

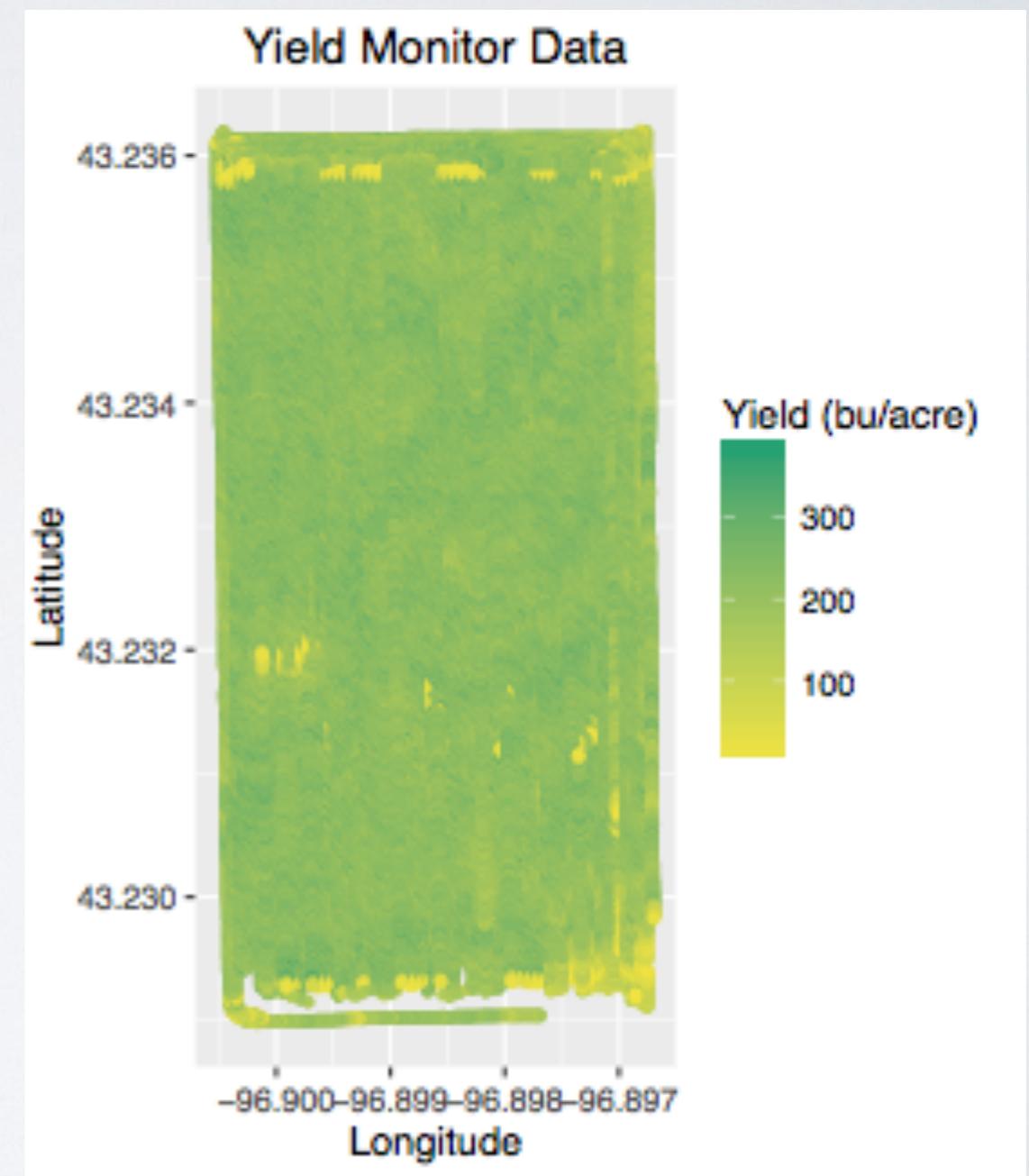
# Optimal Treatment Dispersions in Rectangular Areas

Peter Claussen  
Gylling Data Management

- Credit for the phrase “experiments in rectangular areas” goes to R. A. Bailey, who frequently uses the term “undesirable” layout.
  - "Experiments in rectangular areas: design and randomization." *Journal of Agricultural, Biological, and Environmental Statistics* 17.2 (2012): 176-191.
- What is an undesirable layout? Let us consider the effects of different layouts on simulated uniformity trials.

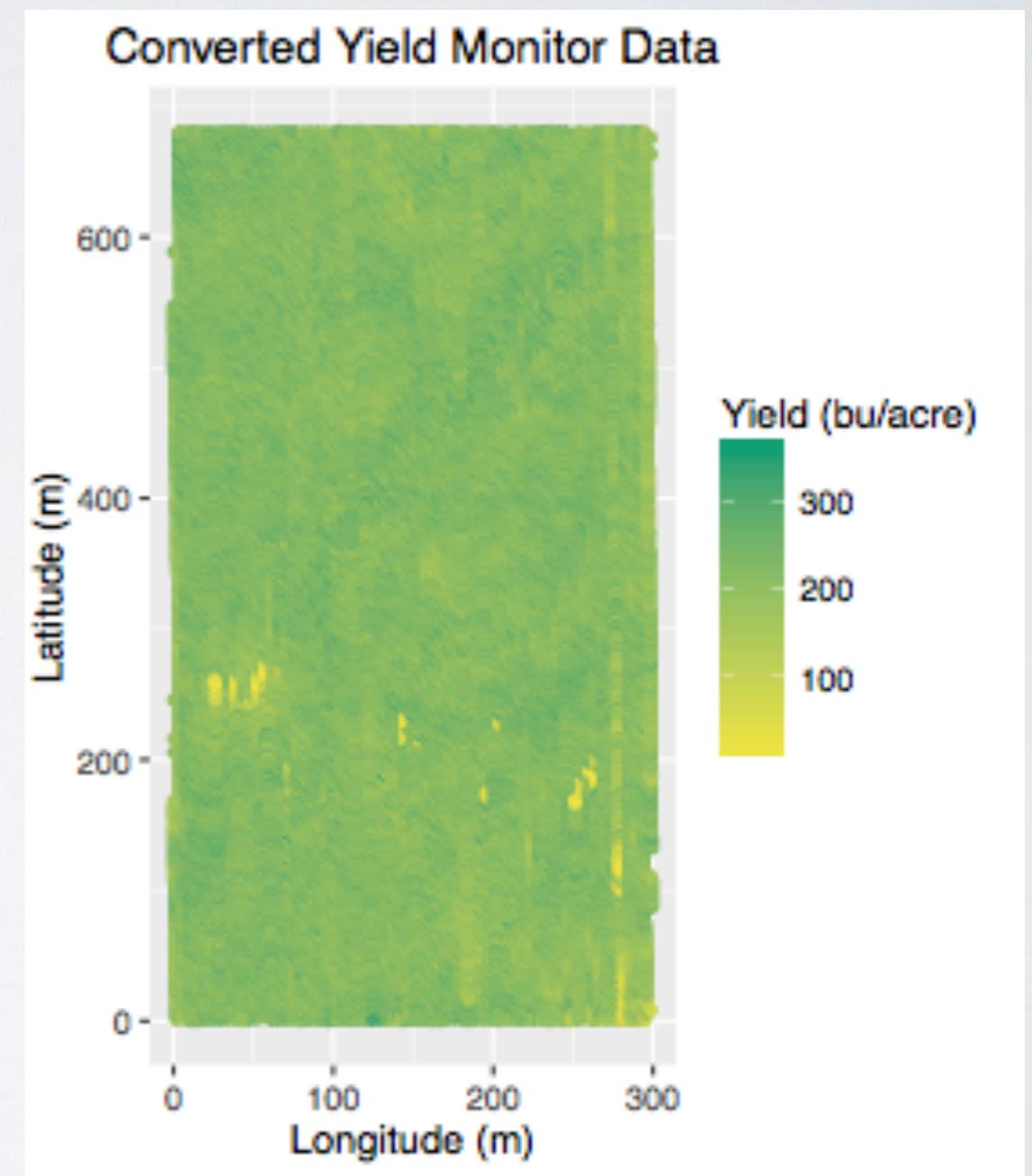
# Simulated Uniformity Trials

- Start with yield monitor data.
  - South East Research Station, Beresford SD
  - 2013
  - Maize



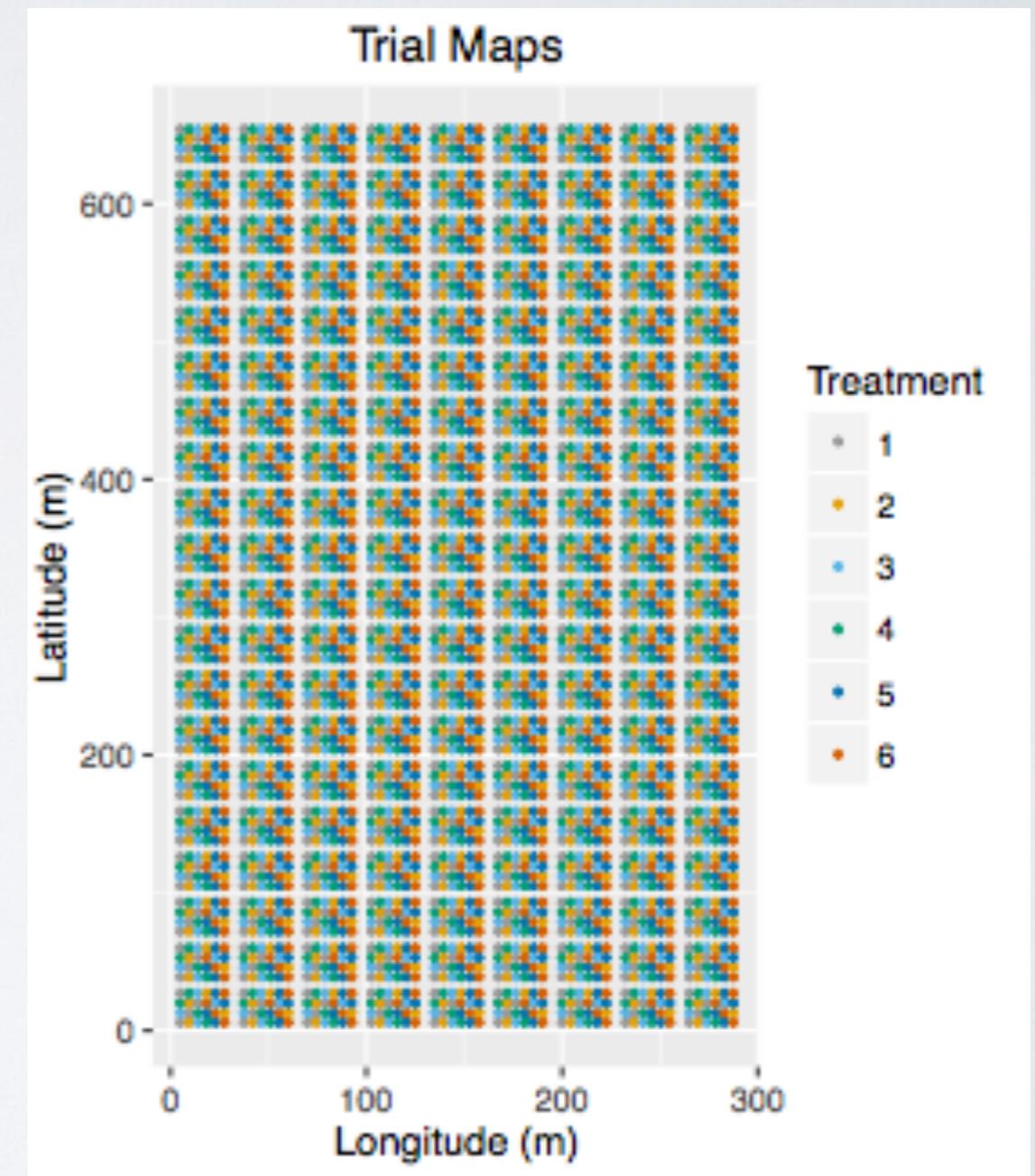
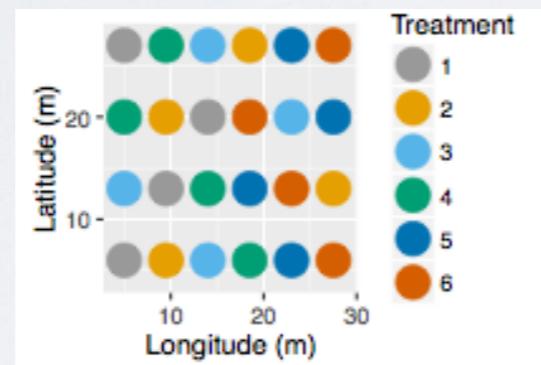
# Simulated Uniformity Data

