

#### Large-Scale Evidence Generation and Evaluation in a Network of Databases (LEGEND)

Patrick Ryan, Martijn Schuemie, Marc Suchard on behalf of the LEGEND team OHDSI Symposium 12 October 2018



#### Trouble with observational research



CLINICAL REVIEW Controversies in cardiovascular medicine

#### Association is not causation: treatment effects cannot be estimated from observational data in heart failure

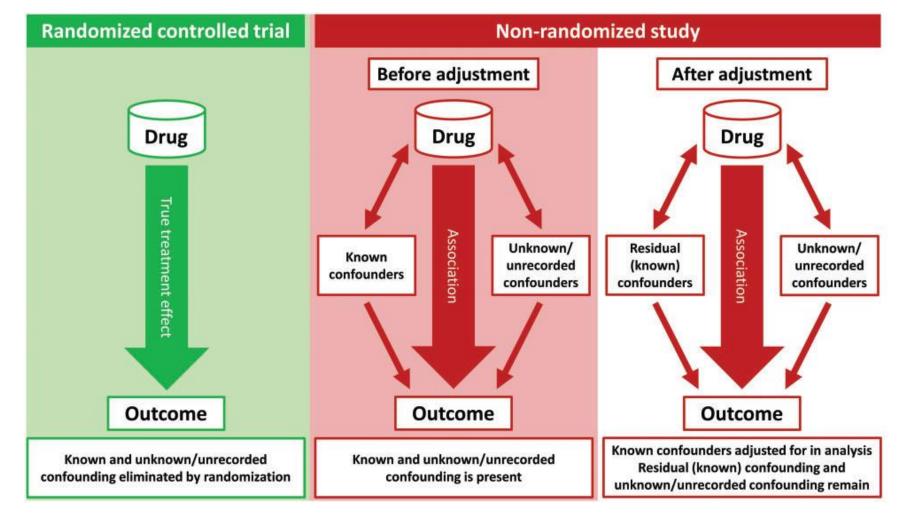
#### Christopher J. Rush, Ross T. Campbell, Pardeep S. Jhund, Mark C. Petrie, and John J.V. McMurray\*

British Heart Foundation Cardiovascular Research Centre, Institute of Cardiovascular and Medical Sciences, University of Glasgow, 126 University Place, Glasgow G12 8TA, UK

Received 16 January 2018; revised 1 April 2018; editorial decision 22 June 2018; accepted 27 June 2018; online publish-ahead-of-print 1 August 2018

Aims	Treatment 'effects' are often inferred from non-randomized and observational studies. These studies have inherent
	biases and limitations, which may make therapeutic inferences based on their results unreliable. We compared the
	conflicting findings of these studies to those of prospective randomized controlled trials (RCTs) in relation to
	pharmacological treatments for heart failure (HF).
Methods	We searched Medline and Embase to identify studies of the association between non-randomized drug therapy and
and results	all cause mortality in patients with HE until 31 December 2017. The treatments of interact works angiotensin

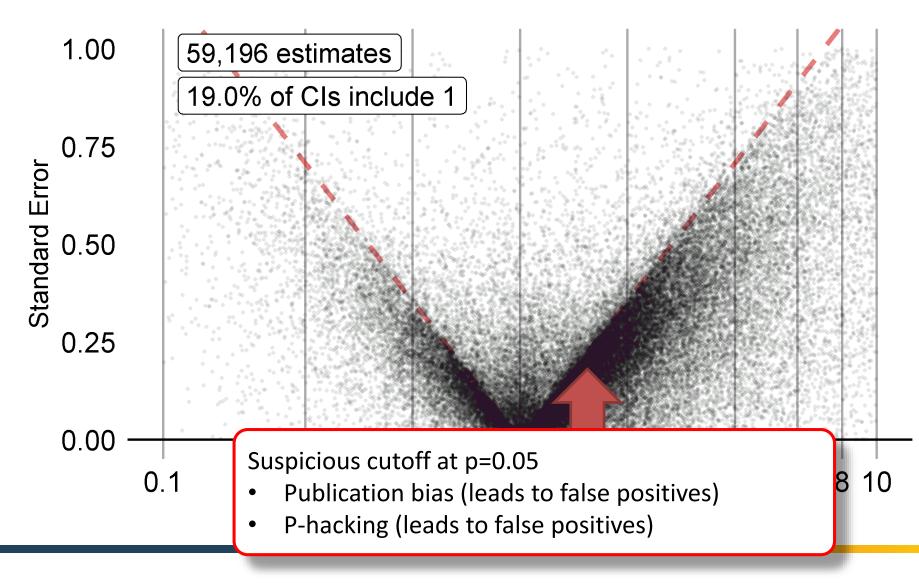
# Residual study bias



Rush et al., 2018



#### Published observational study results





#### Trouble with observational research

- Individual studies are often biased due to confounding, selection bias, and measurement error
- Across studies, observational research as a whole is even more biased due to publication bias and phacking



# Improving methods to address confounding

- Construct large generic set of covariates
  - -10,000 < n < 100,000
- Use regularized regression to fit propensity model
- Match or stratify on propensity score



International Journal of Epidemiology, 2018, 1–10 doi: 10.1093/ije/dyy120 Original article

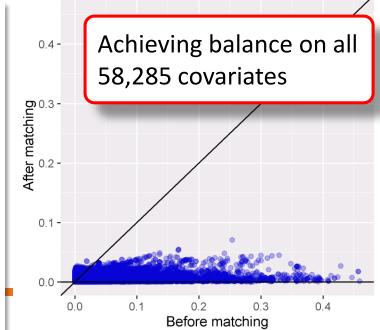


Original article

#### Evaluating large-scale propensity score performance through real-world and synthetic data experiments

Yuxi Tian,<sup>1</sup>\* Martijn J Schuemie<sup>2</sup> and Marc A Suchard<sup>1,3,4</sup>

