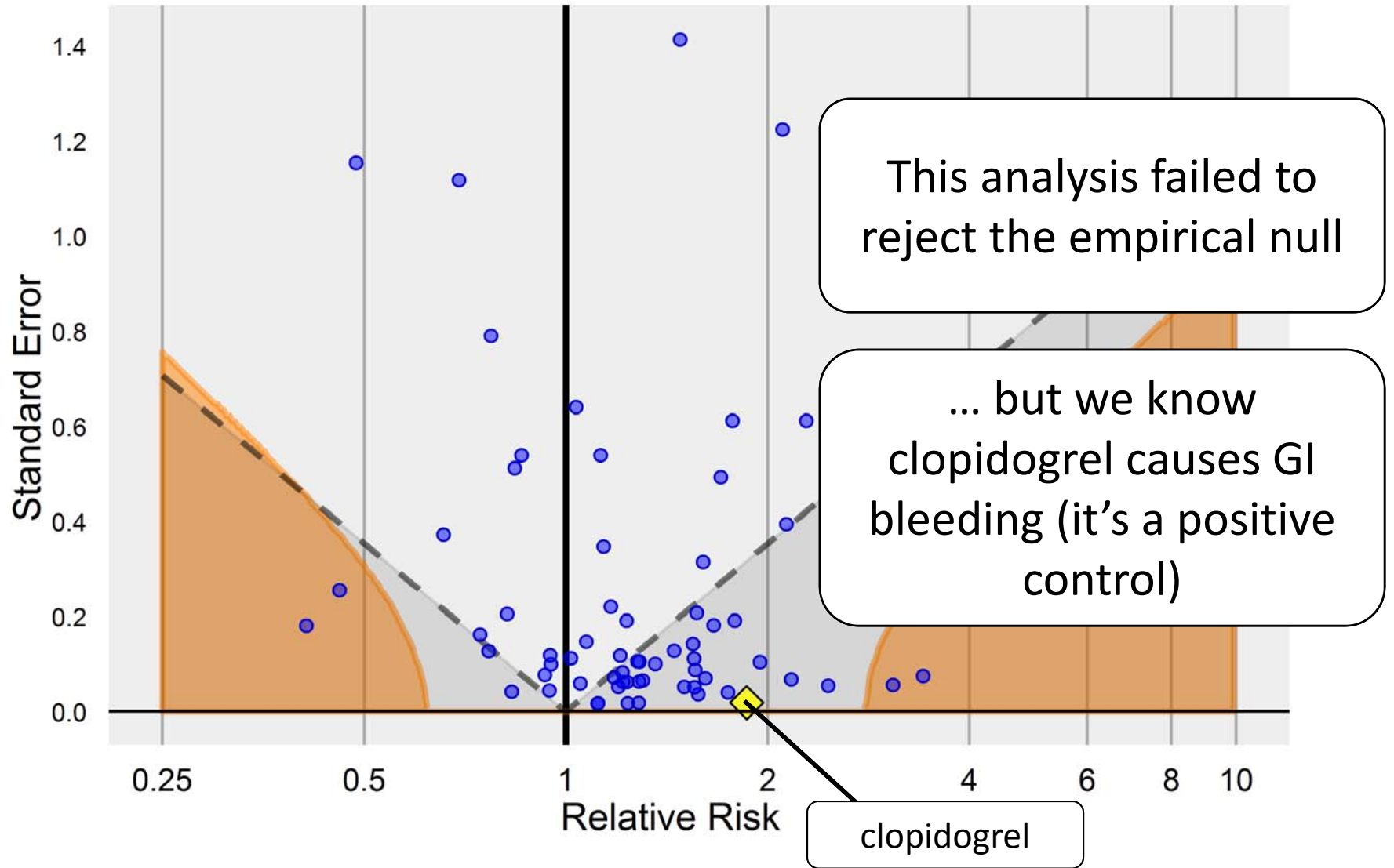
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