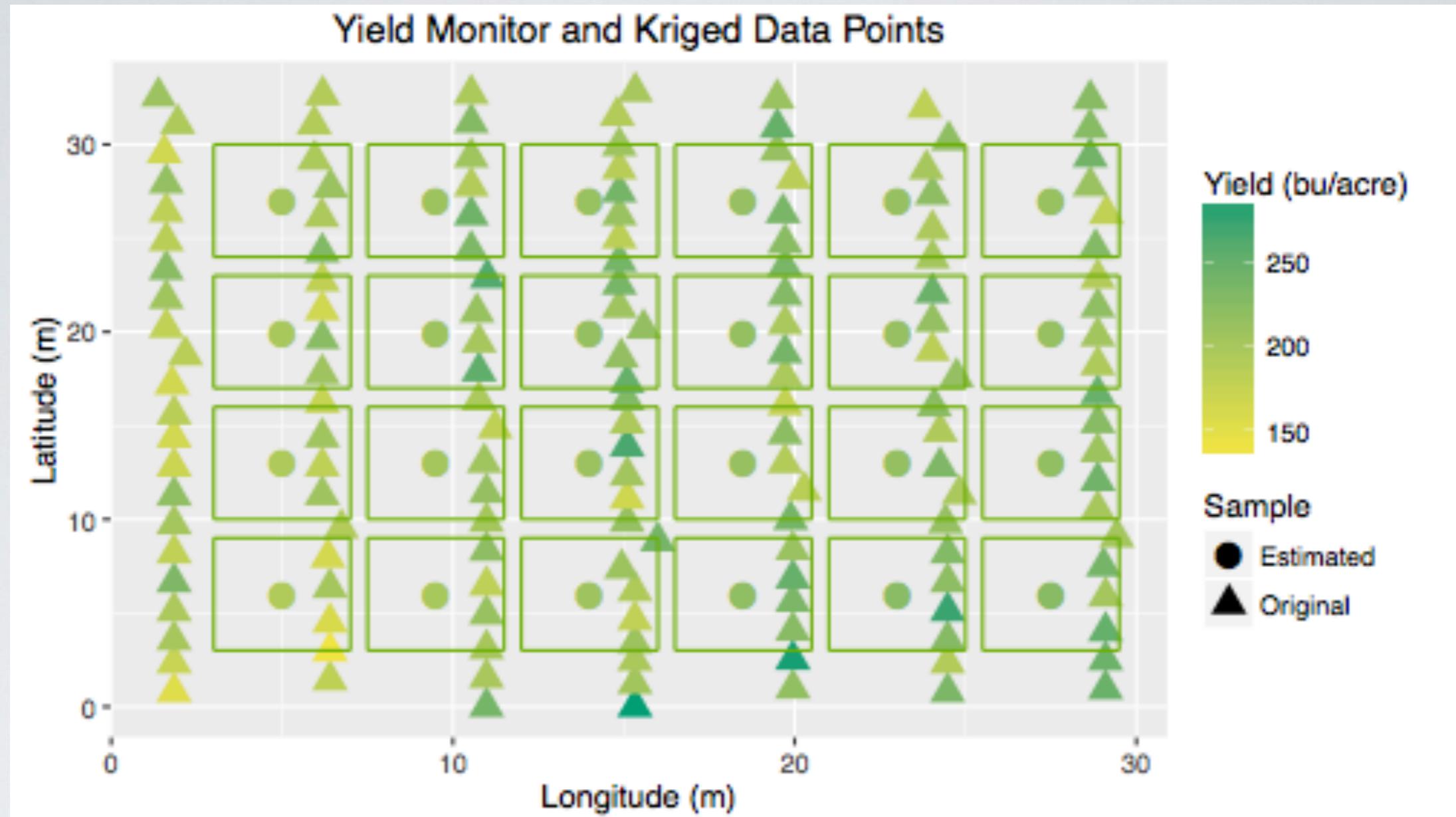
- Trim to remove end-rows and edges
- Convert longitude and latitude coordinates to meters, relative to south-west corner.



# Simulated Repeated Trial Map

- Generate a trial map
  - RCB, 6 treatments and 4 replicates.
- Superimpose over field, starting in lower left corner and adding trials in rows and columns



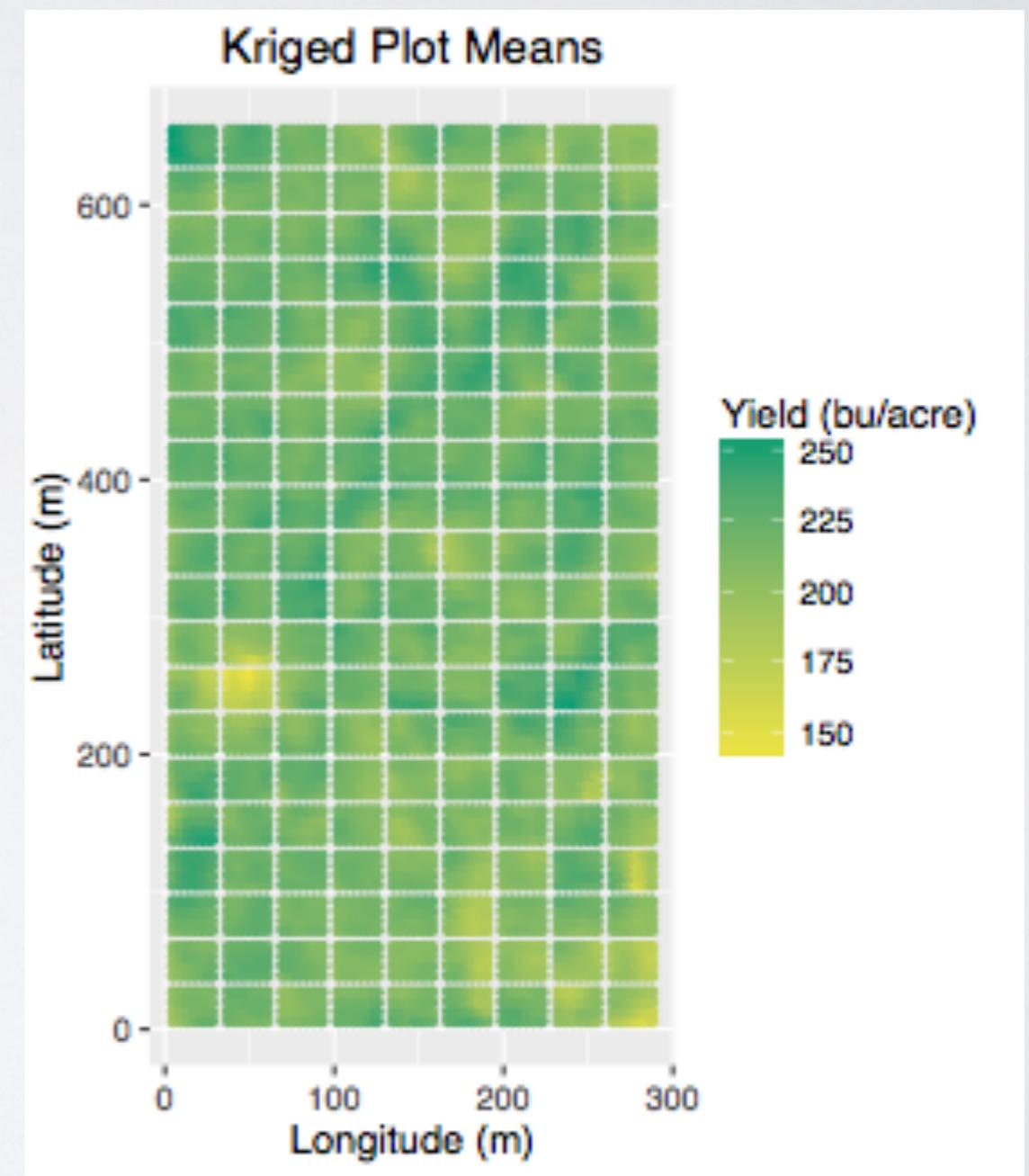


# Estimated Plot Yields

- Interpolate yield at center of plot by kriging yield monitor data. Boxes represent plot borders.

# | 80 Simulated Uniformity Trials

- Repeat for all layouts and analyze each as a different uniformity trial.
- Each trial samples a different part of a large spatial structure.
- We can compare how different randomizations detect spatial variation.
- For our purposes, “undesirable” layouts will confound spatial variability with treatment effects.

