

Better preanalysis plans through design declaration & diagnosis

Graeme Blair, UCLA

**Joint work with Jasper Cooper, Alexander Coppock,
and Macartan Humphreys**



Brian Nosek @BrianNosek · Jan 16



The Journal of Politics is phasing in a requirement for all experimental research to be preregistered. I believe that this is just the second journal across the social-behavioral sciences to require preregistration.

Pre-registration: authors who want to submit manuscripts containing original experimental work, including laboratory, field, and survey experiments are required to submit proof of study/design pre-registration with one of the available research registries (e.g., EGAP, RCT, Open Science). Pre-registration of other types of research design is very much encouraged. The submission of unregistered laboratory, field, and survey experiments will not be accepted. This policy will be phased in: For manuscripts submitted in 2021, authors need to justify in a letter to the editor why the study was not or could not be pre-registered.



Journal of Politics @The_JOP · Jan 16

Dear Colleagues: before submitting to @The_JOP please have a look at the new guidelines for contributors, including pre-registration, replication, ethical considerations etc.: journals.uchicago.edu/journals/jop/i...
@VETroeger



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What should go in a plan?

1. Research design declaration

Model

Inquiry

Data strategy

Answer strategy

2. Research design diagnosis

**What is a
preanalysis plan?**

**What are your hypotheses?
How will you test them?**

Timestamped publicly

Why preanalysis plans?

**Clarify what you thought *before*,
(*in the middle*), and *after***

**What tests are confirmatory vs.
exploratory**



**Writing plans
changes plans**

What goes in a plan?