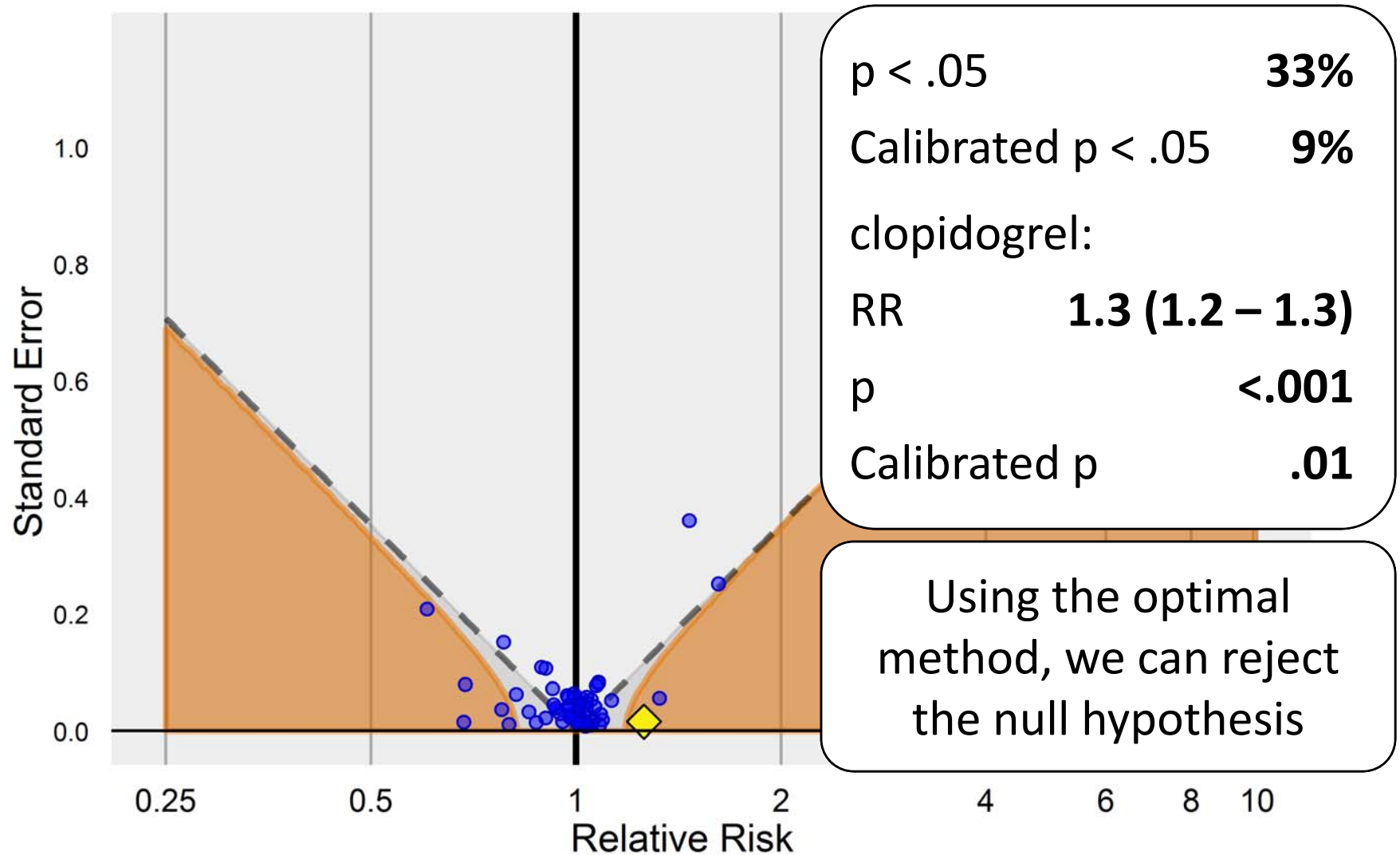
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# p-value calibration plot

