The Need for Equivalence Testing in Economics

Jack Fitzgerald

Vrije Universiteit Amsterdam

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- So what do they mean by **`no detectable e ects?'**

Null Estimates in Bessone et al. (2021)

What they mean: Results are not stat. sig. di erent from zero

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- **They are not alone** in interpreting insigni cant results in this way

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- > 72% of these null claims aren't quali ed by references to statistical signi cance, estimate magnitudes, or a lack of evidence

Researchers and readers interpret such ndings as evidence of null/negligible relationships (McShane & Gal 2016, McShane & Gal 2017)

Why Is This a Problem?

Generally inferring that stat. insig. results are null results is known to be bad scienti c practice (Altman & Bland 1995; Imai, King, & Stuart 2008; Wasserstein & Lazar 2016)

- Statistical insigni cance may just re ect imprecision

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It doesn't have to be this way.

Equivalence Testing in a Nutshell

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Common in medicine, political science, and psychology (see e.g., Piaggio et al. 2012; Hartman & Hidalgo 2018; Lakens, Scheel, & Isager 2018)

This Project

What is equivalence testing?

- I introduce simple frequentist equivalence testing techniques to economists

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How do we perform equivalence testing credibly?

- I develop software commands and guidelines for credible and relatively easy implementation

The Wrong Hypotheses: NHST

Standard NHST hypotheses:

$$H_0: \quad = 0$$
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When trying to show that = 0 using NHST, two key problems:

1. The burden of proof is shifted: Researchers start by assuming they're right
2. Imprecision is `good': Less precision ⇒ higher chance of stat. insig. results

It's thus a logical fallacy to generally infer that stat. insig. results are null results (appeal to ignorance)

The Right Hypotheses: Equivalence Testing

We'll fix these problems by 1) flipping the hypotheses and 2) relaxing the contraints. As a reminder, NHST hypotheses:

$$H_0: \quad = 0$$
$$H_A: \quad \neq 0$$

And now equivalence testing hypotheses:

$$H_0: \quad \geq 0$$
$$H_A: \quad < 0$$

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If we can set a range of values $[\ ;\ _+]$ wherein $\quad 0$, then we can nd stat. sig. evidence for H_A with a simple interval test

The Equivalence Testing Framework

We begin by setting a range of values [$_{+}$], where $<$ $_{+}$, called theregion of practical equivalence (ROPE)

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- I show how to credibly aggregate ROPEs later in this t

Credible ROPE-Setting

The Equivalence Testing Framework

We begin by setting a range of values $[\ _{-}\ _{+}]$, where $\ _{-} < \ _{+}$, called the *region of practical equivalence* (ROPE)

- The ROPE is the range of values we'd call *economically insignificant*
- This is a subjective judgment call that will differ for different relationships of interest
- I show how to credibly aggregate ROPEs later in this talk (Credible ROPE-Setting)

Once we have a ROPE, we can set up the equivalence testing hypotheses:

$$H_0: \ \not\in [\ _{-};\ _{+}]$$
$$H_A: \ \in [\ _{-};\ _{+}]$$

Two One-Sided Tests (TOST)

We can identically write the equivalence testing hypotheses as

H_0 : $<$ or $>$ $+$

H_A : and $+$

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$$H_0: \quad < \quad \text{or} \quad > \quad +$$
$$H_A: \quad \quad \text{and} \quad +$$

Further, we can assess the joint H_A using two one-sided tests:

$$H_0: \quad < \qquad\qquad H_0: \quad > \quad +$$
$$H_A: \qquad\qquad H_A: \quad +$$

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$$H_A: \qquad\qquad H_A: \quad \quad +$$

Stat. sig. evidence for both H_A statements using one-sided tests is stat. sig. evidence that 0 (Schuirmann 1987; Berger & Hsu 1996)

Procedural Details Visualization

Equivalence Con dence Intervals (ECIs)

^'s (1) equivalence con dence interval (ECI) is just its (1 2) CI

- If ^'s (1) ECI is entirely bounded in the ROPE, then we have size- evidence under the TOST procedure that 0 (Berger & Hsu 1996)

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- 71% aren't signi cantly bounded beneath $|\delta| = 0.1$

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- 71% aren't signi cantly bounded beneath $|r| = 0.1$

Takeaway: Bessone et al. (2021) cannot guarantee precise nulls for a large proportion of their `null' estimates, which `fail' lenient equivalence tests