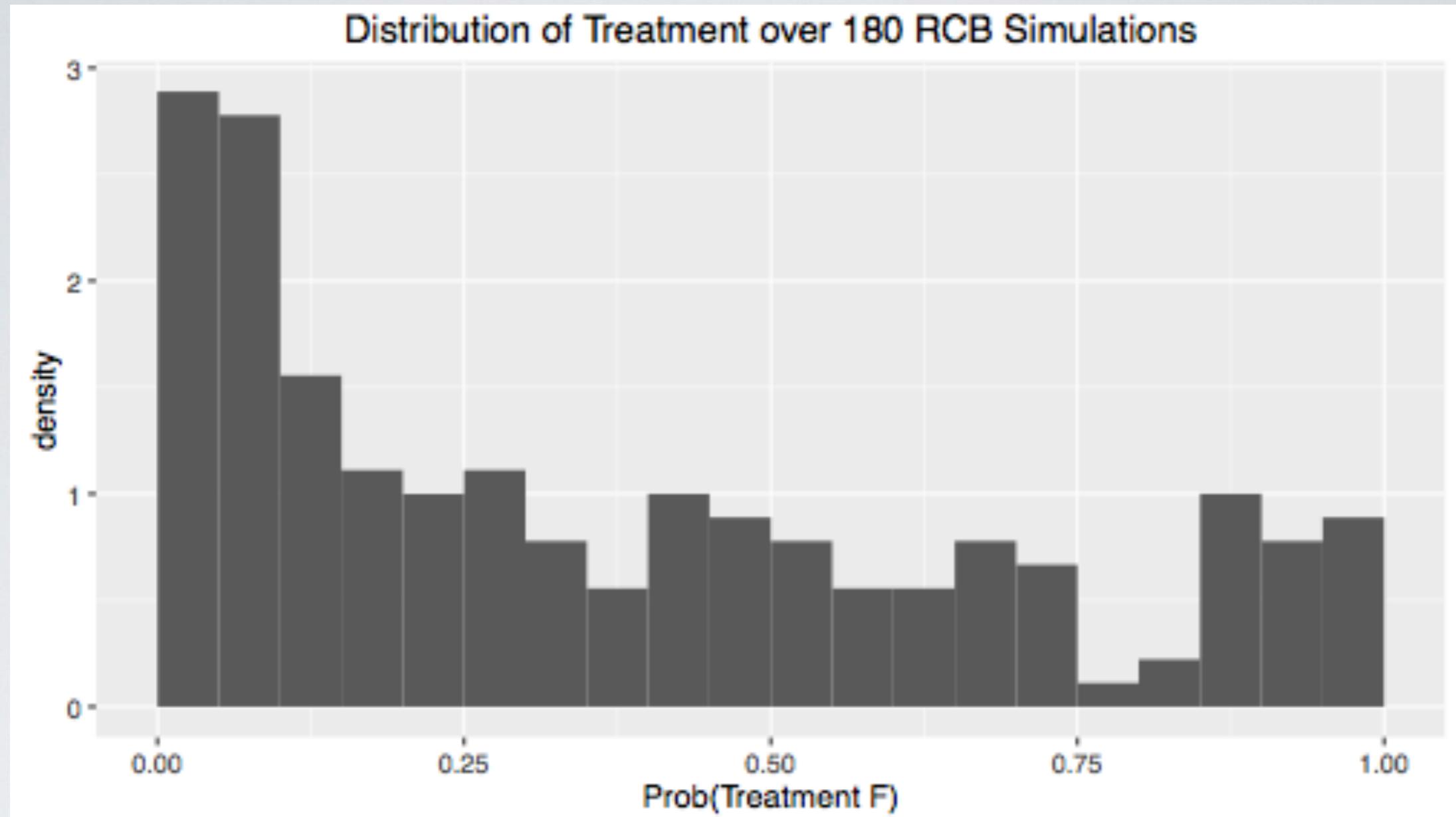


# Types of Confounding

	Significant Replicate						Non-Significant Replicate					
Significant Treatment	401 1 4	402 4	403 3	404 2	405 5	406 6	401 1 4	402 4	403 3	404 2	405 5	406 6
Non-Significant Treatment	401 1 4	402 4	403 3	404 2	405 5	406 6	401 1 4	402 4	403 3	404 2	405 5	406 6
Source	DF	Sum of Squares	Mean Square	F	Prob(F)		Source	DF	Sum of Squares	Mean Square	F	Prob(F)
Total	23	1418.823599					Total	23	1394.230940			
Replicate	3	433.208148	144.402716	4.520	0.0189		Replicate	3	32.934429	10.978143	0.268	0.8471
Treatment	5	506.441848	101.288370	3.171	0.0377		Treatment	5	747.858169	149.571634	3.657	0.0231
Error	15	479.173603	31.944907				Error	15	613.438341	40.895889		
Source	DF	Sum of Squares	Mean Square	F	Prob(F)		Source	DF	Sum of Squares	Mean Square	F	Prob(F)
Total	23	1182.769646					Total	23	1252.097954			
Replicate	3	919.308124	306.436041	18.435	0.0001		Replicate	3	26.101813	8.700604	0.117	0.9489
Treatment	5	14.129328	2.825866	0.170	0.9698		Treatment	5	107.615609	21.523122	0.289	0.9119
Error	15	249.332194	16.622146				Error	15	1118.380532	74.558702		

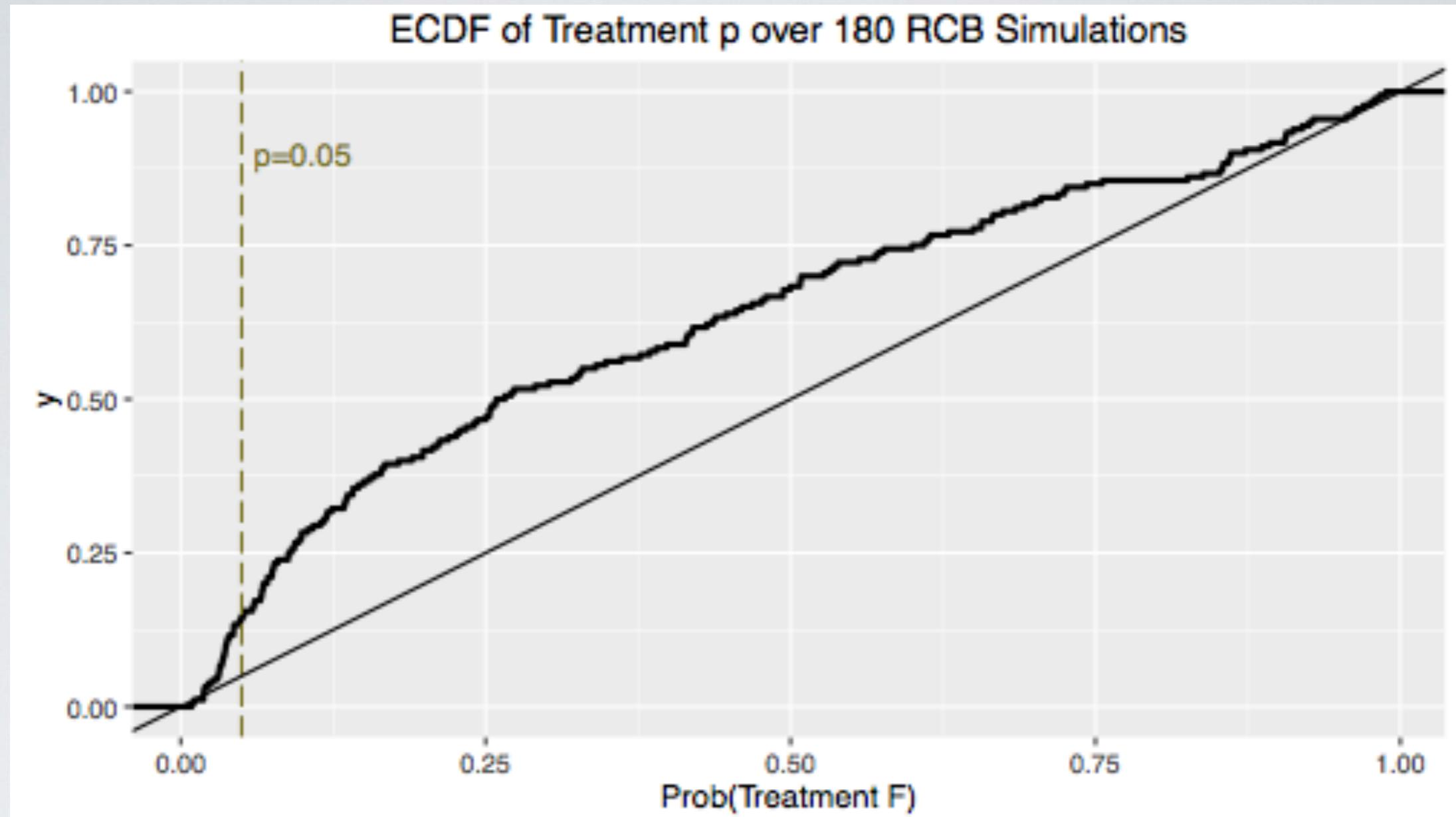
# Type I Error

- Since there are no real treatment effects, analysis of variance of a uniformity trial should produce a non-significant p-value for the Treatment F statistic.
- At a nominal error rate of 5%, we can expect 1 out of 20 trials to achieve a Treatment  $p < 0.05$ .
- In 180 simulated trials, the example RCB produced 26 trials with Treatment  $p < 0.05$ , for an achieved error rate of 14.44%.
- We can visualize this by plotting the distribution of p-values for these 180 trials.



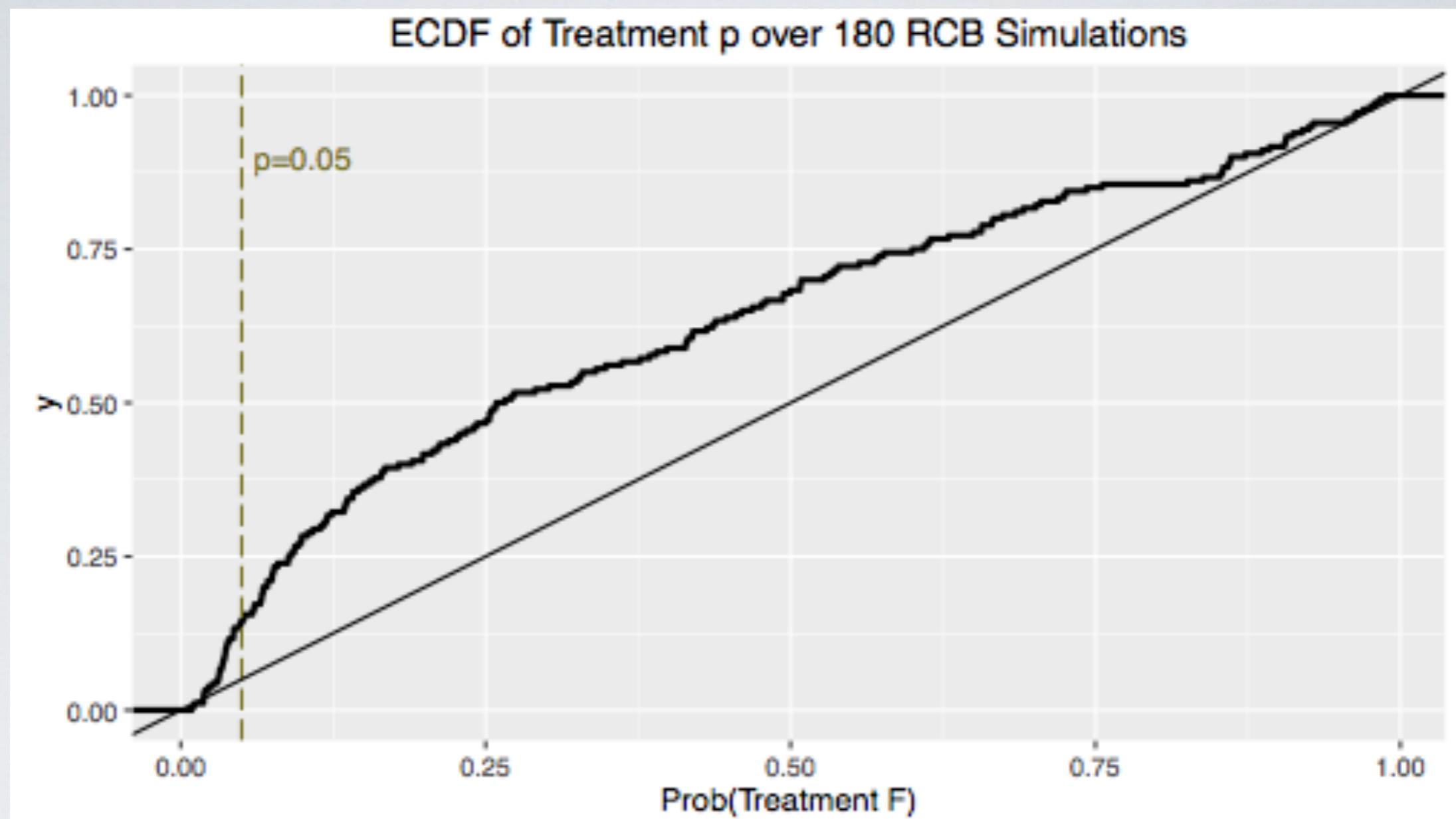
## Distribution of Treatment p-values.