Optimal method: SCCS:1931010, CCAE, GI Bleed



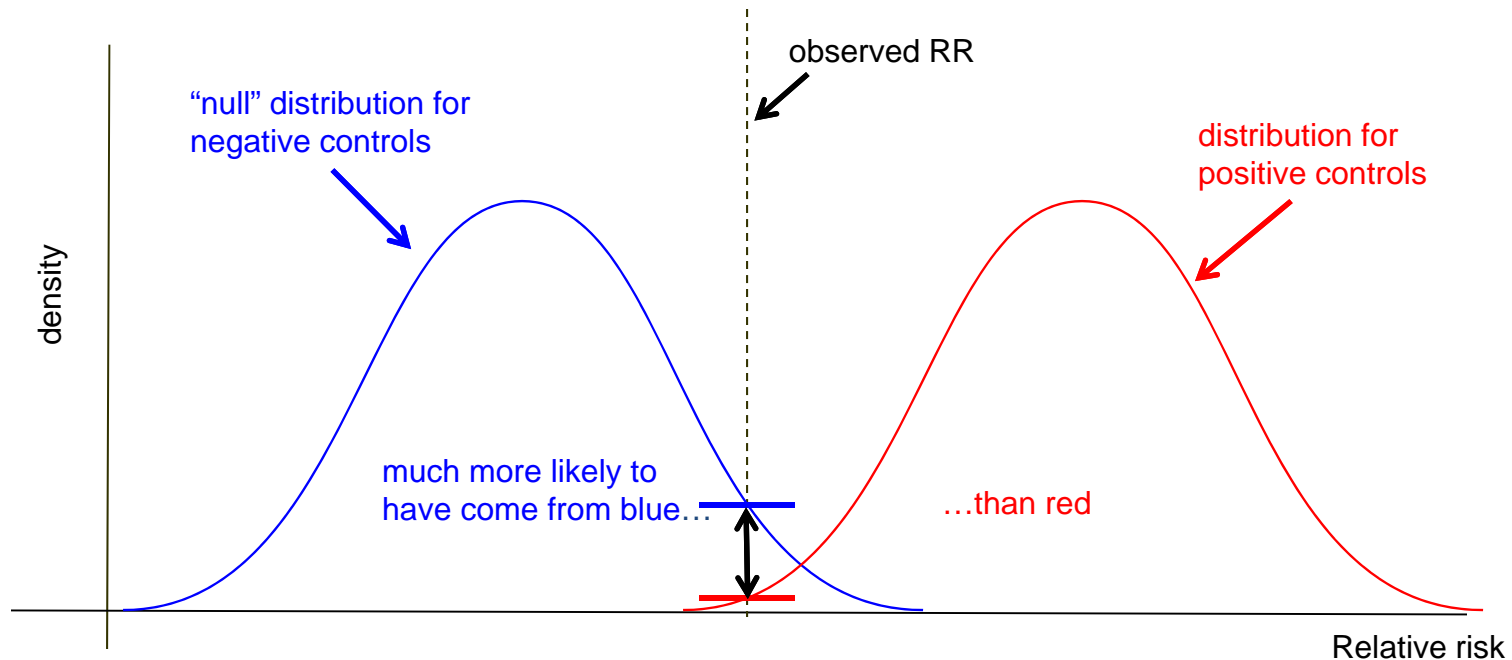


## Recap

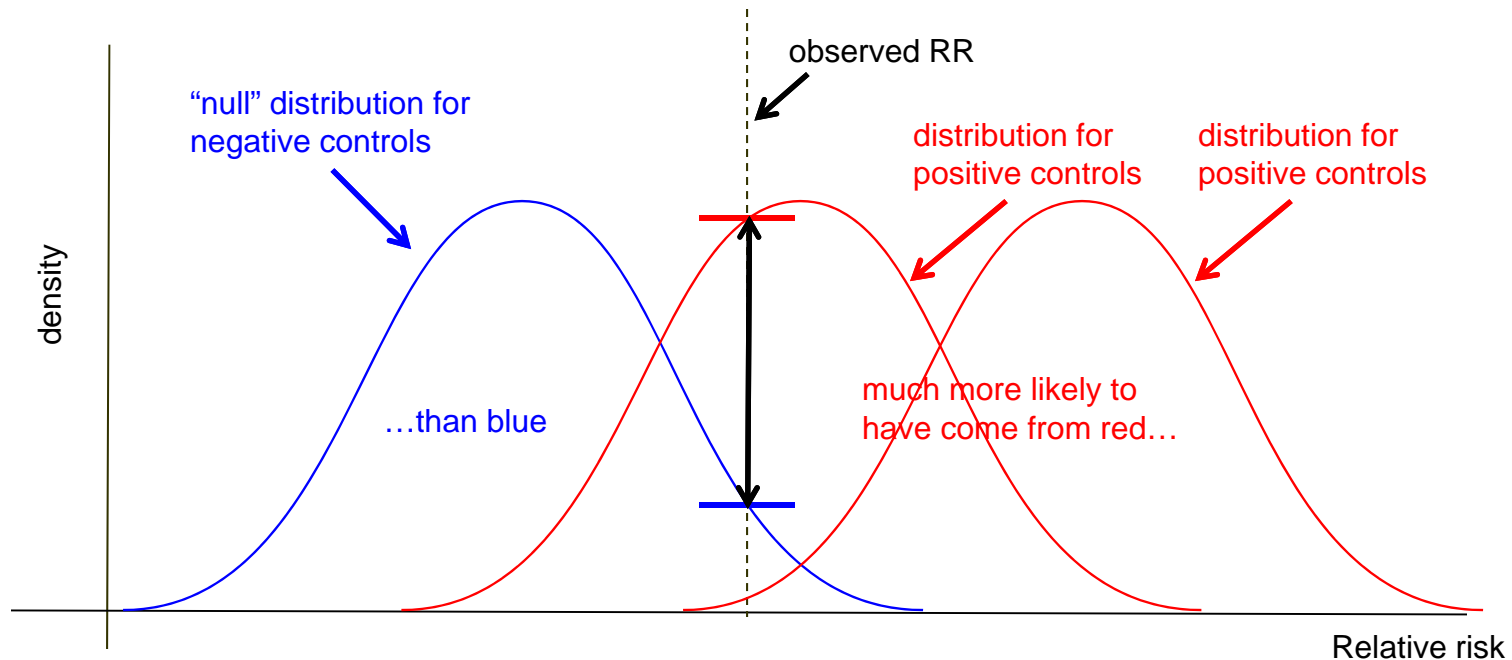
- Traditional p-values are based on a theoretical null distribution assuming an unbiased estimator, but that assumption rarely holds in our examples
- One can estimate the empirical null distribution using negative controls
- Many observational study results with traditional  $p < .05$  fail to reject the empirical null: we cannot distinguish them from negative controls
- Applying optimal methods, tailored to the outcome and database, can provide estimates that reject the null hypothesis for some of our positive controls
- Using adjusted p-values will provide a more calibrated assessment of whether an observed estimate is different from 'no effect'