Data

1. Systematically-selected replication sample
   - 876 estimates defending 135 null claims in abstracts of 81 articles in T5 economics journals published from 2020-202 Claim Example
   - Estimates defending these null claims are reproducible with publicly-available data

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2. Prediction platform data
   - I survey 62 researchers on the Social Science Prediction Platform for predictions and judgments on equivalence testing results in my sample

Equivalence Testing Failure Rates

I compute avg. equivalence testing failure rates in the replication sample

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- $|r| = 0.1$ is larger than over 25% of published results in economics (Doucouliagos 2011)

Effect Size Standardization

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  E ect Size Standardization
- Second ROPE: $\in [-0.2, 0.2]$
- $|\ | = 0.2$ is quite large for economic e ect sizes Benchmarking Sample

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Models defending null claims in T5 journals should have no trouble signi cantly bounding estimates within ROPEs this wide

Equivalence Testing Failure Rates are Unacceptably High

Equivalence testing failure rates range from 36-63%

Robustness Checks TST Framework Mechanisms

Equivalence Testing Failure Rates are Unacceptably High

Equivalence testing failure rates range from 36-63% Robustness Checks TST Framework Mechanisms

- Interpretation : 62% of estimates defending the average null claim can't signi cantly bound their estimates beneath $|r_j| = 0.1$ (see Model 4)

Failure Curves

Equivalence testing failure rates stay unacceptably high even as ROPEs become ridiculously large

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Equivalence testing failure rates stay unacceptably high even as ROPEs become ridiculously large

- To obtain acceptable failure rates, you'd need to argue that $|\hat{\beta}| < 0.317\sigma_{\hat{\beta}}$ is practically equal to zero
- $|\hat{\beta}| < 0.317\sigma_{\hat{\beta}}$ is larger than nearly 75% of published effects in economics (Doucouliagos 2011)

Researchers Anticipate Unacceptably High Failure Rates

The median researcher nds failure rates from 11-13% acceptable, but (pretty accurately) predicts failure rates from 35-38%.Takeaways:

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1. Researchers don't trust null results under standard NHST, but this mistrust is well-placed
2. More credible testing frameworks are necessary to restore trust

Credible ROPE-Setting

ROPEs need to be set independently to be credible (Lange & Freitag 2005; Ofori et al. 2023)

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- Example from this project : Alongside predictions of failure rates, I elicit what failure rates researchers deem acceptable

The Equivalence Testing Framework

Software Commands & More Information

tsti Stata command (QR: Github)	equivtest R package, containing tst command (QR: Github)	Working paper (QR: PDF link, personal website)

Website: https://jack- tzgerald.github.io
Email: j.f. tzgerald@vu.nl

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Null Claim Classi cation

This Happens All the Time

The TOST Procedure

First, compute test statistics

$$t = \frac{\hat{}}{s} \qquad t_+ = \frac{\hat{} \; +}{s}$$

The relevant test statistic is the smaller of the two:

$$t_{TOST} = \arg\min_{t \; 2 \; f t \; ; t_+ g} f j \, t j g$$

The critical value for a size- TOST procedure is the one-sided critical value t

1. If $t_{TOST} = t$, then there is stat. sig. evidence that 2 [; +] i t t
2. If $t_{TOST} = t_+$, then there is stat. sig. evidence that 2 [; +] i t_+ t

A single TOST procedure maintains size even without multiple hypothesis corrections (Berger & Hsu 1996)

TOST Concept

TOST Example

Claim Example

The bolded text represents the two null claims made by this abstract:

> \This article estimates peer e ects originating from the ability composition of tutorial groups for undergraduate students in economics. We manipulated the composition of groups to achieve a wide range of support, and assigned students-conditional on their prior ability-randomly to these groups. The data support a speci cation in which the impact of group composition on achievement is captured by the mean and standard deviation of peers' prior ability, their interaction, and interactions with students' own prior ability. When we assess the aggregate implications of these peer e ects regressions for group assignment, we nd that low-and medium-ability students gain on an average 0.19 SD units of achievement by switching from ability mixing to three-way tracking. Their dropout rate is reduced by 12 percentage points (relative to a mean of 0.6). High-ability students are una ected . Analysis of survey data indicates that in tracked groups, low-ability students have more positive interactions with other students, and are more involved. We nd no evidence that teachers adjust their teaching to the composition of groups. "