<sup>1</sup>Department of Biomathematics, David Geffen School of Medicine at UCLA, University of California, Los Angeles, CA, USA, <sup>2</sup>Epidemiology Department, Janssen Research and Development LLC, Titusville, NJ, USA, <sup>3</sup>Department of Biostatistics, UCLA Fielding School of Public Health, University of California, Los Angeles, CA, USA and <sup>4</sup>Department of Human Genetics, David Geffen School of Medicine at UCLA, University of California, Los Angeles, CA, USA



Standardized difference of mean



# Measuring residual bias

#### **Control questions:**

- exposure-outcome pairs with known effect size
- negative and positive controls

#### **Empirical calibration:**

 Adjust p-value and confidence interval using estimates for controls



# Empirical confidence interval calibration for population-level effect estimation studies in observational healthcare data

Martijn J. Schuemie<sup>a,b,1</sup>, George Hripcsak<sup>a,c,d</sup>, Patrick B. Ryan<sup>a,b,c</sup>, David Madigan<sup>a,e</sup>, and Marc A. Suchard<sup>a,f,g,h</sup>

<sup>a</sup>Observational Health Data Sciences and Informatics, New York, NY 10032; <sup>b</sup>Epidemiology Analytics, Janssen Research & Development, Titusville, NJ 08560; <sup>c</sup>Department of Biomedical Informatics, Columbia University, New York, NY 10032; <sup>d</sup>Medical Informatics Services, New York–Presbyterian Hospital, New York, NY 10032; <sup>a</sup>Department of Statistics, Columbia University, New York, NY 10027; <sup>f</sup>Department of Biomathematics, University of California, Los Angeles, CA 90095; <sup>a</sup>Department of Biostatistics, University of California, Los Angeles, CA 90095; <sup>a</sup>Department of Human Genetics, University of California, Los Angeles, CA 90095

Edited by Victoria Stodden, University of Illinois at Urbana–Champaign, Champaign, IL, and accepted by Editorial Board Member Susan T. Fiske October 26, 2017 (received for review June 15, 2017)

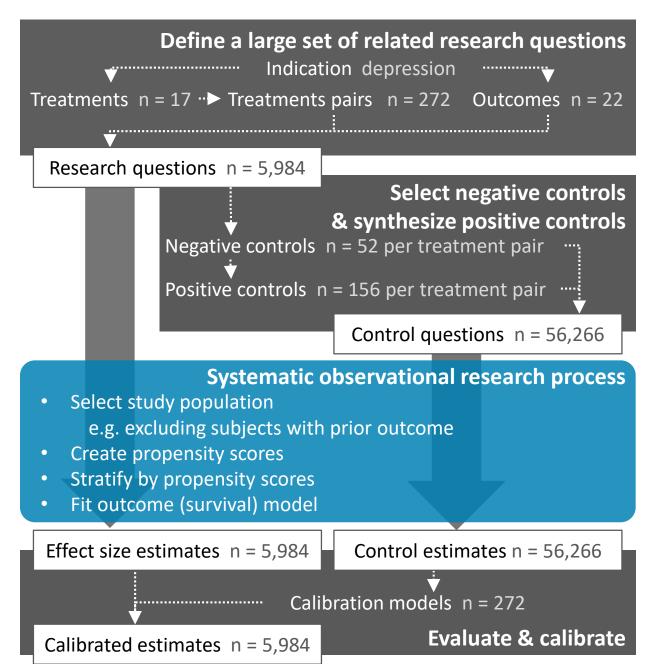
Observational healthcare data, such as electronic health records and administrative claims, offer potential to estimate effects of medical products at scale. Observational studies have often been found to be nonreproducible, however, generating conflicting results even when using the same database to answer the come question. One course of diversities is earch both can age treatment effect. Systematic error can manifest from multiple sources, including confounding, selection bias, and measurement error. While there is widespread awareness of the potential for systematic error in observational studies and a large body of research that examines how to diagnose and statistically adjust for specific sources of bias, there has hear an comparingly little



### Solving publication bias and p-hacking

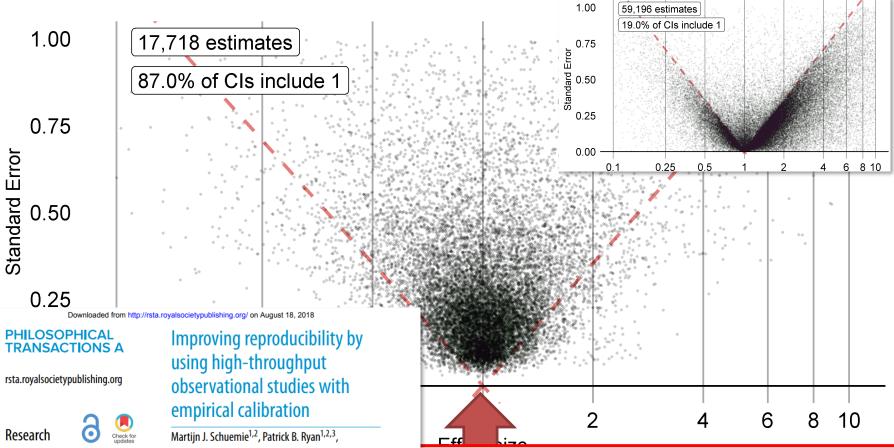
- Fully specified protocols
- Pre-registering studies
- Open science
- Large-scale studies...

#### Depression proof of concept





## **Results of proposed solution**



Cite this article: Schuemie MJ, Ryan PB, Hripcsak G, Madigan D, Suchard MA. 2018 Improving reproducibility by using high-throughput observational studies with empirical calibration, Phil. Trans, R. Soc, A 376: 20170356 http://dx.doi.org/10.1098/rsta.2017.0356

Accepted: 8 May 2018

George Hripcsak<sup>1,3,4</sup>, David Madigan<sup>1,5</sup> and Marc A. Suchard<sup>1,6,7,8</sup>

<sup>1</sup>Observational Health Data Sciences and Informatics (OHDSI), New York, NY 10032, USA <sup>2</sup>Epidemiology Analytics, Janssen Research and Development, Titusville, NJ 08560, USA <sup>3</sup>Department of Biomedical Informatics, Columbia University Modical Contor New York NV 10022 LISA

hation on small effect sizes ssed using negative and positive controls no publication bias



#### Depression results publicly available

#### http://data.ohdsi.org/SystematicEvidence/

Supplementary data for 'Improving reproducibility using high-throughput observational studies with empirical calibration'

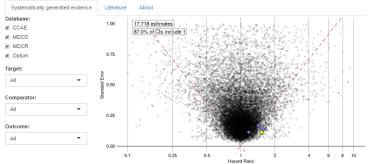


Figure S1. Systematically generated evidence from observational data. Each dot represents a calibrated hazard ratio and confidence interval for a comparison of two depression treatments with respect to an outcome of interest in one of the four databases. Use the controls on the left to filter the result set. After selecting an estimate, details will be shown below.