As Predicted: 9 items

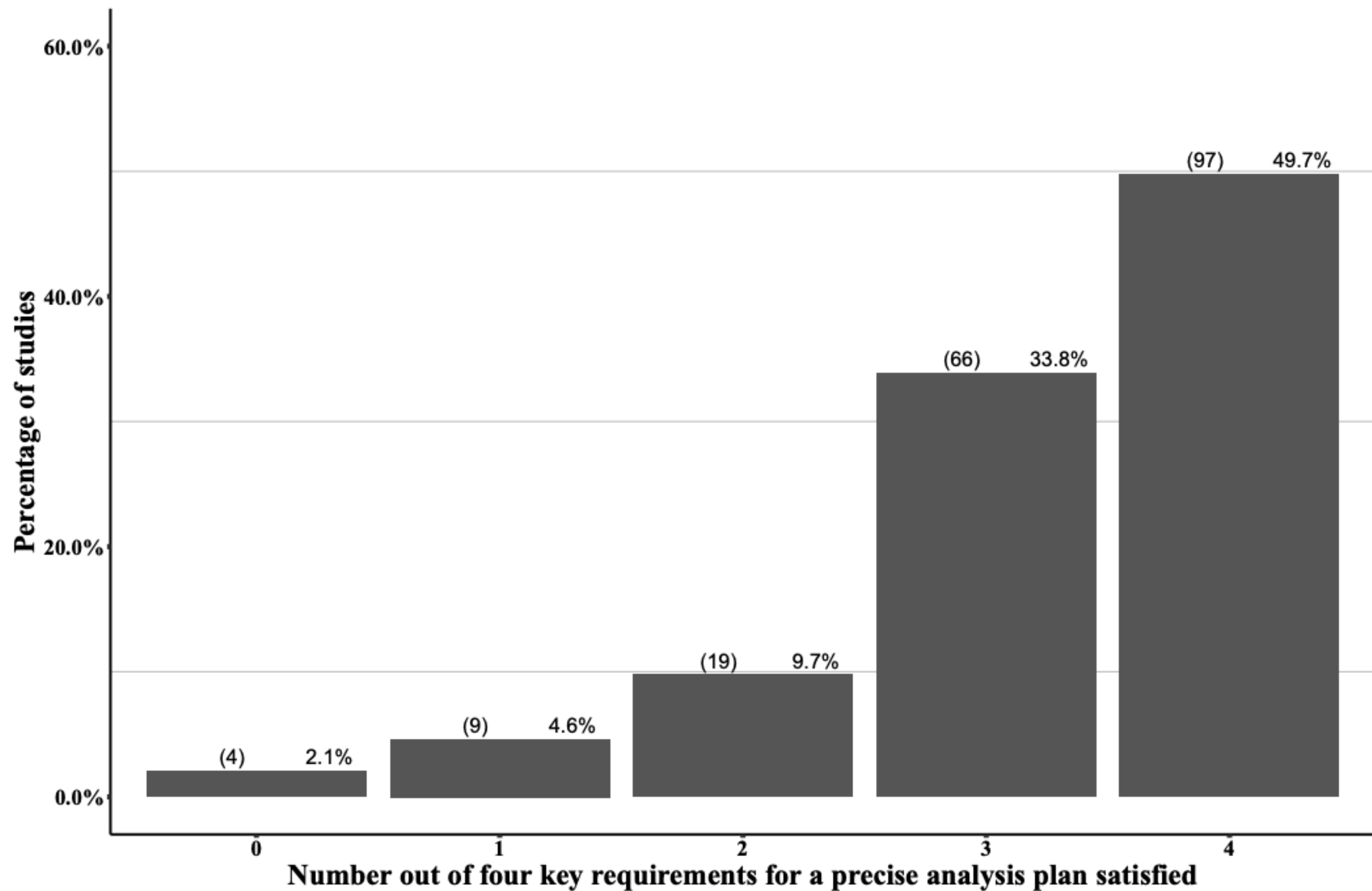
McKenzie (2012): 10 items

AEA registry: ~ 30 items

EGAP registry: ~ 30 items

Journal of Development Economics: 44 items

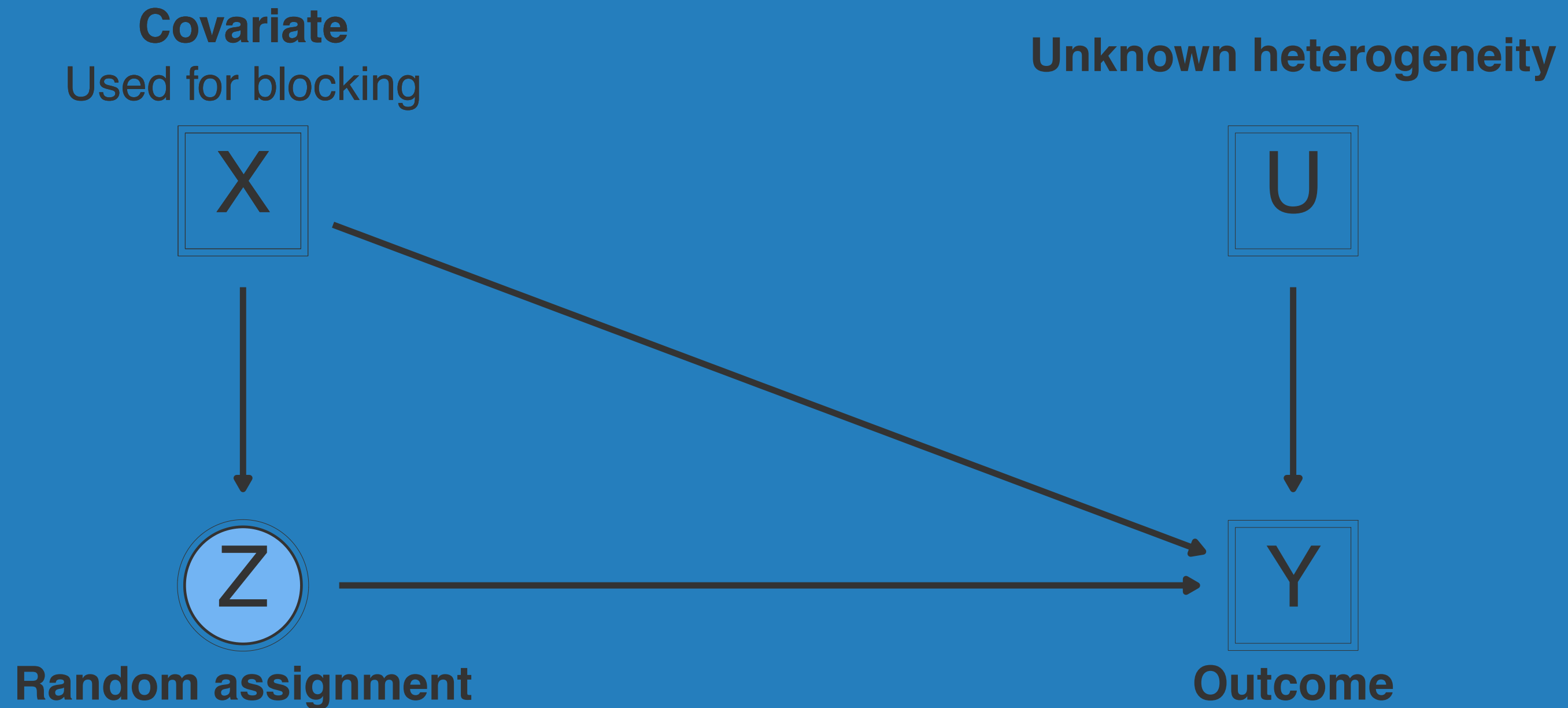
Ganimian (2018): 60 items



We need

- 1. Language for research designs**
- 2. Algorithm for choosing one**

Graphical models



Structural models

$$Y = 0.1 * Z + X + U$$

$$X \sim \text{binom}(1, 0.3)$$

$$U \sim \mu(0, 1)$$

Design declaration

Model

Inquiry

Data strategy

Answer strategy

Model

Theory of the system under study

- What causes what — and how
- How variables are distributed
- Correlations between variables
- Sequence of events
- Theory if we are right, and if we are wrong

Inquiry

Features of the model you want to study

- **Units**
- **Conditions**
- **Outcomes**
- **Descriptive, causal, predictive**

Data strategy

Procedures to gather information about the world

- **Sampling**
- **Random assignment**
- **Measurement**

Answer strategy

How you summarize data from the data strategy

- **Data cleaning**
- **Data transformation**
- **Estimation**
- **Visualization**
- **Interpretation**

Answer strategy

How you summarize data from the data strategy

- Data cleaning
- Data transformation
- Estimation
- Visualization
- Interpretation
- Document selection
- Coding procedures
- Narrative

Declaring a design in practice

R package `DeclareDesign`


```
design <-
```

```
# Model
```

```
declare_model(  
  N = 100,  
  X = rbinom(N, 1, 0.3),  
  U = rnorm(N),  
  potential_outcomes(Y ~ 0.1 * Z + X + U)  
) +
```

```
# Inquiry
```

```
declare_inquiry(ATE = mean(Y_Z_1 - Y_Z_0)) +