For an unbiased trial, we would expect the distribution of p-values to be approximately uniform. This set of trials has a greater than expected number of small p-values.



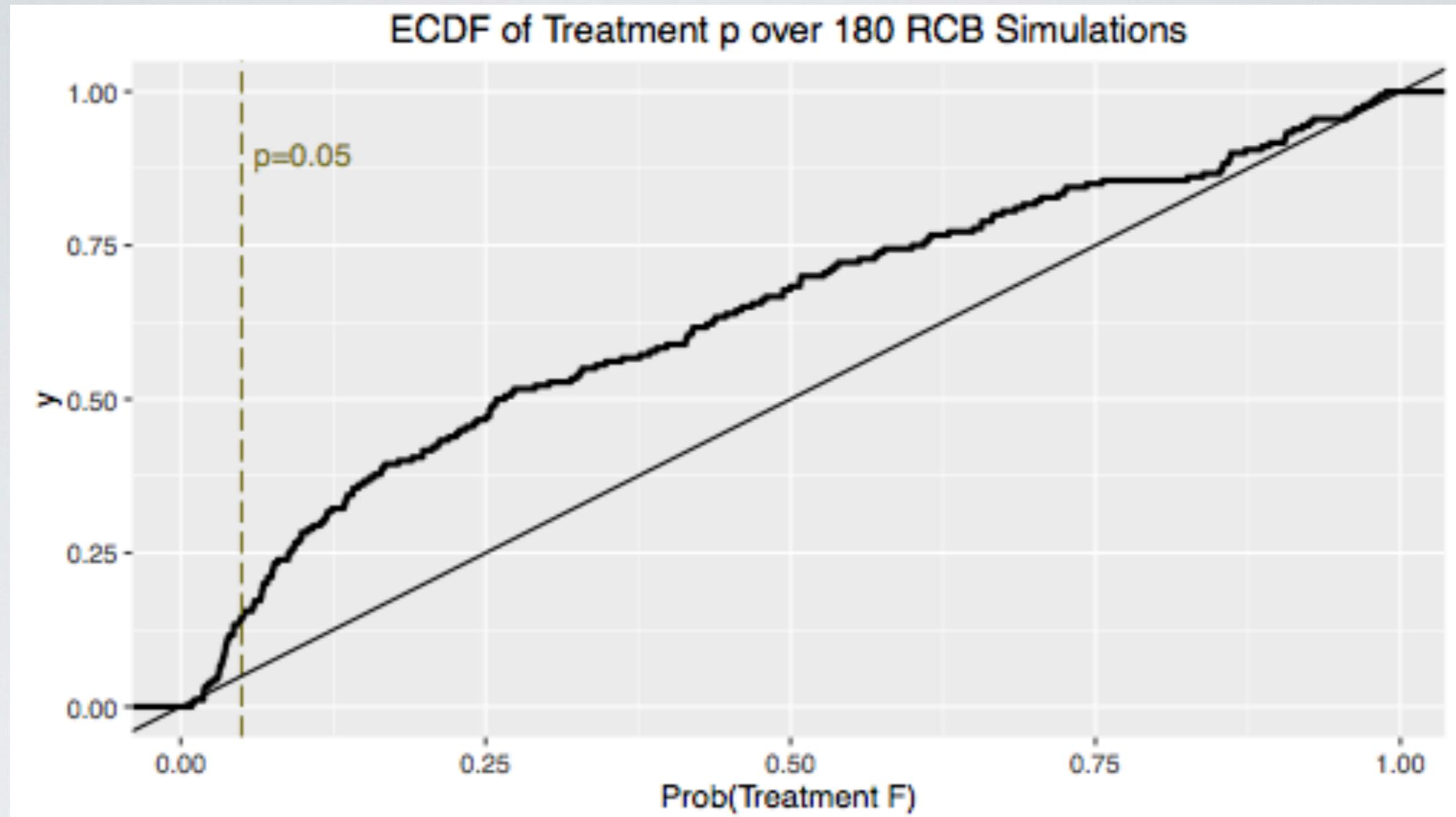
# Empirical Cumulative Distribution

Same data as previous graph, but plotted as the total count of trials at or less than the nominal probability on the x-axis.



# Empirical Cumulative Distribution

The diagonal line represents a uniform distribution, where the accumulated proportion of trials at a nominal probability equals that probability.

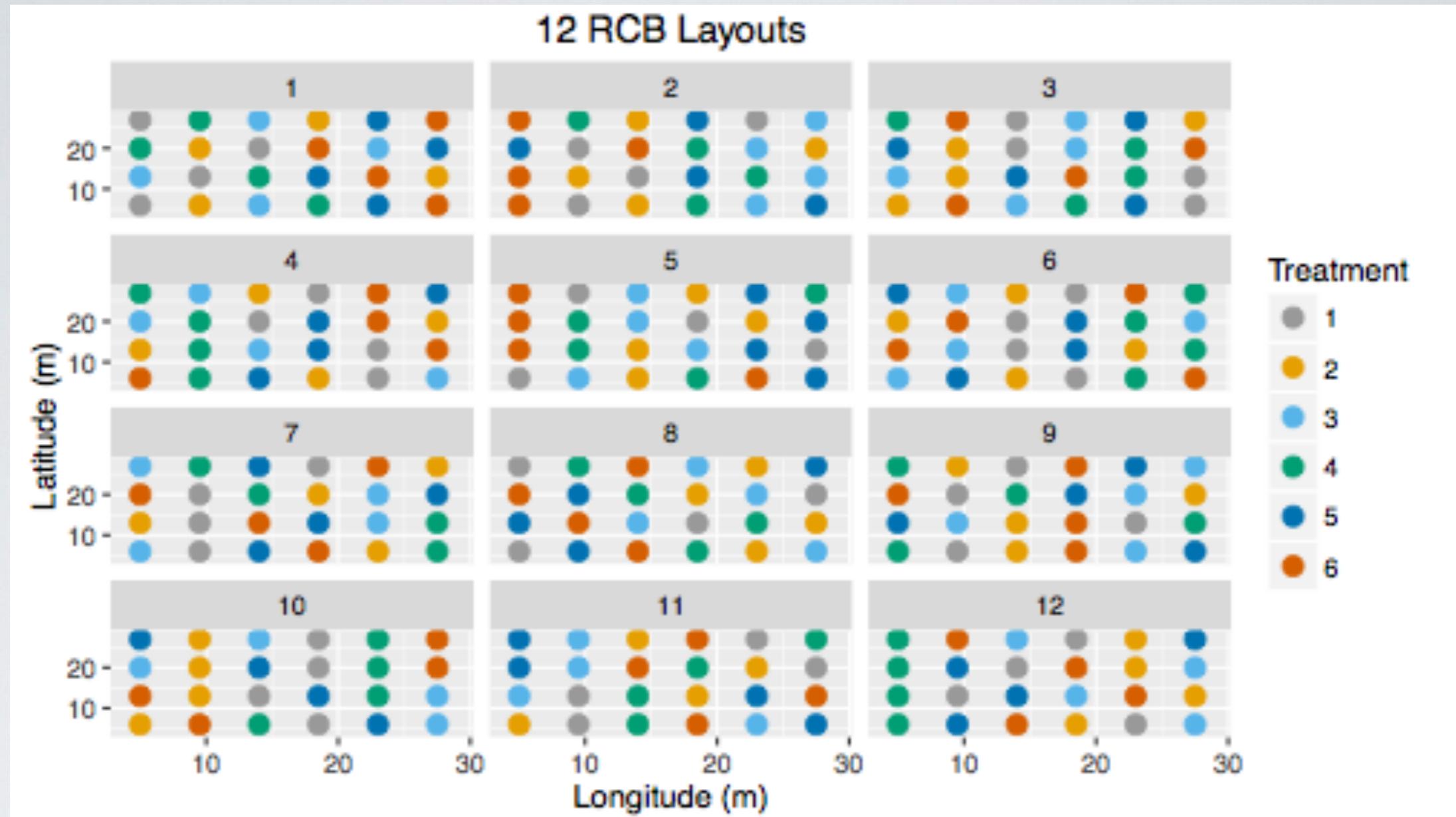


# Empirical Cumulative Distribution

The ECDF at a nominal probability of 0.05 has an accumulated proportion of 0.144, implying the **achieved** Type I error rate is higher than the **nominal** error rate.

# Comparing Different Randomizations

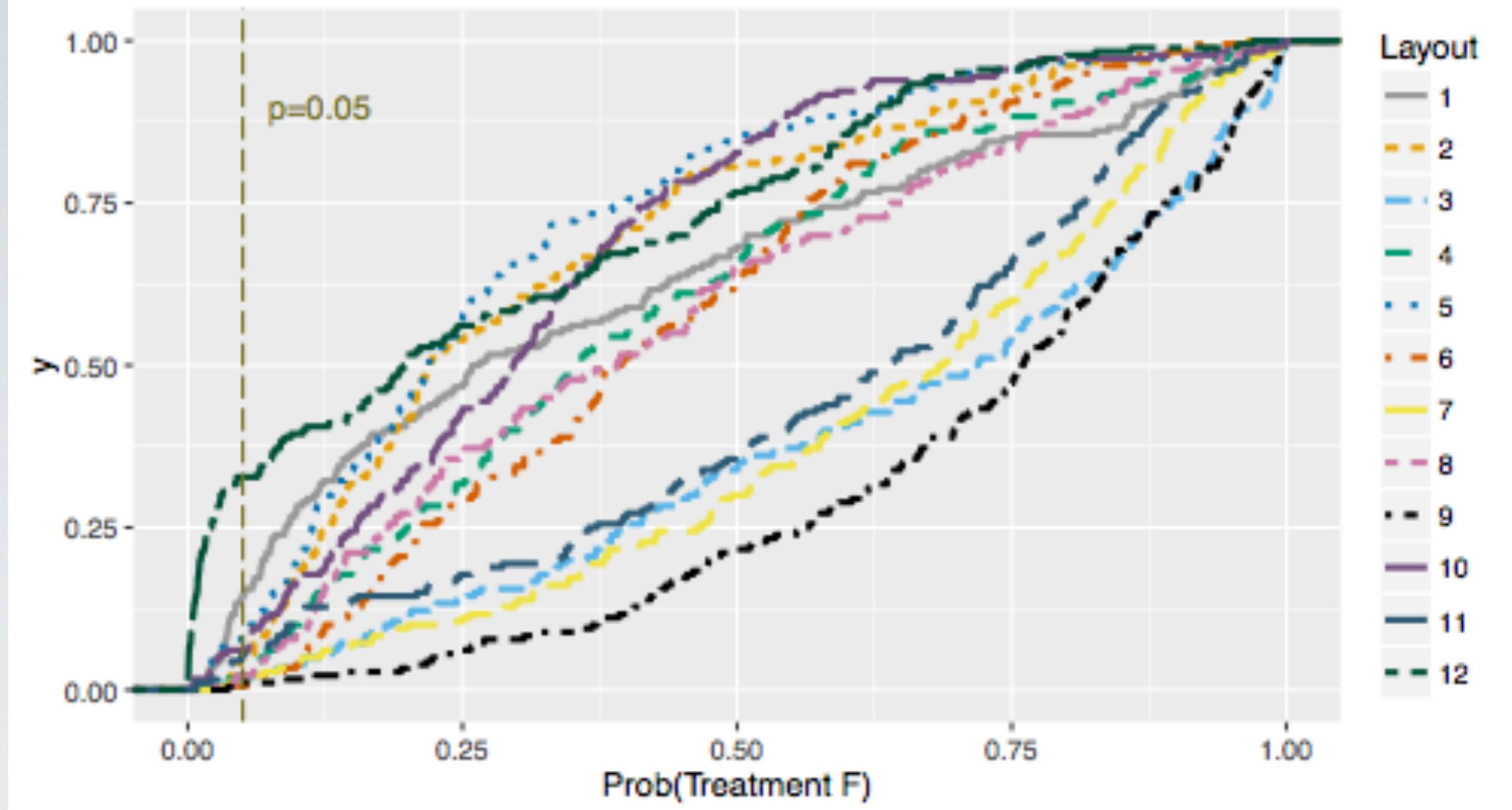
- We've focused on a single RCB experiment, repeated 180 times.
- This layout achieved a higher Type I error rate, 14.4%, than our nominal rate of 5%.
- This might simply be bad luck - the randomization we chose is “undesirable”.
- We'll repeat the simulation with 11 other RCB layouts.