Details for Mirtazapine vs. duloxetine for Insomnia (MDCR)

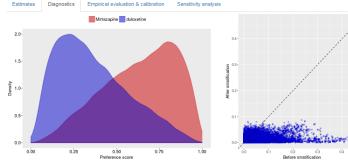


Figure S1.2. Preference score distribution. The preference score is a transformation of the propensity score that adjusts for differences in the sizes of the two treatment groups. A higher overlap indicates subjects in the two groups were more similar in terms of their predicted probability of receivind one treatment over the other. Figure S1.3. Covariate balance before and after stratification. Each dot represents the standardizes difference in means for a single covariate before and after stratifying on the propensity score. Move the mouse arrow over a dot for more details.





# Building the process to generate the evidence





## **LEGEND** Guiding Principles

- 1. Evidence will be generated at **large-scale**.
- 2. Dissemination of the evidence will not depend on the estimated effects.
- 3. Evidence will be generated by consistently applying a **systematic approach** across all research questions.
- 4. The evidence will be generated using a **pre-specified** analysis design.
- 5. The evidence will be generated using **open source** software that is freely available to all.
- 6. The evidence generation process will be **empirically evaluated** by including control research questions where the true effect size is known.
- 7. The evidence will be generated using **best-practices**.
- 8. LEGEND will **not** be used to **evaluate methods**.
- 9. The evidence will be **updated** on a regular basis.
- **10.** No patient-level data will be shared between sites in the network, only aggregated data.



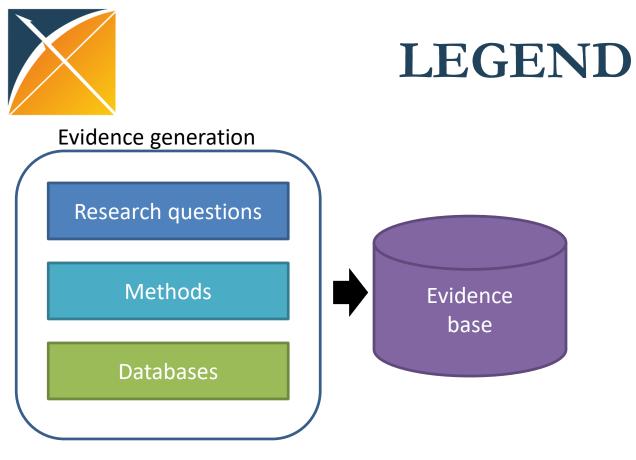
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	Resea
Evidence generation	Prev
Research questions	This
Methods	
Databases	

## Research questions

Previously: Depression treatments

This run: Hypertension treatments



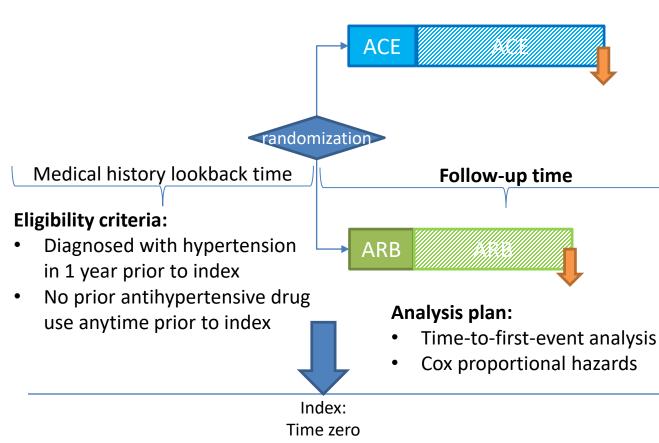
#### 'Target trial' to compare two initial therapies

#### **Treatment strategies:**

- Monotherapy with ACE
- Monotherapy with ARB

#### **Causal contrasts of interest:**

- Intent-to-treat effect
- On-treatment effect



#### Outcomes:

- Efficacy:
  - Myocardial infarction
  - Stroke
  - Heart Failure
- Safety:
  - Known or potential adverse events, e.g.
  - Acute renal failure
  - Angioedema
  - Cough
  - Diarrhea
  - Fall
  - Gout
  - Headache
  - Hyperkalemia
  - Hyponatremia
  - Hypotension
  - Impotence
  - Syncope
  - Vertigo



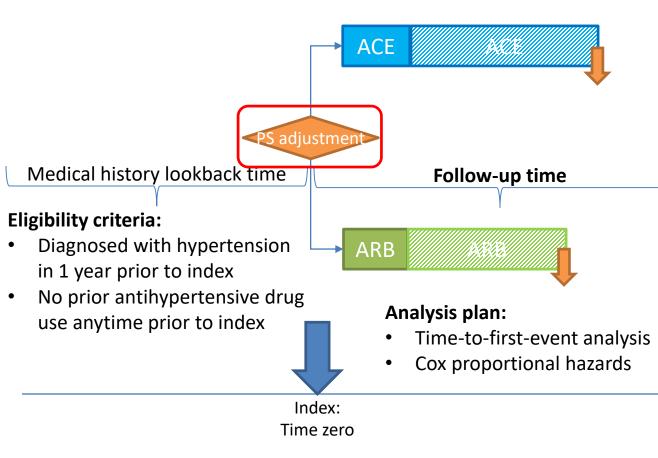
# Observational study to compare two initial therapies