```

```
# Data strategy
```

```
declare_assignment(blocks = X, block_prob = c(0.1, 0.5)) +  
declare_measurement(Y = reveal_outcomes(Y ~ Z)) +
```

```
# Answer strategy
```

```
declare_estimator(Y ~ Z, model = lm, inquiry = "ATE")
```

Draw simulated data

draw_data(design)

ID	X	U	Y_Z_0	Y_Z_1	Z	Z_prob	Y
001	1	0.66	1.66	1.76	0	0.5	1.66
002	1	-1.69	-0.69	-0.59	1	0.5	-0.59
003	0	-1.03	-1.03	-0.93	0	0.9	-1.03
004	1	-0.62	0.38	0.48	0	0.5	0.38
005	0	0.03	0.03	0.13	0	0.9	0.03
006	1	0.34	1.34	1.44	0	0.5	1.34

Draw mock estimates

```
draw_estimates(design)
```

est	std.err	statistic	p.value	conf.lo	conf.hi
0.64	0.29	2.22	0.03	0.07	1.22

Draw mock estimand

```
draw_estimands(design)
```

estimand_label	estimand
ATE	0.1

Descriptive inquiries

```
# survey targeting average policy preferences  
declare_inquiry(mean_preferences = mean(Y))
```

```
# list experiment studying binary trait  
declare_inquiry(proportion = mean(Y_star))
```

Observational research designs

```
# regression discontinuity
cutoff <- 0.5
control <- function(X) {
  as.vector(poly(X, 4, raw = TRUE) %*% c(.7, -.8, .5, 1))}
treatment <- function(X) {
  as.vector(poly(X, 4, raw = TRUE) %*% c(0, -1.5, .5, .8)) + .15}

declare_model(
  N = 1000,
  U = rnorm(N, 0, 0.1),
  X = runif(N, 0, 1) + U - cutoff,
  potential_outcomes(Y ~ Z * treatment(Z) + (1 - Z) * control(X) + U),
  Z = 1 * (X > 0)
) +
declare_measurement(Y = reveal_outcomes(Y ~ Z))
```


Algorithm for selecting designs

Declare

Diagnose

Redesign

Algorithm for selecting designs

Declare

Diagnose

Redesign



Diagnosing a design

What are the properties of a research design?