# Twelve Proposed Layouts

Number 1 is the layout shown previously

### ECDF of Treatment p for 12 RCB Layouts

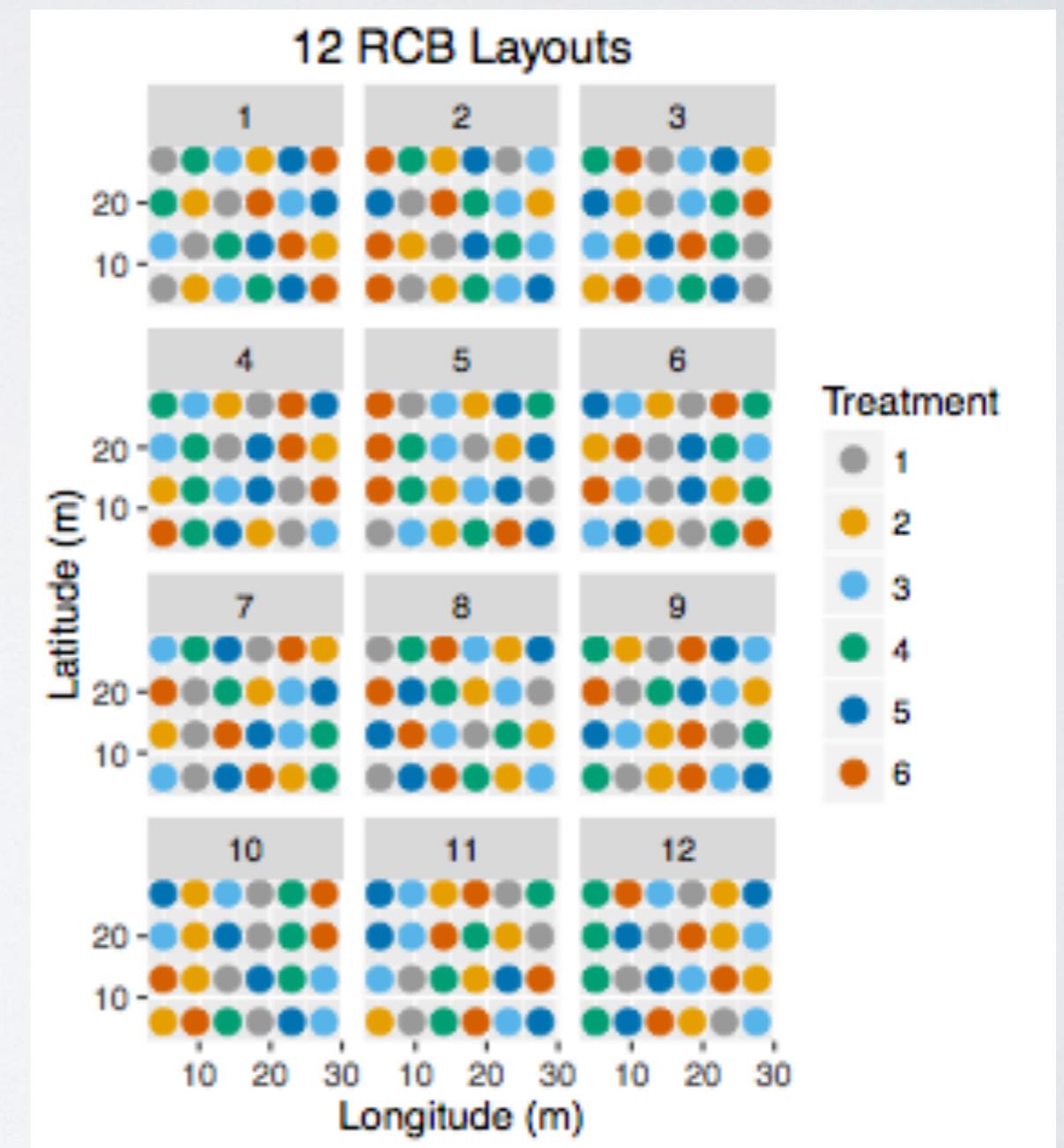


# Treatment p Distributions

Some layouts are biased towards smaller p-values, some are biased towards larger p-values.

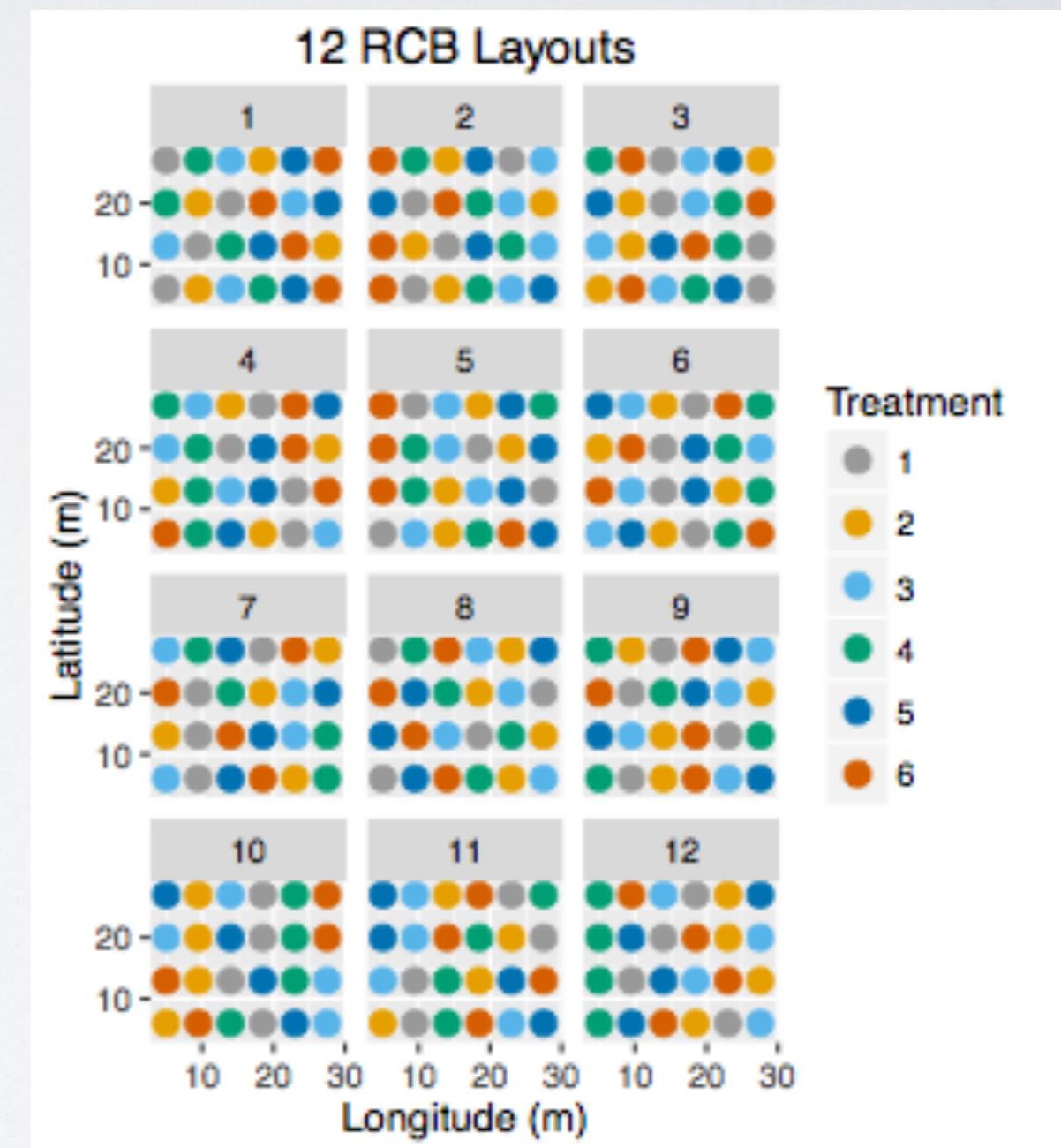
# Simple Restricted Randomization

- Which of these layouts would you reject out of hand as being potentially biased?
- If you would reject any, you are practicing a form of restricted randomization.
- This can be inefficient, since it may require many randomizations to achieve a desired layout.



# Comparative Error Rates

Layout	Type I Error Rate
1	14.44
2	5.00
3	1.67
4	2.22
5	8.33
6	0.56
7	2.22
8	2.22
9	1.11
10	6.11
11	5.55
12	32.8
Mean	6.85
SD	9.05



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Layout 1

401 1	402 4	403 3	404 2	405 5	406 6
301 4	302 2	303 1	304 6	305 3	306 5
201 3	202 1	203 4	204 5	205 6	206 2
101 1	102 2	103 3	104 4	105 5	106 6

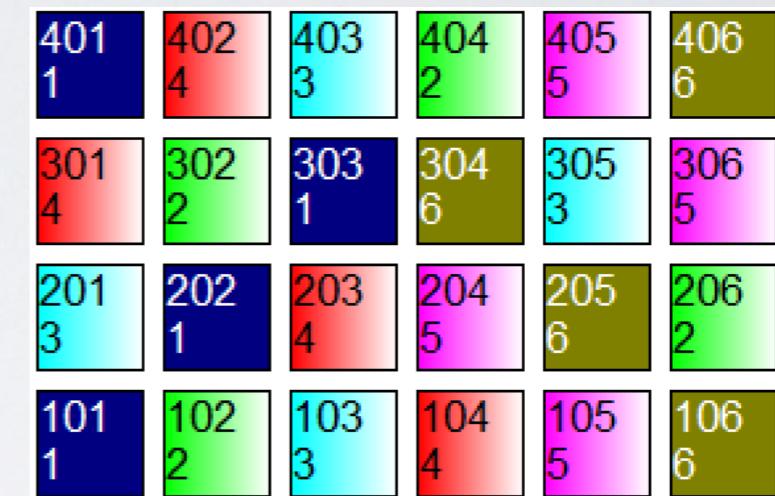
Layout 12

401 4	402 6	403 3	404 1	405 2	406 5
301 4	302 5	303 1	304 6	305 2	306 3
201 4	202 1	203 5	204 3	205 6	206 2
101 4	102 5	103 6	104 2	105 1	106 3