#### Treatment strategies:

- Monotherapy with ACE
- Monotherapy with ARB

#### **Causal contrasts of interest:**

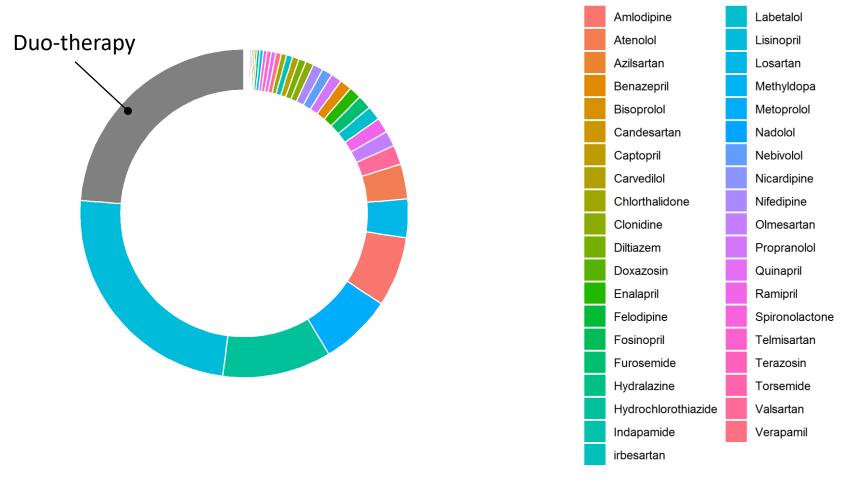
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# Hypertension mono-therapy



Truven Health MarketScan CCAE. Therapies > 2 ingredients not shown

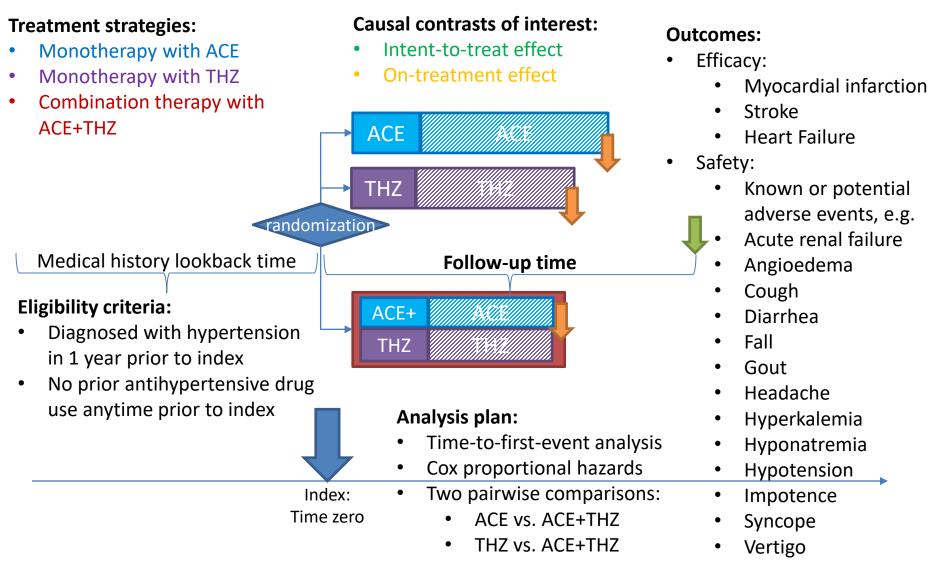




	Theoretical	Observed (n > 2,500)
Single ingredients	58	39
Single ingredient comparisons	58 * 57 = 3,306	1,296
Single drug classes	15	13
Single class comparisons	15 * 14 = 210	156