1. Through analytical expressions

2. Through simulation

Is my design powered?

$$\text{power} \approx \Phi \left(\frac{|\mu_t - \mu_c| \sqrt{N}}{2\sigma} - \Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right)$$

Is my design powered?

$$\text{power} \approx \Phi \left(\frac{|\mu_t - \mu_c| \sqrt{N}}{2\sigma} - \Phi^{-1} \left(1 - \frac{\alpha}{2} \right) \right)$$

- Model: normally-distributed outcome; $\sigma_t = \sigma_c$
- Data strategy: simple random assignment
- Answer strategy: equal-variance t-test with N-2 degrees of freedom

Is my design biased?

- **Blocking with varying assignment probabilities**
- **Random assignment of clusters of different sizes**
- **Differential attrition**
- **Logit with fixed effects**
- **Posttreatment bias**

How many people should I interview?

How many men and women?

How often should I interview them?

Should I assign 2 or 3 treatment arms?

Is it important in this case to use blocking?

How many items should I include in my index?

More survey items or more respondents?

Robust or cluster-robust standard errors?

Should I control for emotions in my regression?

Is it okay to drop people who didn't respond?

To where can I generalize these results?

Diagnosing a design through simulation

Simulated results from the study

run_design(design)

est	std.err	statistic	p.value	conf.lo	conf.hi
0.64	0.29	2.22	0.03	0.07	1.22
estimand_label				estimand	
ATE				0.1	