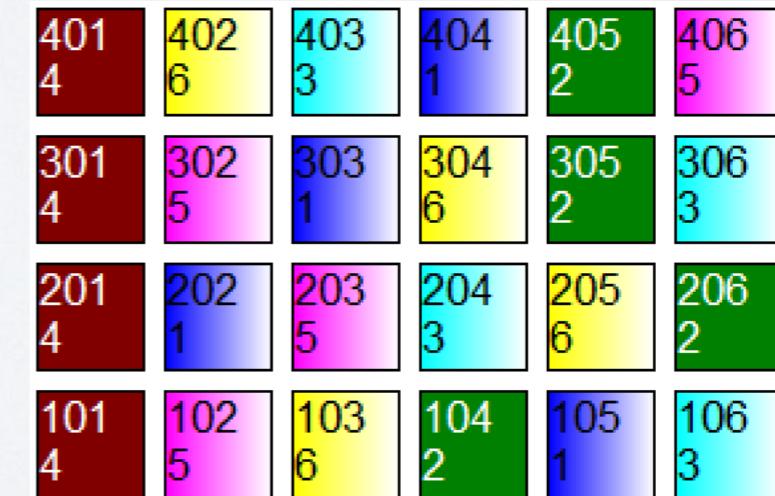
# Comparative Error Rates

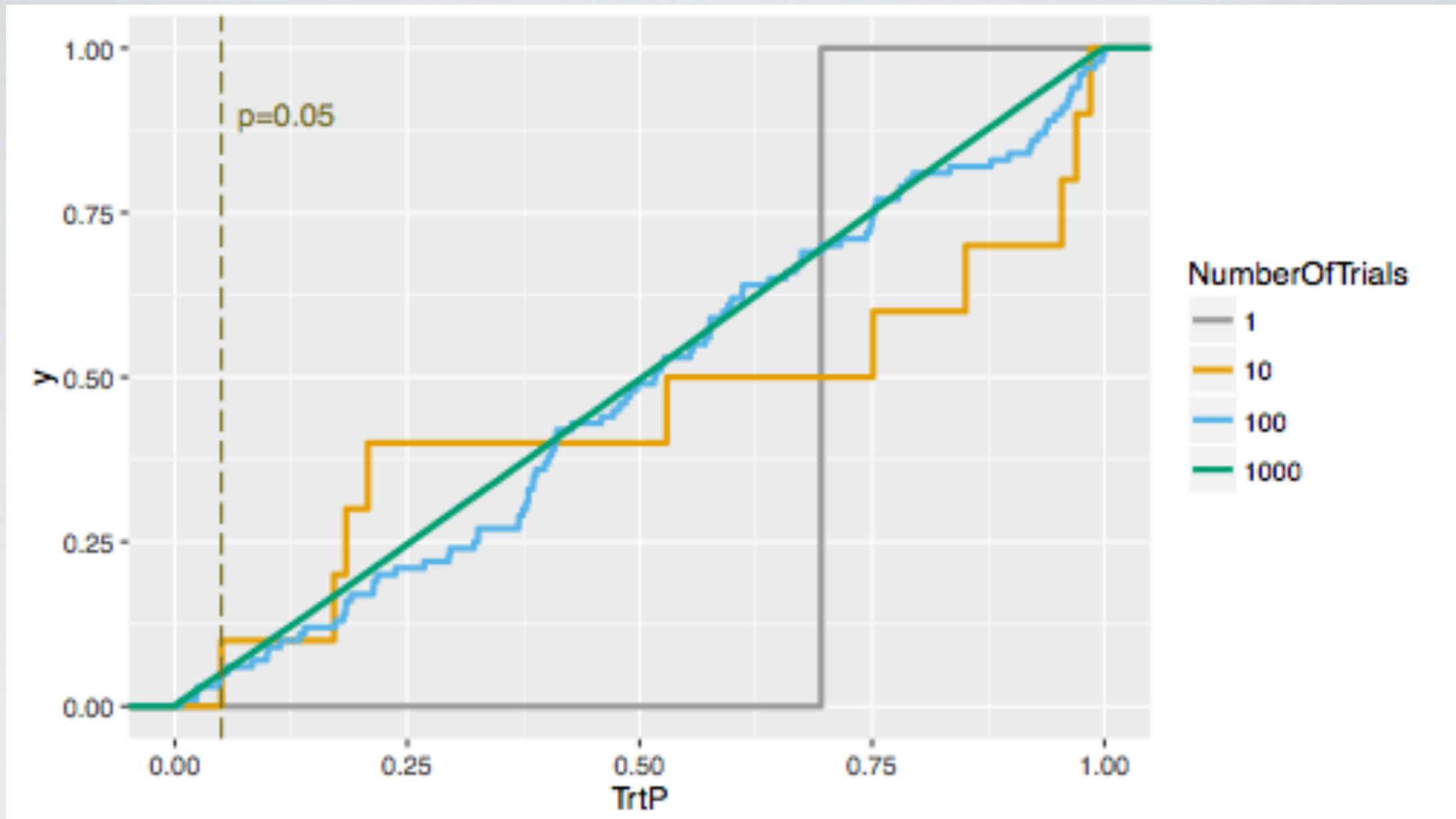
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Layout 1



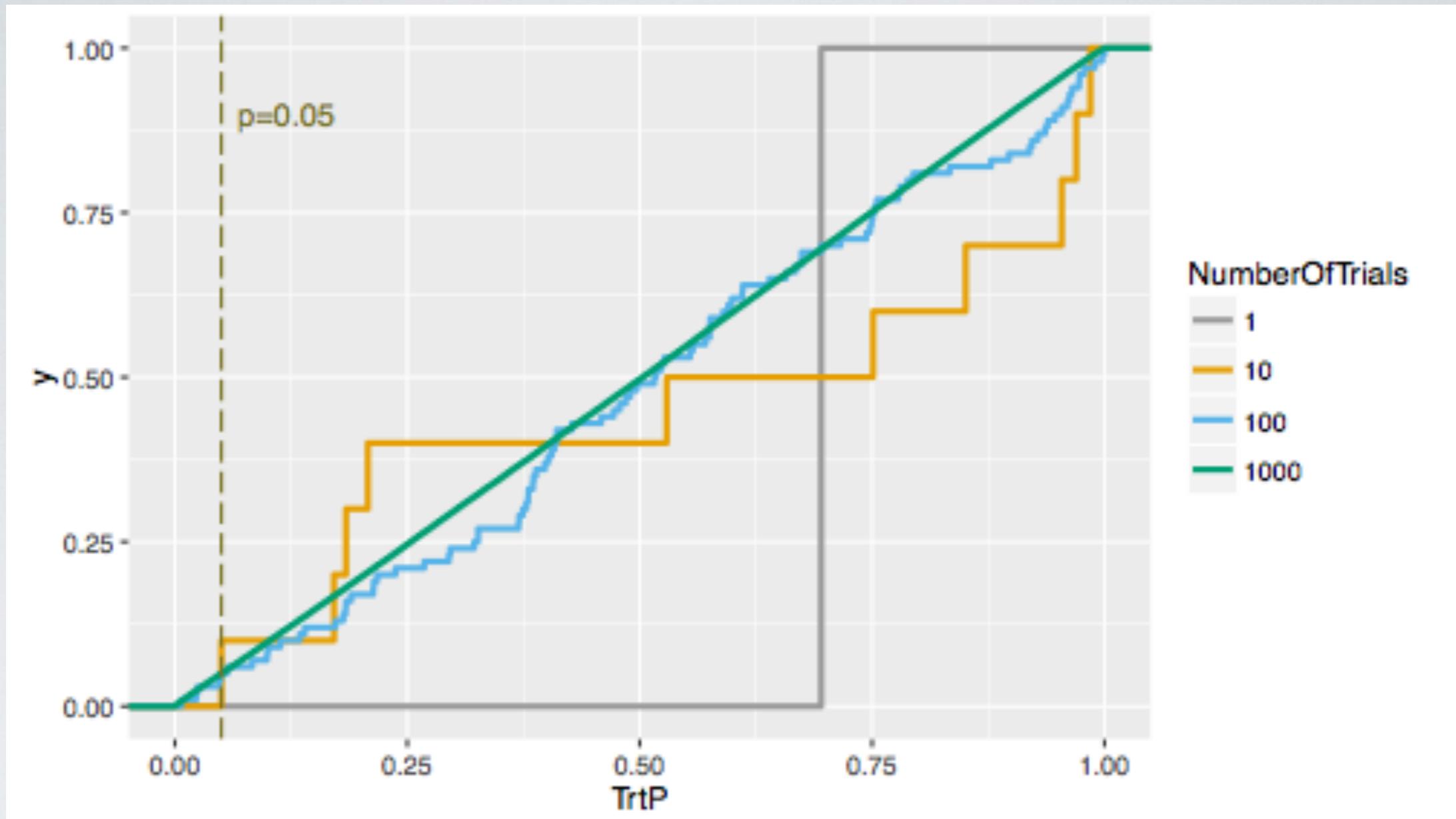
Layout 12





# Large Sample Theory

Combined treatment p for increasing numbers of RCB layouts, simulated over 180 experiments. As the number of trials increases, the distribution of p becomes uniform.



# Large Sample Theory

In these data, the null hypothesis is true. Uniformity implies that the probability of rejecting the null hypothesis is exactly equal to any chosen critical p-value.

# Restricted Randomization

- How can we control for undesirable layouts?
- The universe of potential randomized complete block layouts includes some that place multiple plots with the same treatment in close proximity.
- Researchers might recognize and reject these designs out of hand, and re-randomize.
- This is an informal method of restricted randomization.
- Several systematic restricted randomizations have been proposed.

# Systematic Restricted Randomization

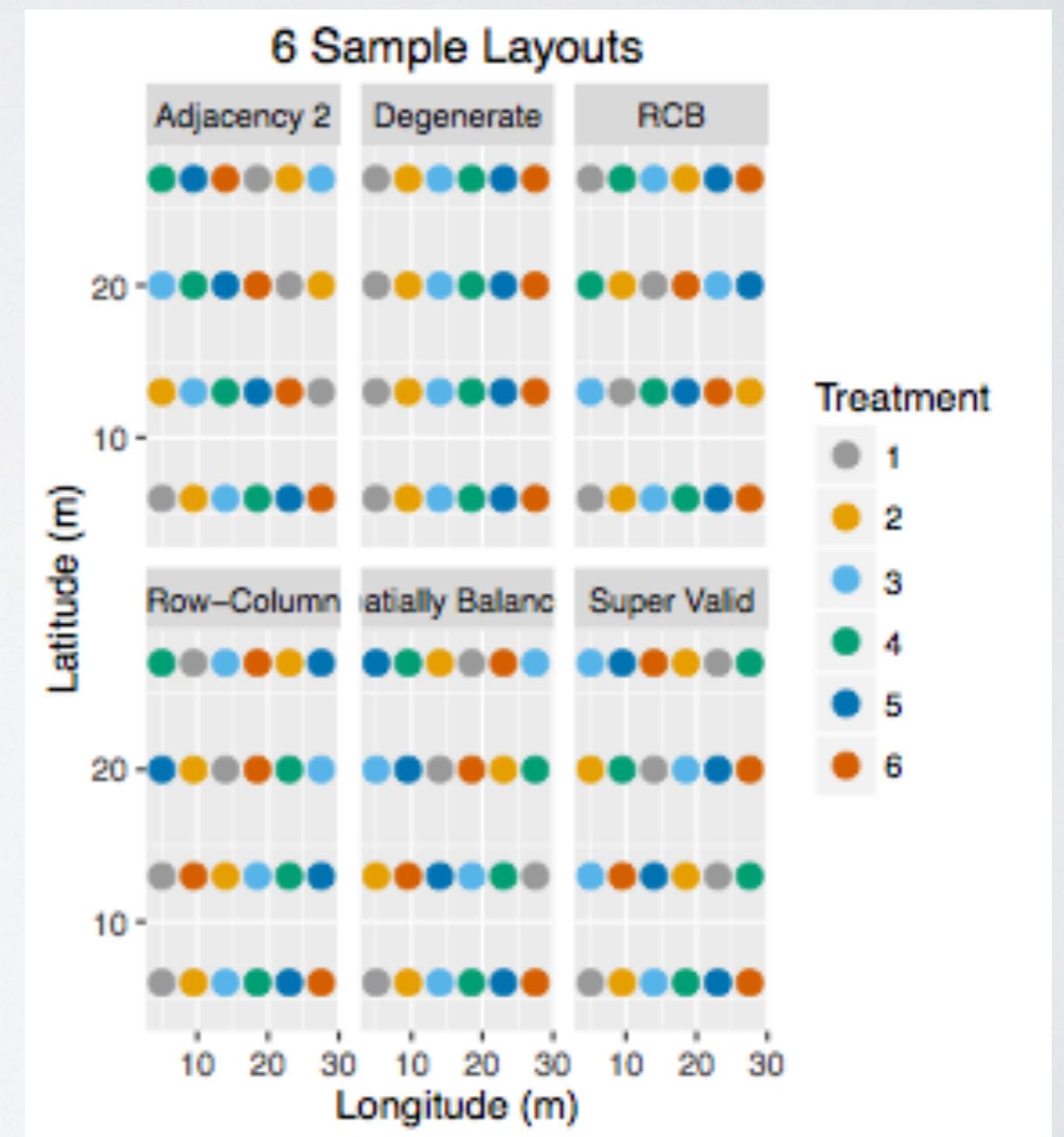
- Degenerate
  - unrandomized
- Randomized Complete Block
  - unrestricted randomization
- Restricted Adjacency
  - ARM setting = number of columns between identical treatments in adjacent blocks
- Super-valid
  - for each pair of rows, a single treatment may appear twice in the same column
- Row-column
  - Latin Rectangle
- Spatially-Balanced
  - spatial balance among treatment contrasts