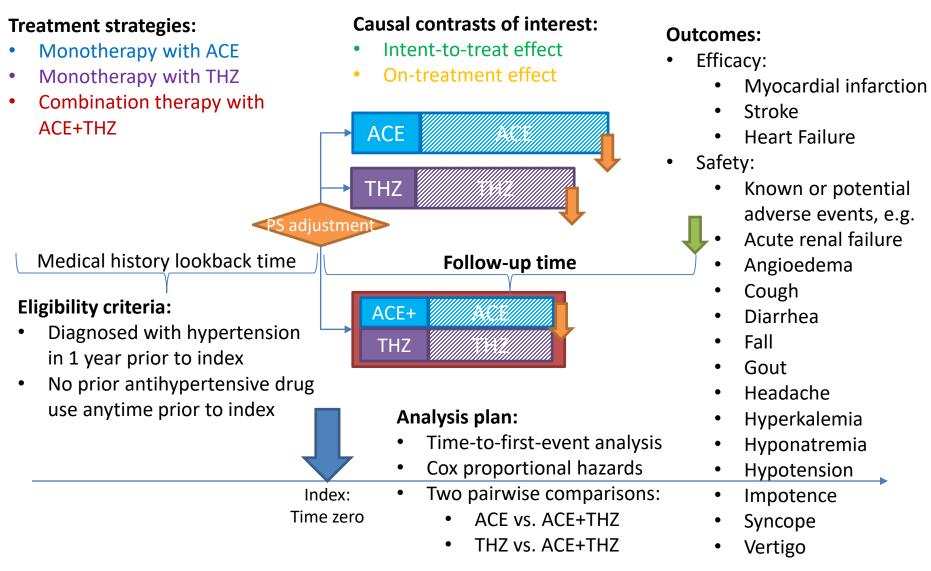


#### 'Target trial' to compare mono vs combination therapy



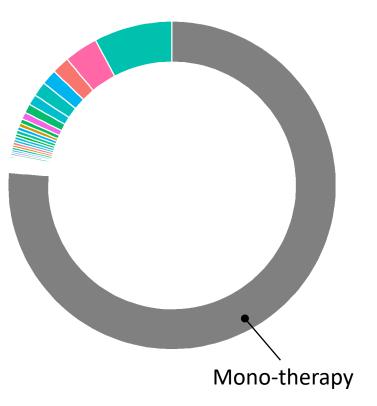


# Observational study to compare mono vs combination therapy





### Hypertension duo-therapy



Amlodipine & Benazepril Amlodipine & Carvedilol Amlodipine & Clonidine Amlodipine & Losartan Amlodipine & Olmesartan Amlodipine & Ramipril Atenolol & Amlodipine Atenolol & Chlorthalidone Atenolol & Losartan Carvedilol & Losartan Furosemide & Amlodipine Furosemide & Atenolol Furosemide & Carvedilol Furosemide & Diltiazem Furosemide & Lisinopril Furosemide & Losartan Furosemide & Metoprolol Furosemide & Spironolactone Hydralazine & Labetalol Hydrochlorothiazide & Amlodipine Hvdrochlorothiazide & Atenolol Hydrochlorothiazide & Benazepril Hydrochlorothiazide & Bisoprolol Hydrochlorothiazide & Candesartan Hvdrochlorothiazide & Diltiazem Hydrochlorothiazide & Enalapril Hydrochlorothiazide & irbesartan Hydrochlorothiazide & Lisinopril Hydrochlorothiazide & Losartan Hydrochlorothiazide & Metoprolol Hydrochlorothiazide & Olmesartan Hydrochlorothiazide & Quinapril Hydrochlorothiazide & Ramipril Hydrochlorothiazide & Telmisartan Hydrochlorothiazide & Valsartan Lisinopril & Amlodipine Lisinopril & Atenolol Lisinopril & Carvedilol Lisinopril & Clonidine Lisinopril & Diltiazem

Lisinopril & Labetalol Lisinopril & Losartan Lisinopril & Propranolol Metoprolol & Amlodipine Metoprolol & Diltiazem Metoprolol & Enalapril Metoprolol & Hydralazine Metoprolol & Labetalol Metoprolol & Lisinopril Metoprolol & Losartan Metoprolol & Ramipril Metoprolol & Valsartan Nifedipine & Labetalol Ramipril & Bisoprolol Triamterene & Hydrochlorothiazide Valsartan & Amlodipine Verapamil & Lisinopril Verapamil & Trandolapril

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Single class comparisons	15 * 14 = 210	156
Dual ingredients	58 * 57 / 2 = 1,653	58
Single vs duo drug comparisons	58 * 1,653 = 95,874	3,810
Dual classes	15 * 14 / 2 = 105	32
Single vs duo class comparisons	15 * 105 = 1,575	832



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Duo vs duo drug comparisons	1,653 * 1,652 = 2,730,756	2,784
Duo vs duo class comparisons	105 * 104 = 10,920	992

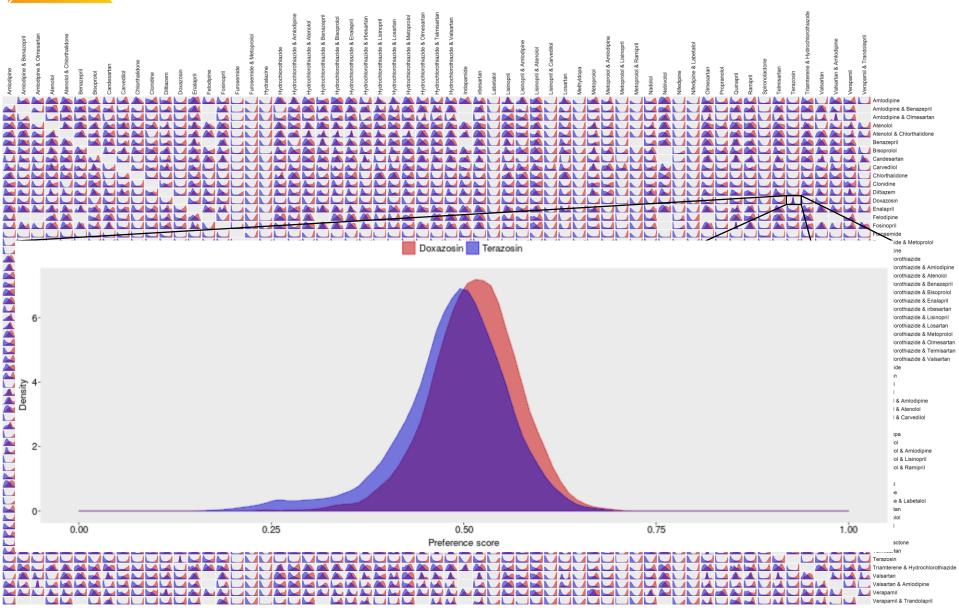


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Total comparisons	2,843,250	10,278