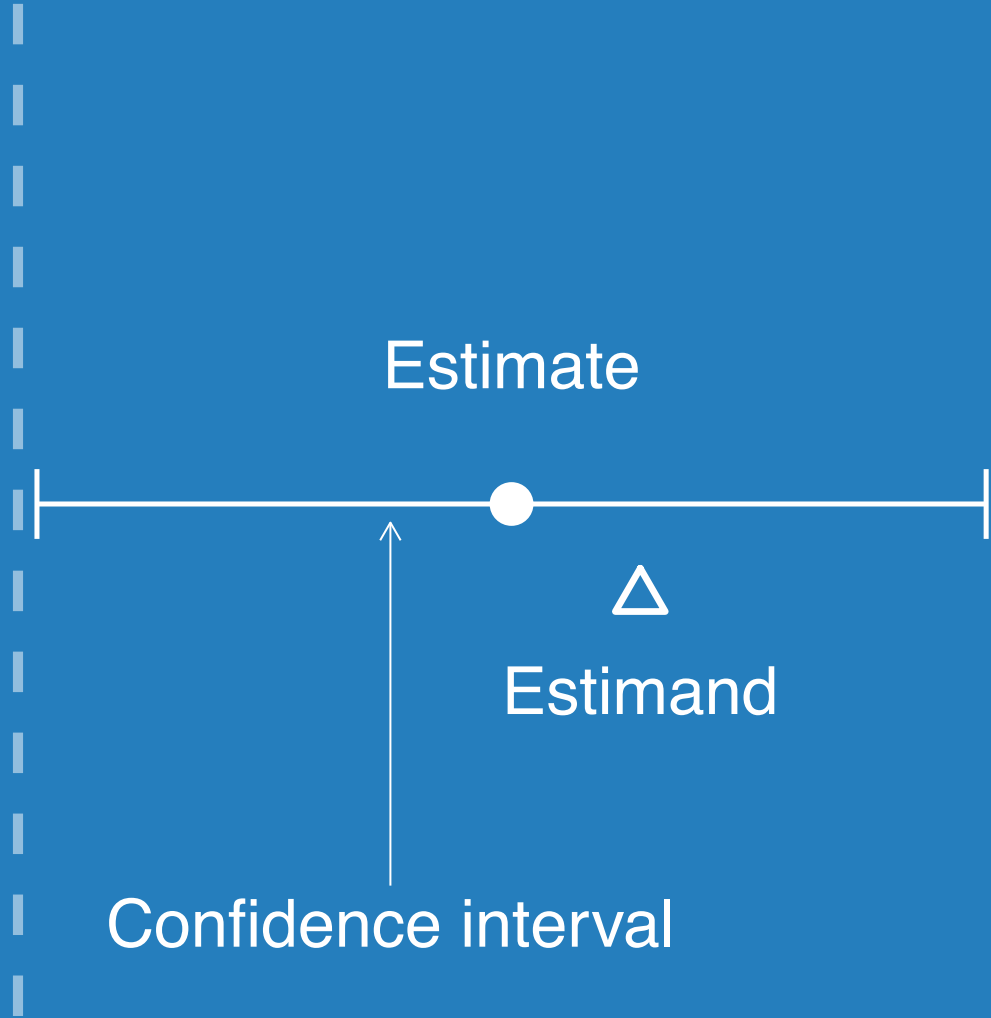
$x = 0$

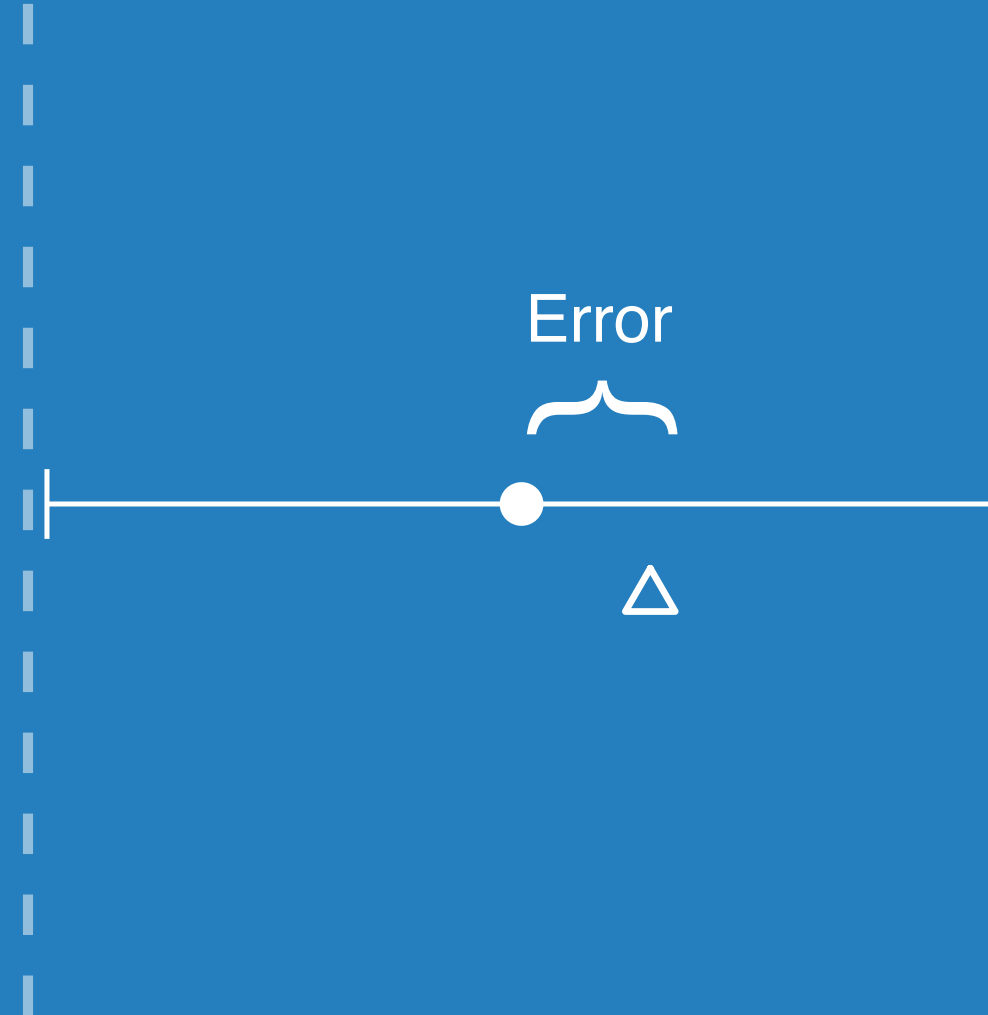
Estimate

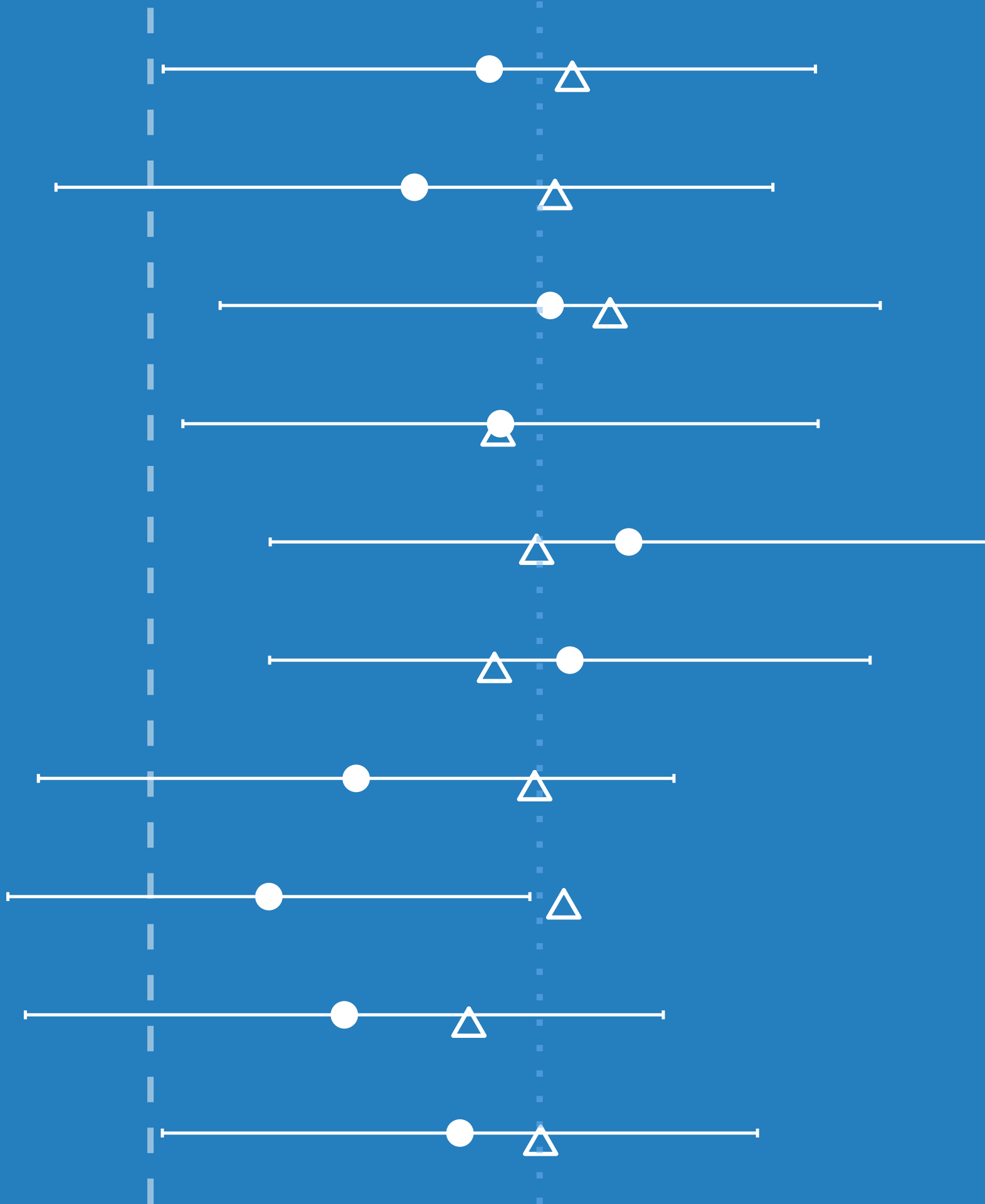
Δ

Estimand

Confidence interval







Simulations data frame

sim_ID	estimate	std.error	conf.low	conf.high	p.value	estimand
1	0.08	0.04	0.00	0.16	0.04	0.10
2	0.03	0.04	-0.05	0.11	0.45	0.08
3	0.12	0.04	0.04	0.20	0.00	0.11
4	0.10	0.04	0.02	0.18	0.01	0.10
5	0.07	0.04	-0.01	0.15	0.10	0.10
6	0.05	0.04	-0.03	0.14	0.21	0.09
7	0.09	0.04	0.01	0.17	0.03	0.11
8	0.03	0.04	-0.05	0.12	0.44	0.12
9	0.16	0.04	0.09	0.24	0.00	0.09
10	0.04	0.04	-0.04	0.13	0.33	0.10

Diagnosands

What are your objectives and does your design meet them?