**Beyond p-values: Computing  
the probability of a true  
association**

# We also have positive controls



# But if AUC is small...



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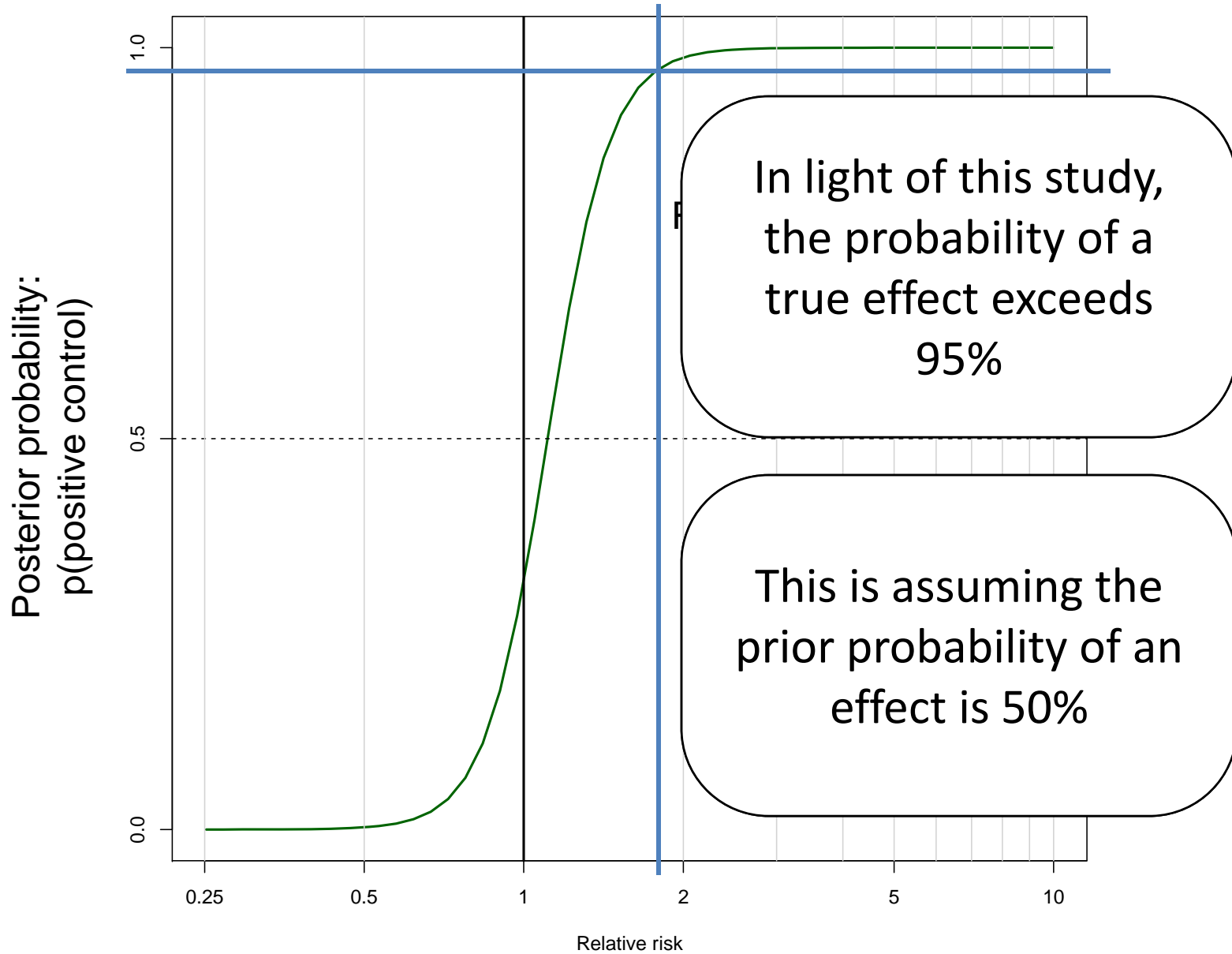
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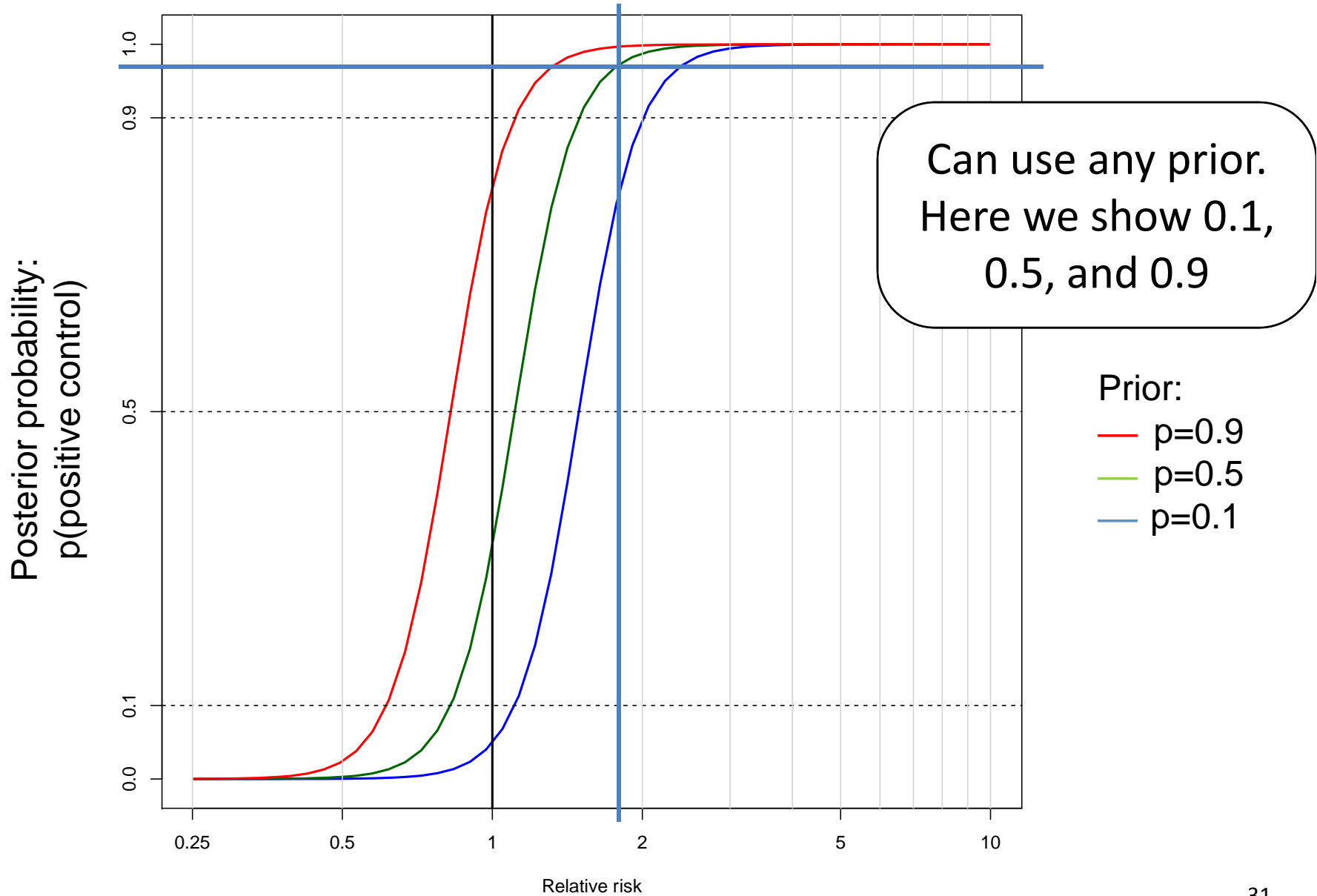
# Clopidogrel – GI Bleed