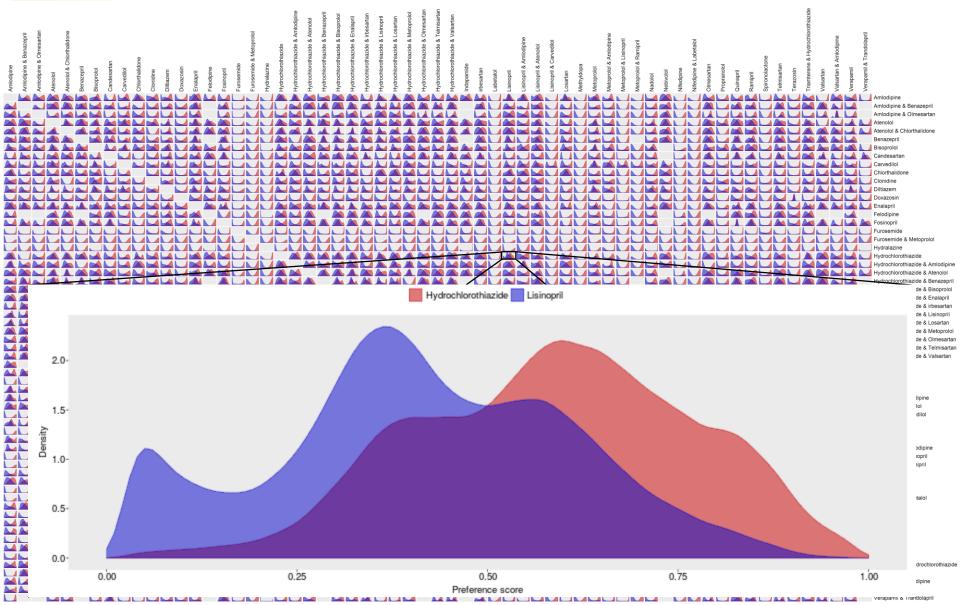


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Amini Amini	
	Amlodipine Amlodipine & Benazepril
	Amlodipine & Olmesartan
	Atenolol & Chlorthalidone
	Benazepril Bisoprolol
	Candesartan
	Carvediloi Chlorthalidone
	Clonidine Diltiazem
Antilation     Antilation     Antilation       Antilation     Anti	Doxazosin
	Felodipine
	Fosinopril Furosemide
	Furosemide & Metoprolol
	Hydralazine Hydrochlorothiazide
	Hydrochlorothiazide & Amlodipine Hydrochlorothiazide & Atenolol
	Hydrochlorothiazide & Benazepril
	Hydrochlorothiazide & Bisoprolol Hydrochlorothiazide & Enalapril
	Hydrochlorothiazide & irbesartan Hydrochlorothiazide & Lisinopril
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	Hydrochlorothiazide & Metoprolol Hydrochlorothiazide & Olmesartan
	Hydrochlorothiazide & Telmisartan
	Indapamide
	irbesartan Labetalol
	Lisinopril Lisinopril & Amlodinine
	Lisinopril & Atenolol
	Lisinopril & Carvedilol Losartan
	Methyldopa Metoprolol
	Metoprolol & Amlodipine
	Metoprolol & Ramipril
	Nadolol
	Nifedipine & Labetalol Olmesartan
	Propranolol
	Ramipril
	Spironolactone Telmisartan
	Terazosin
	Triamterene & Hydrochlorothiazide Valsartan
	Valsartan & Amlodipine
	Verapamil & Trandolapril

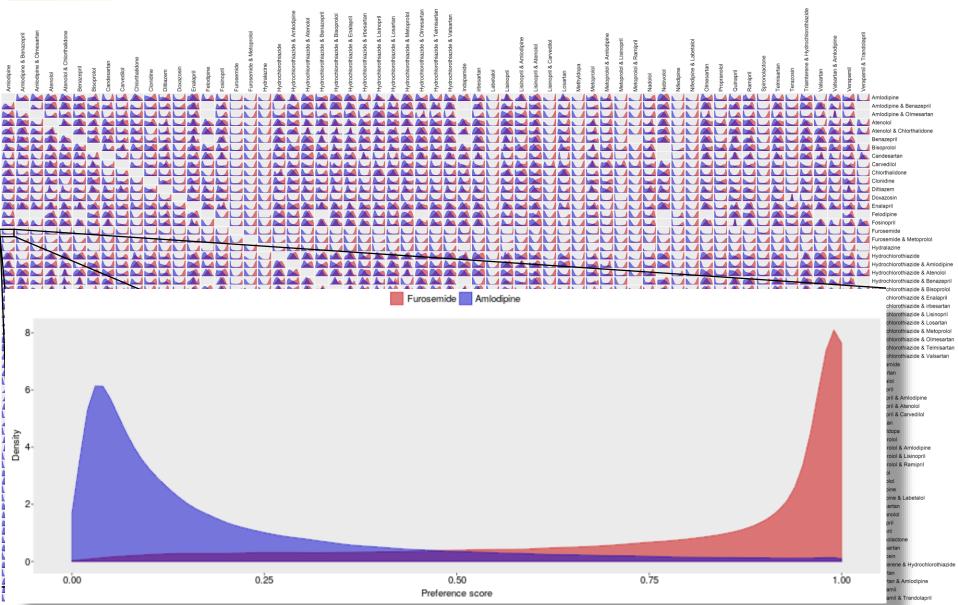














### 58 outcomes of interest

Abdominal pain Abnormal weight gain Abnormal weight loss Acute myocardial infarction Acute pancreatitis Acute renal failure All-cause mortality Anaphylactoid reaction Anemia Angioedema Anxiety Bradycardia Cardiac arrhythmia Cardiovascular disease Cardiovascular-related mortality Chest pain or angina Chronic kidney disease Coronary heart disease Cough Decreased libido

Dementia Depression Diarrhea Edema End stage renal disease Fall Gastrointestinal bleeding Gout Headache Heart failure Hemorrhagic stroke Hepatic failure Hospitalization with heart failure Hospitalization with preinfarction syndrome Hyperkalemia Hypokalemia Hypomagnesemia Hyponatremia **Hypotension** Impotence

Ischemic stroke **Kidney disease** Malignant neoplasm Measured renal dysfunction Nausea Neutropenia or agranulocytosis Rash Rhabdomyolysis Stroke Sudden cardiac death Syncope Thrombocytopenia Transient ischemic attack Type 2 diabetes mellitus Vasculitis Venous thromboembolic events Vertigo Vomiting



### 58 outcomes of interest

Abdominal pain Dementia		tia	Isc	hemic stroke
Abnormal weight gain	Depress	sion	Kid	lney disease
Abnormal weight loss	Diarrhe	a	Ma	alignant neoplasm
Acute myocardial infarction	Edema		Measured renal dysfunction	
Acute pancreatitis	End stag	ge renal disease	Na	usea
Acute renal failure	Fall		Ne	utropenia or agranulocytosis
All-cause mortality	Gastroi	ntestinal bleeding	Ras	sh
		Theoreti	cal	Observed (n > 2,500)
Outcomes of interest			58	58
Target-comparator-outcomes		2,843,250 * 58 = 164,908,5	500	587,020
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Cardiac arrhythmia	Hospita	lization with heart failure lization with preinfarction syndrome	Tra Typ	nsient ischemic attack
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Cardiac arrhythmia Cardiovascular disease Cardiovascular-related mortality	Hospita Hospita Hyperka Hypoka	lization with heart failure lization with preinfarction syndrome alemia	Tra Typ Vas Ver	nsient ischemic attack pe 2 diabetes mellitus sculitis
Cardiac arrhythmia Cardiovascular disease Cardiovascular-related mortality Chest pain or angina	Hospita Hospita Hyperka Hypoka	lization with heart failure lization with preinfarction syndrome alemia lemia agnesemia	Tra Typ Vas Vei Vei	nsient ischemic attack pe 2 diabetes mellitus sculitis nous thromboembolic events
Cardiac arrhythmia Cardiovascular disease Cardiovascular-related mortality Chest pain or angina Chronic kidney disease	Hospita Hospita Hyperka Hypoka Hypoma	lization with heart failure lization with preinfarction syndrome alemia lemia agnesemia tremia	Tra Typ Vas Vei Vei	nsient ischemic attack pe 2 diabetes mellitus sculitis nous thromboembolic events rtigo