Ethics: `min(subjects_harmed)`

Cost: `mean(cost), max(cost)`

Bias: `mean(estimate - estimand)`

Power: `mean(p.value <= 0.05)`

Probability of getting sign wrong:

`mean(sign(estimate) != sign(estimand))`

Diagnose design

diagnose_design(design)

Bias

RMSE

Power

**Pr(sign
wrong)**

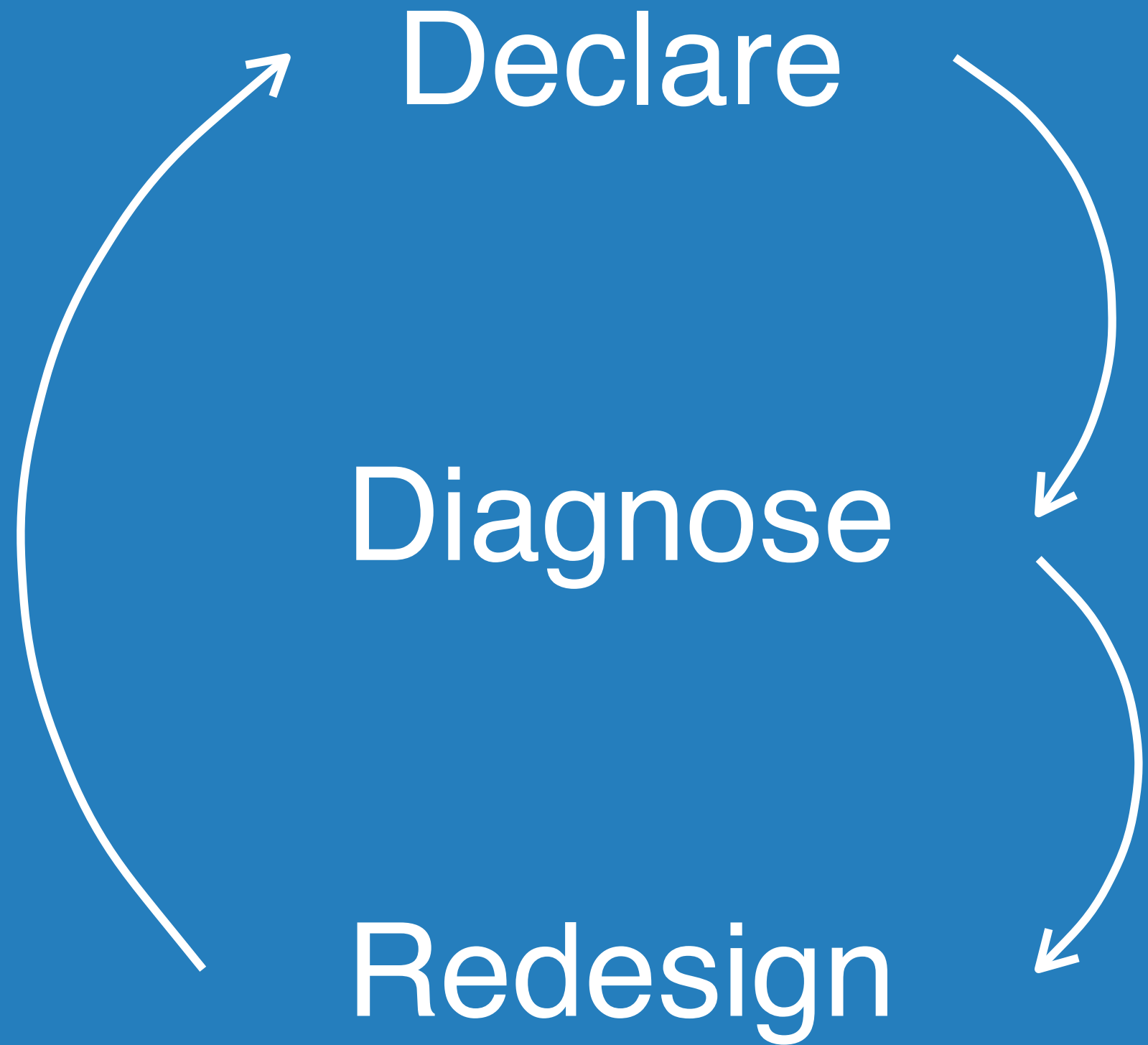
0.5

0.56

0.65

0.01

Algorithm for selecting designs



Back to preanalysis plans

Declare your design in MIDA

Present a diagnosis

Register it for a timestamp

Research lifecycle

Brainstorming

Planning

Realization

Integration

Planning

Ethics

Partners

Funding

Piloting

Criticism

Preadanalysis plan

