Abstract: In finite population causal inference exact randomization tests can be constructed for sharp null hypotheses, hypotheses which fully impute the missing potential outcomes. Oftentimes inference is instead desired for the weak null that the sample average of the treatment effects takes on a particular value while leaving the subject-specific treatment effects unspecified. Without proper care, tests valid for sharp null hypotheses may be anti-conservative even asymptotically should only the weak null hold, creating the risk of misinterpretation when randomization tests are deployed in practice. We develop a general framework for unifying modes of inference for sharp and weak nulls, wherein a single procedure simultaneously delivers exact inference for sharp nulls and asymptotically valid inference for weak nulls. To do this, we employ randomization tests based upon prepivoted test statistics, wherein a test statistic is first transformed by a suitably constructed cumulative distribution function and its randomization distribution assuming the sharp null is then enumerated. For a large class of test statistics common in practice, we show that prepivoting may be accomplished by employing a sample-based Gaussian measure governed by a suitably constructed covariance estimator. In essence, the approach enumerates the randomization distribution (assuming the sharp null) of a p-value for a large-sample test known to be valid under the weak null, and uses the resulting randomization distribution to perform inference. The versatility of the method is demonstrated through various examples, including inference for rerandomized experiments.

Bio: Colin Fogarty is the Sarofim Family Career Development Professor and an Assistant Professor of Operations Research and Statistics at the MIT Sloan School of Management. His research interests lie in the design and analysis both of randomized experiments, and of observational studies while assessing the robustness of a study's findings to hidden biases. Much of his work explores the extent to which classical randomization-based approaches for inference in experiments and observational studies extend to circumstances where heterogeneous treatment effects are suspected. His work also illustrates tangible benefits for many quasi-experimental devices in terms of improved robustness to hidden bias in observational studies. Before joining MIT he completed his Ph.D. in Statistics at the Wharton School of the University of Pennsylvania, where he was advised by Professor Dylan Small.