Method: CC-2000314, Source: CCAE, HOI: GI Bleed



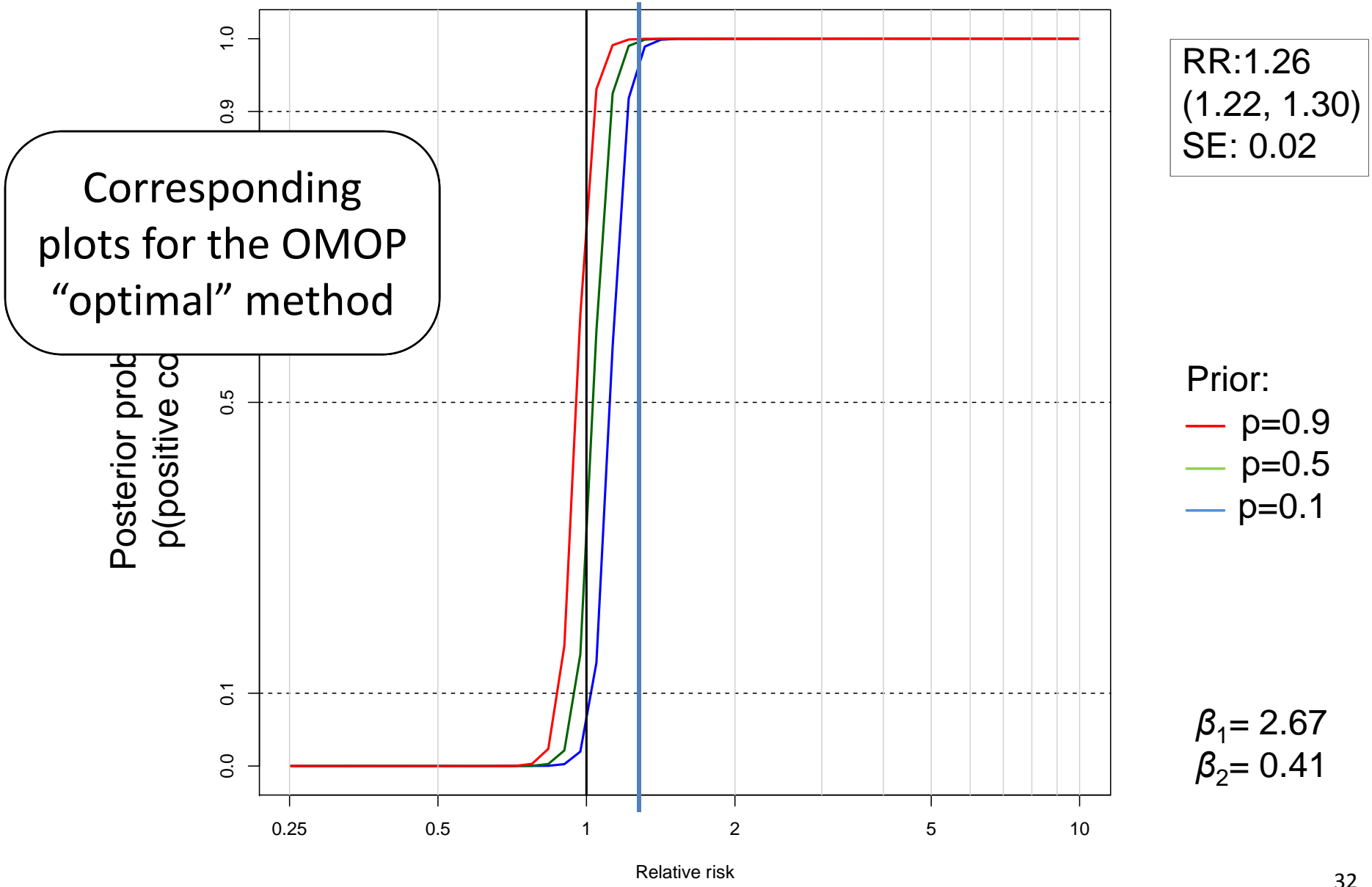
# Clopidogrel – GI Bleed

Method: CC-2000314, Source: CCAE, HOI: GI Bleed



# Clopidogrel – GI Bleed

Method: SCCS-1931010, Source: CCAE, HOI: GI Bleed





## Recap

- We have developed an empirical approach to quantifying the posterior probability of a true effect, given an observed estimate and prior beliefs
- Comparing the distribution of negative controls with the distribution of positive controls provides complementary information beyond the p-value
  - $p < 0.05$  doesn't guarantee a true effect exists
  - $p > 0.05$  doesn't guarantee no effect is present

## Recap (continued)

- For each outcome, different methods may provide different weights of evidence
  - Some methods have greater discrimination and are more informative for interpreting a new estimate
  - Sometimes prior beliefs will drive the revised understanding
  - Other times, evidence will be sufficiently compelling that everyone, with different prior beliefs, should reach similar conclusions

## Conclusions

- Calibration of p-values, using an empirical null distribution, in order to take into account the biases in database studies, may be feasible
- It is possible to calculate the posterior probability of an association, given a prior belief and the observed data