Declare

Diagnose

Redesign



Realization

Implementation

Pivoting

Populated PAP

Reconciliation

Writing

Publication

Declare

Diagnose

Redesign



Integration

Archiving

Reanalysis

Replication

Disputes

Synthesis

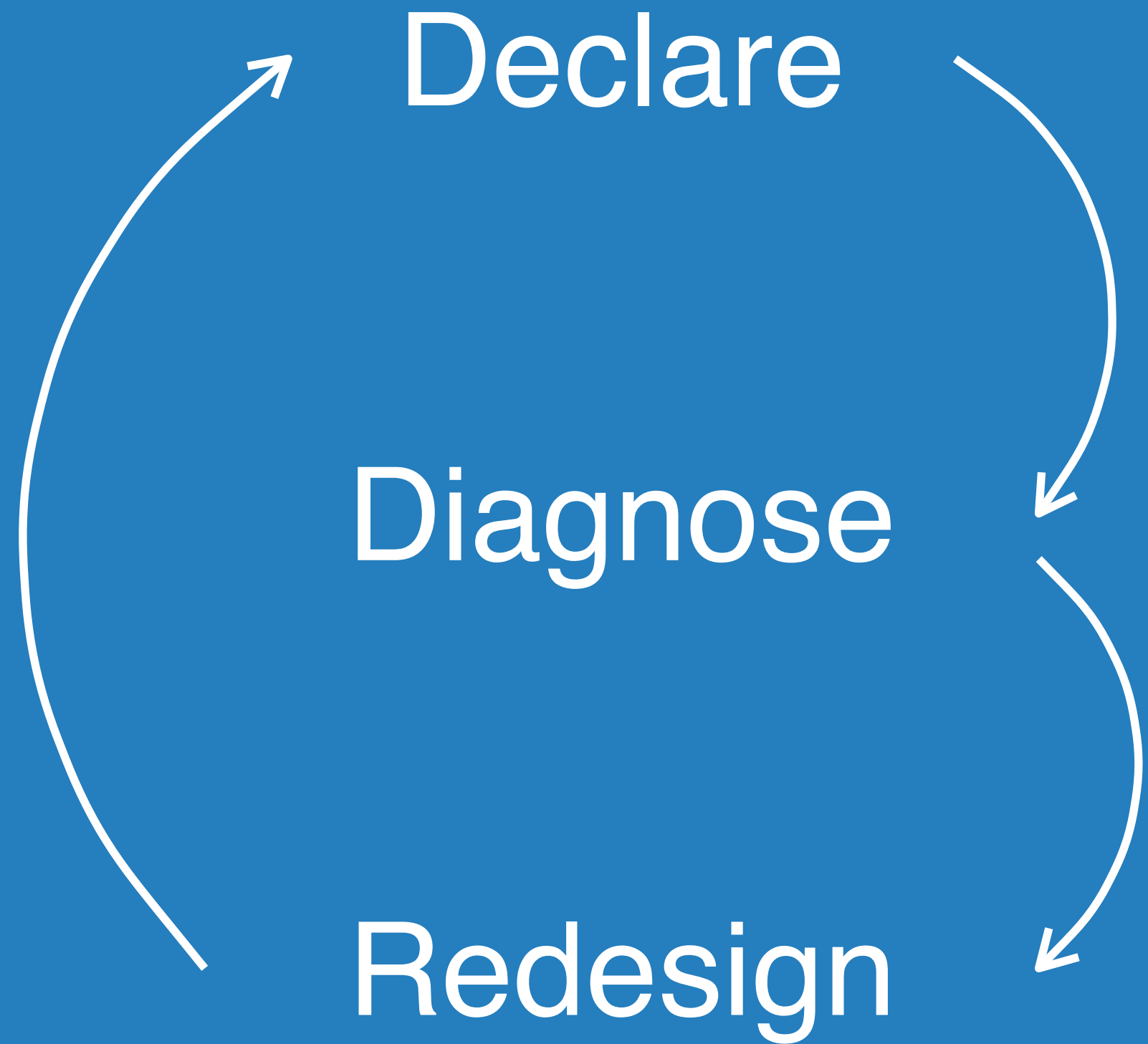
Declare

Diagnose

Redesign



**We're caught
between higher
research
standards and
lack of ideas for
how to assess
and communicate
about designs**



Take aways

Minimum:

Write a plan to change your plan

Medium: Register your plan

Maximum:

Declare in code, diagnose

Thank you

More at declaredesign.org

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