## Each research question requires

- Evaluation of the propensity score distribution
- Evaluation of covariate balance
- Inclusion of negative and positive controls
- Empirical calibration



### 76 negative controls

Abnormal cervical smear Abnormal pupil Abrasion and/or friction burn of trunk without infection Endometriosis Absence of breast Absent kidney Acid reflux Acquired hallux valgus Acquired keratoderma Acquired trigger finger Acute conjunctivitis Amputated foot Anal and rectal polyp Burn of forearm Calcaneal spur Cannabis abuse Cervical somatic dysfunction Changes in skin texture Chondromalacia of patella Cocaine abuse Colostomy present Complication due to Crohn's disease Contact dermatitis Contusion of knee Crohn's disease Derangement of knee **Difficulty sleeping** 

Disproportion of reconstructed breast Effects of hunger Epidermoid cyst Feces contents abnormal Foreign body in orifice Ganglion cyst Genetic predisposition Hammer toe Hereditary thrombophilia Herpes zoster without complication High risk sexual behavior Homocystinuria Human papilloma virus infection lleostomy present Impacted cerumen Impingement syndrome of shoulder region Sprain of ankle Ingrowing nail Injury of knee Irregular periods Kwashiorkor Late effect of contusion Late effect of motor vehicle accident Leukorrhea Macular drusen Melena

Nicotine dependence Noise effects on inner ear Nonspecific tuberculin test reaction Non-toxic multinodular goiter Onychomycosis due to dermatophyte **Opioid** abuse Passing flatus Postviral fatigue syndrome Presbyopia Problem related to lifestyle Psychalgia Ptotic breast **Regular** astigmatism Senile hyperkeratosis Somatic dysfunction of lumbar region Splinter of face, without major open wound Strain of rotator cuff capsule Tear film insufficiency Tobacco dependence syndrome Vaginitis and vulvovaginitis Verruca vulgaris Wrist joint pain Wristdrop



### 76 negative controls

Abnormal cervical smear Abnormal pupil Abrasion and/or friction burn of trunk without infection Absence of breast Absent kidney Acid reflux Acquired hallux valgus Acquired keratoderma Acquired trigger finger	Disproportion of reconstructed breast Effects of hunger n Endometriosis Epidermoid cyst Feces contents abnormal Foreign body in orifice Ganglion cyst Genetic predisposition Hammer toe	Nicotine dependence Noise effects on inner ear Nonspecific tuberculin test reaction Non-toxic multinodular goiter Onychomycosis due to dermatophyte Opioid abuse Passing flatus Postviral fatigue syndrome Presbyopia	
ρ ρ	Theore	etical	Observed (n > 2,500)
<sup>6</sup> <sub>B</sub> Negative control outcomes		76	76
C Target-comparator-neg controls	2,843,250 * 76 = 216,087	,000	769,476
C Positive control outcomes	76 * 3 =	228	228
Target-comparator-pos controls	2,843,250 * 228 = 648,261	,000	662,484
C Total control C target-comparator- outcomes	864,348	,000	1,431,960
Contusion of knee Crohn's disease Derangement of knee Difficulty sleeping	Late effect of motor vehicle accident Leukorrhea Macular drusen Melena	Wrist jo Wristdro	-



# Methods

	Evidence generation	
		$\mathcal{A}$
	Research questions	
1		
	Methods	
I		
	Databases	
		$\mathcal{I}$

This run:

- Emulate target trial: new-user cohort design
- Expert-crafted outcome definitions
- Large scale propensity models
- Stratification + variable ratio matching
- Empirical calibration

Not static. Driven by **defined best practices**, driven by **empirical evaluation** 

