

Working with pre-registrations in the context of already existing data

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Uppsala, May 9th

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- A methodological ideal: pre-registered studies.
- Decide on crucial design choices and plan analyses before data is gathered.
- Increases confidence in results because design choices were made when still “blind” to the data.

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- This poses challenges in the context of preregistering analyses:
 - 1 You have to deal with the limitations that exist – can't design your ideal study.
 - 2 Lowers credibility of “data blindness” – in theory, you could have seen (parts of) the data already.

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- Makes violations of “data blindness” invariably artificially “deflate your alpha”

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- Someone else may have published results with data is auto-correlated with your data

Example: Pick variable definitions from prior research!

	X_1	X_2	X_3
Y_1	0.1	0.3	0.2
Y_2	0.2	0.3	0.4
Y_3	0.1	0.2	0.5

Table: Fictional correlation table

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- If data partially overlaps, or has autocorrelation over time, merely knowing this can lead to a milder form of “p-hacking”

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- Can be a difficult balance to strike.

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- Build on data that you have been unable to see beforehand (because you didn't previously have access)
- Build on data that *could not* have been seen beforehand

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- Plan several studies ahead!
 - Expensive and time consuming to order (especially) register data
 - Planning one study and seeing data that is also informative for future studies effectively ruins (or decreases) blinding
 - Solution: plan (long) ahead – better spend an extra month or two on planning future studies, than spending additional years and 100Ks of SEK ordering multiple batches of data and compromising blinding

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- Pre-registering analyses even with existing data poses unique challenges, and still relies on trust, but is arguably better than the prior status quo.

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- There are more subtle ways than outright fraud that can distort the scientific record – awareness of these is a great first step.
- Pre-registering analyses even with existing data poses unique challenges, and still relies on trust, but is arguably better than the prior status quo.
- Transparency is key!