# Column Restrictions

- Degenerate
  - treatment number same as column number
- Randomized Complete Block
  - any treatment may be applied to any column in a block
- Restricted Adjacency
  - treatments not allowed to appear in the same column in adjacent blocks
- Super-valid
  - no treatment may appear more than twice in the same column
- Row-column
  - no treatment may appear more than once in the same column
- Spatially-Balanced
  - no treatment may appear more than once in the same column

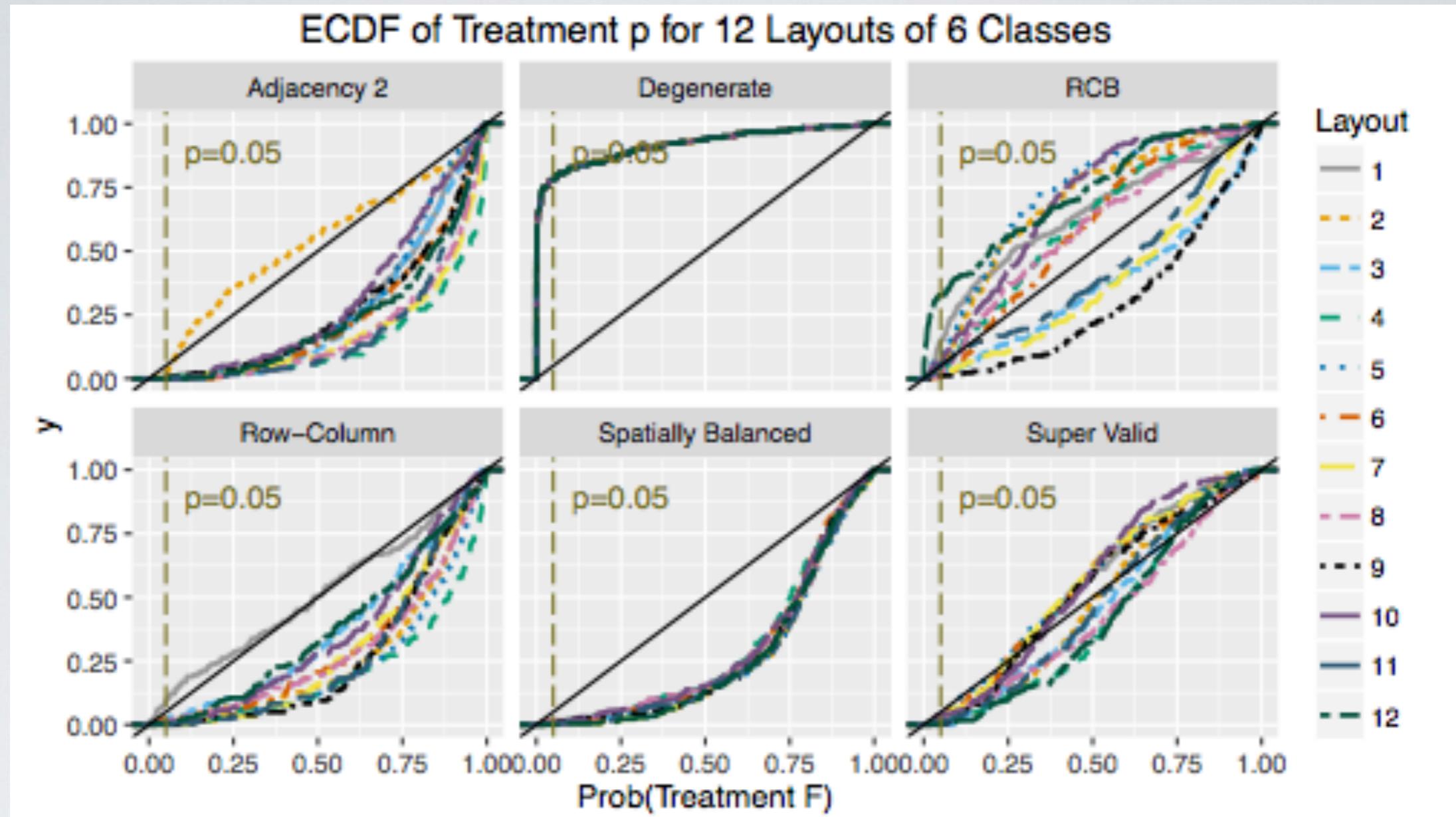
# Example Randomizations

- Degenerate
- Randomized
- Complete Block
- Row-column
- Super-valid
- Restricted Adjacency
- Spatially-Balanced



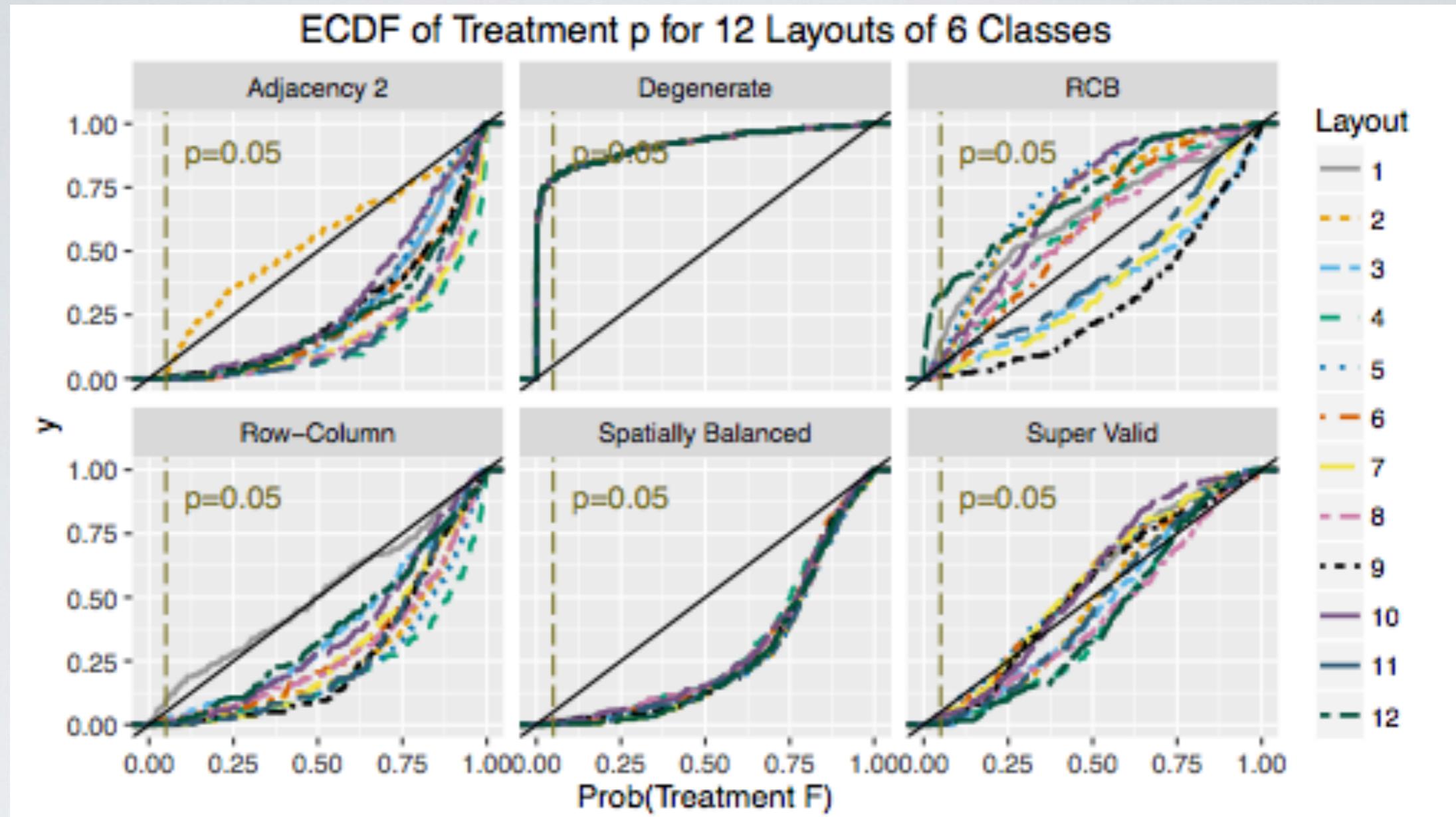
# Classes of Layouts

- To compare the different classes of restricted randomization schemes, 12 instances of each were created.
- Classic Fisher randomization allows independent randomization of treatments in each block, as previously described.
- New adjacency layouts were recreated by independent randomizations with the same setting (treatment adjacency=2).
- The properties of row-column and super-valid designs allow new layouts to be produced by independently permuting (swapping) rows and columns.
- Spatially-optimal layouts are optimized for average distance between treatments in rows, so permutations are limited to swapping rows only.