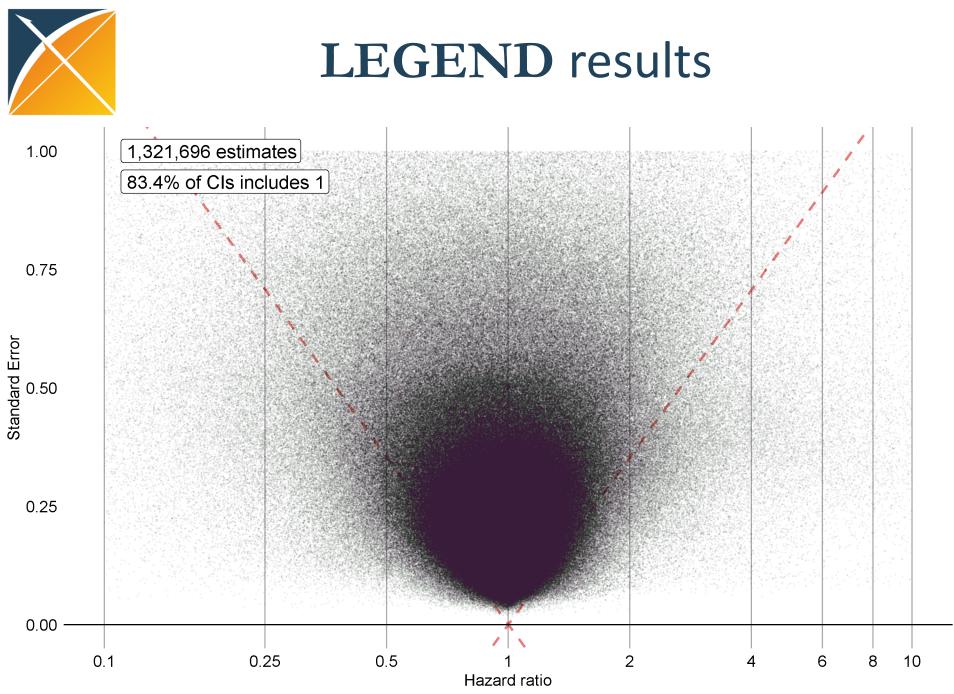


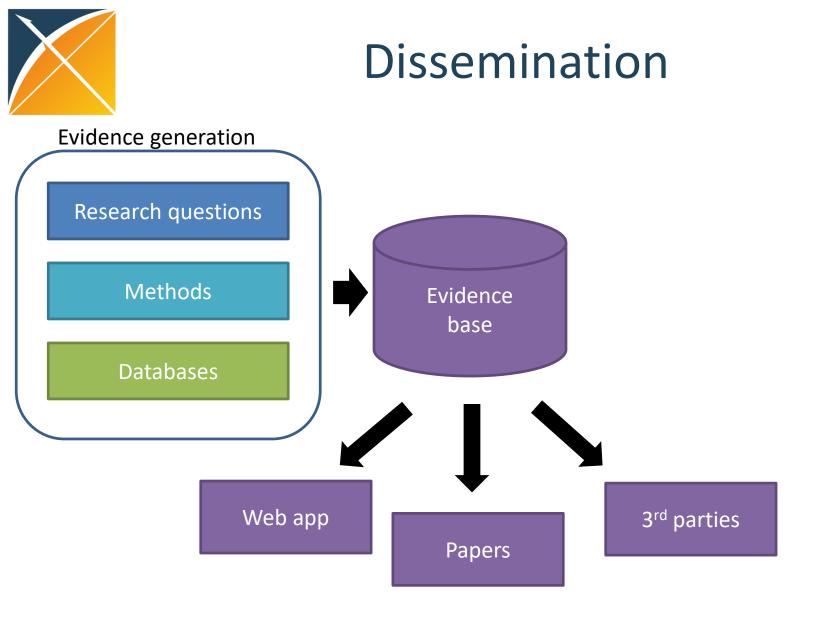
# Databases

#### Previously: 4 US insurance databases

This run:

- US insurance databases
  - IBM<sup>®</sup> MarketScan<sup>®</sup> CCAE
  - IBM<sup>®</sup> MarketScan<sup>®</sup> MDCD
  - IBM<sup>®</sup> MarketScan<sup>®</sup> MDCR
  - Optum<sup>©</sup> Clinformatics<sup>®</sup>
- Japanese insurance database
  - Japan Medical Data Center
- Korean national insurance database
  - NHIS-NSC
- US EHR databases
  - Columbia University Medical Center
  - Optum<sup>©</sup> PANTHER<sup>®</sup>
- German EHR database
  - QuintilesIMS Disease Analyzer (DA) Germany







#### **LEGEND** results model

Study specification		Gene	erated results		
indications	metadata		main results		diagnostics
indication         - indication_name         - definition         analyses         cohort_method_analysis         - analysis_id         - definition         - definition         - definition         - definition         - definition         - definition         - incidence_analysis_id         - incidence_analysis_id         - incidence_analysis_name         exposure_id         - exposure_id         - exposure_id         - exposure_ids         - description         - indication_id         - description         - indication_id         - filter_concept_ids         exposure_group         exposure_id         - outcome_id         - outcome_id	metadata         database         -       database_id         -       description         -       is_meta_analysis         exposure_summary         -       database_id         -       exposure_id         -       min_date         -       max_date         comparison_summary       -         -       database_id         -       target_id         -       comparator_id         -       max_date         attrition       -         -       farget_id         -       [comparator_id]         -       [sequence_number         -       description         -       subjects*	cm_follow_up_dist         -       database_id         -       target_id         -       comparator_id         -       outcome_id         -       analysis_id         -       target_pl0_days         -       target_p25_days         -       target_p275_days         -       target_p90_days         -       target_p275_days         -       target_p275_days         -       target_max_days         -       comparator_p10_days         -       comparator_p25_days         -       comparator_p25_days         -       comparator_p25_days         -       comparator_p75_days         -       comparator_p75_days         -       comparator_max_days         Covariate       database_id         -       covariate_id         -       covariate_analysis_id	main results         cohort_method_result         -       database_id         -       comparator_id         -       outcome_id         -       analysis_id         -       rr         -       ci_95_lb         -       ci_95_ub         -       p         -       [1_2]         -       log_rr         -       sse_log_rr         -       target_subjects*         -       comparator_subjects*         -       calibrated_re         -       calibrated_ci_95_lb         -       calibrated_ies_log_rr         -       ca	cm_interaction_result         -       database_id         -       target_id         -       comparator_id         -       outcome_id         -       analysis_id         -       interaction_covariate_id         -       interaction_covariate_id         -       interaction_covariate_id         -       interaction_covariate_id         -       rrr         -       ci_95_lb         -       ci_95_ub         -       p         -       [l_2]         -       log_rrr         -       se_log_rrr         -       target_subjects*         -       comparator_subjects*         -       comparator_outcomes*         -       colibrated_p         incidence       -         -       finteraction_covariate_id]         -       poutcome_id         -       subjects*         -       days         -       outcomes*	diagnostics  covariate_balance  database_id  comparator_id  formaline in the image is the image
negative_control_outcome	underscore indicates prima	ary key			- comparator_survival_ub
- <u>outcome_id</u> - outcome_name - concept_id - indication_id	[ ] indicates nullable * indicates fields with a min identifiability	nimum value to avoid			propensity_model - database_id - target_id - comparator_id - covariate_id - coefficient



#### **LEGEND** basic viewer

#### http://data.ohdsi.org/LegendBasicViewer/



#### **LEGEND**Med Central

#### http://data.ohdsi.org/LegendMedCentral/



## **Concluding remarks**

- Grave concerns exist over published observational research results, due to study bias, publication bias, and p-hacking
- Large-scale observational studies allow for
  - Empirical evaluation and calibration
  - Unbiased dissemination
  - Providing a more complete evidence base
- LEGEND applies this to real world problems
  - Depression
  - Hypertension