Data

Standardized E ect Sizes

I aggregate all regression results into two e ect size measures

1. Standardized coe cients :

$$= \begin{cases} \frac{}{Y} & \text{if D is binary} \\ \frac{D}{Y} & \text{otherwise} \end{cases} \qquad s = \begin{cases} \frac{SE(\ )}{Y} & \text{if D is binary} \\ \frac{SE(\ )\ D}{Y} & \text{otherwise} \end{cases}$$

$_Y$ and $_D$ are respectively within-sample SDs of Y and D

- is closely related to the classical Cohen's d e ect size

2. Partial correlation coe cients (PCCs) :

$$r = p\frac{t_{NHST}}{t_{NHST}^2 + df} \qquad SE(r) = \frac{1}{p}\frac{r^2}{df}:$$

t_{NHST} is the usual t-statistic and df is degrees of freedom

- PCCs are widely-used in economic meta-analyses

Failure Rates Introduction

Benchmarking Sample

The Three-Sided Testing Framework

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2. TOST procedure: Is 2 [; $_{+}$]?
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- If no *p*-value < , then results are *inconclusive*: the researcher must stay agnostic about the practical signi cance of
- Embracing this uncertainty may be uncomfortable/limiting, but my results show that standard practice tolerates high error rates

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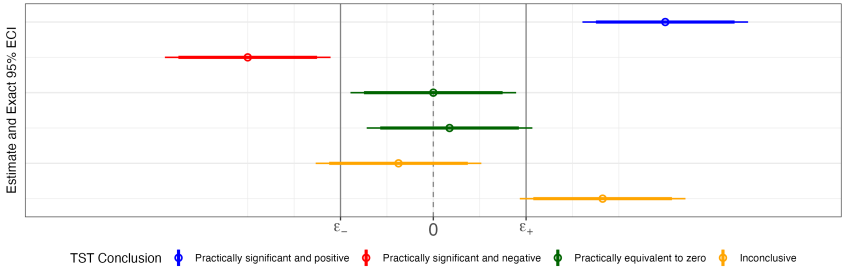
2. TOST procedure: Is 2 [; $_{+}$]?
3. Two-sided test: Is > $_{+}$?

Signi cance conclusions can be derived from the smallest of these three p-values (Sha er 1986; Finner & Strassburger 2002)

- If no p-value < , then results are *inconclusive*: the researcher must stay agnostic about the practical signi cance of
- Embracing this uncertainty may be uncomfortable/limiting, but my results show that standard practice tolerates high error rates

Example from this project: I show that my failure rates are signi cantly bounded above the median failure rates that researchers deem acceptable Main Results

The TST Framework Visualized



Under TST, given their 95% ECIs and CIs, these estimates are respectively:

- Practically signi cant and above the ROPE
- Practically signi cant and below the ROPE
- Practically equivalent to zero
- Inconclusive

Main Results

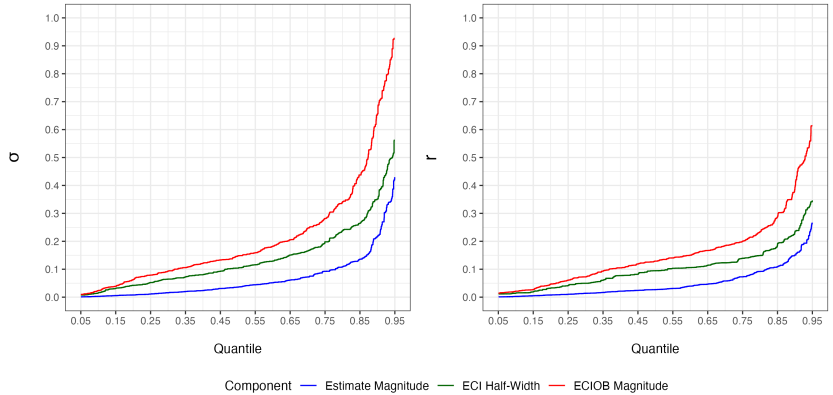
Failure Rate Robustness

These failure rates remain large and significant when...

- Switching from to r
- Switching from exact to asymptotically approximate tests
- Switching aggregation procedures
- Removing initially stat. sig. estimates
- Separating models by regressor type combination (i.e., binary vs. non-binary)
- Removing non-replicable estimates from the sample
- Removing models that require conformability modifications from the sample (e.g., logit/probit models put through `margins, dydx()`)

Main Results

Mechanisms



Power is a greater driver of equivalence testing failure rates than effect size

Main Results