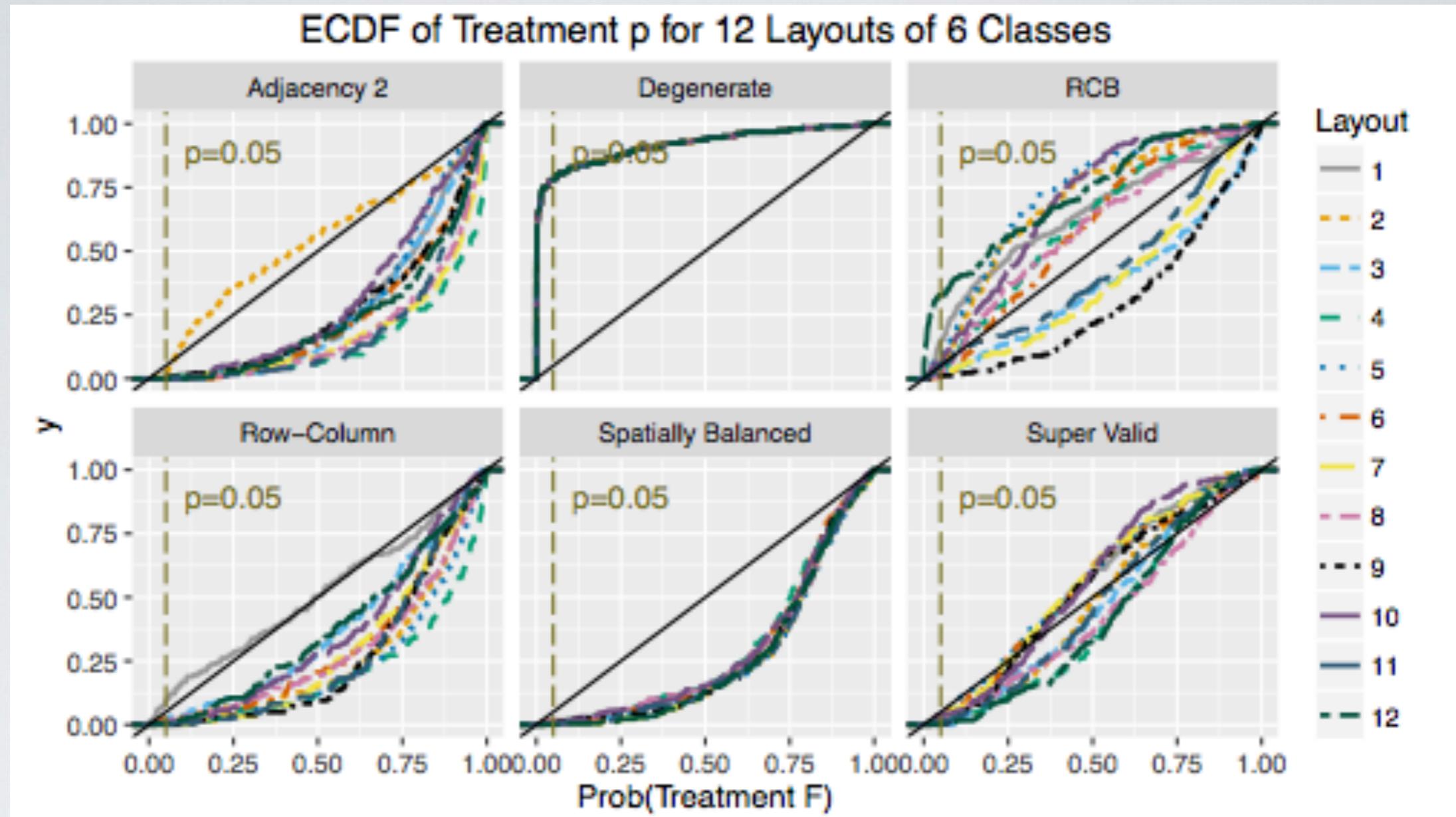
# Probability Distributions, 12 Layouts

Restricted randomization tends to exclude designs that produce left-skewed distributions.



# Probability Distributions, 12 Layouts

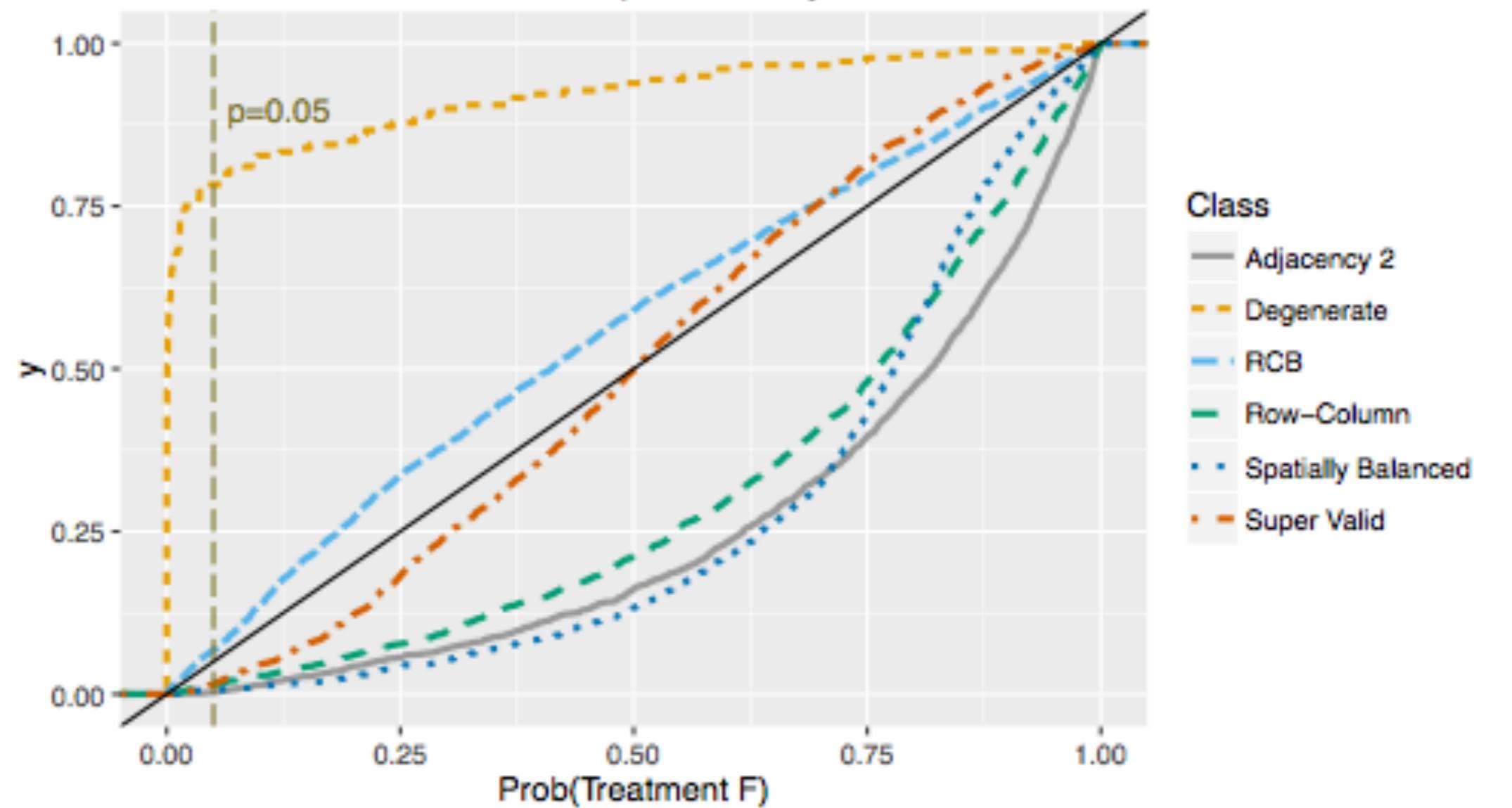
Super-valid designs, which allow two treatments to appear in the same columns, tend to be centrally distributed.



# Probability Distributions, 12 Layouts

Spatially balanced designs, which are generated by row-permutations only, are a more homogeneous class of randomization.

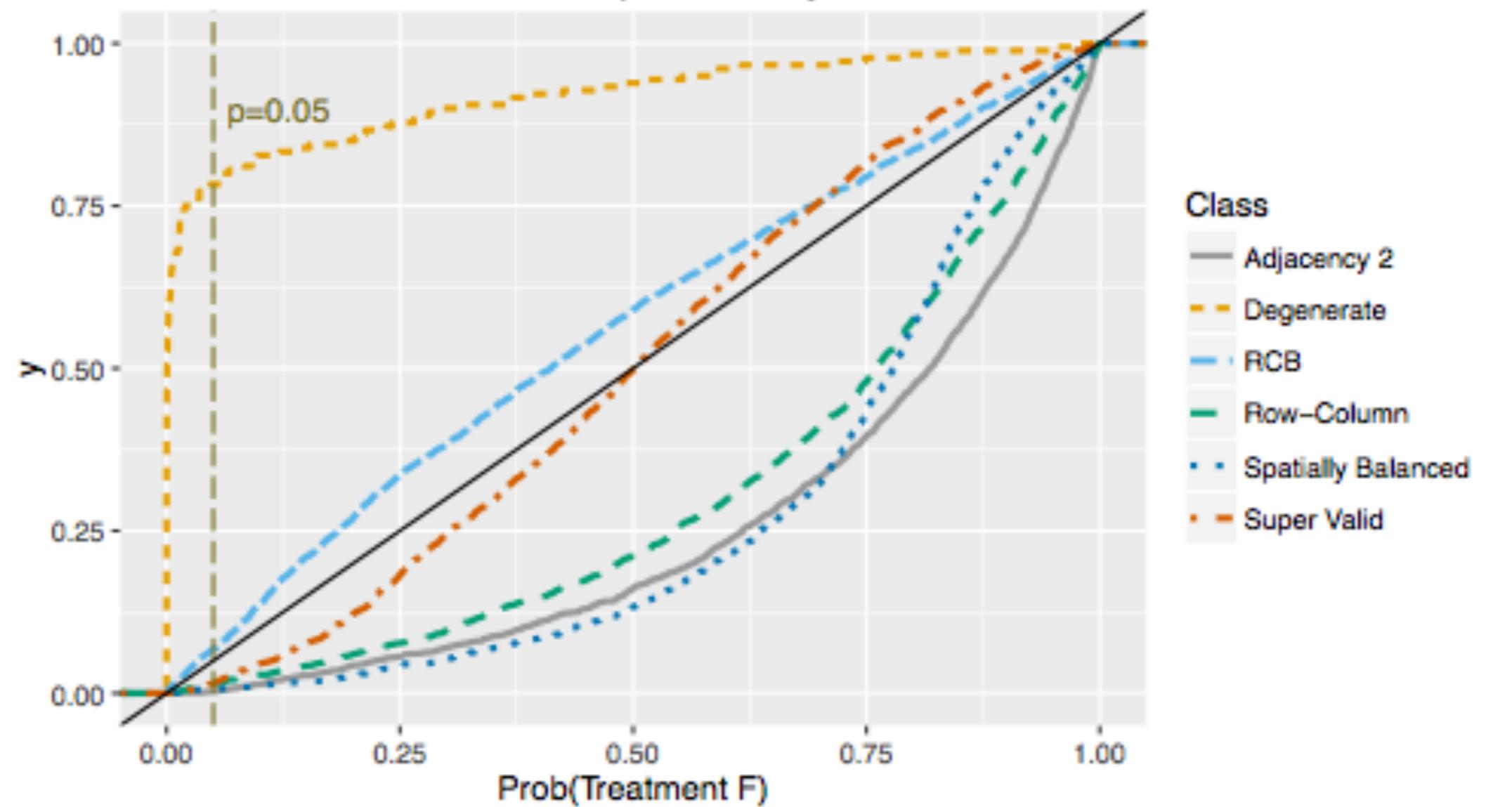
Pooled ECDF of Treatment p for 12 Layouts of 6 Classes



Pooled Distributions, 12 layouts Each

Row-column, spatially balanced and restricted adjacency  
show similar tendencies away from smaller p-values

Pooled ECDF of Treatment p for 12 Layouts of 6 Classes



Pooled Distributions, 12 Layouts Each

At a nominal probability of 0.50, the super-valid layouts tend toward an achieved rate of 0.50.

# Power Analysis

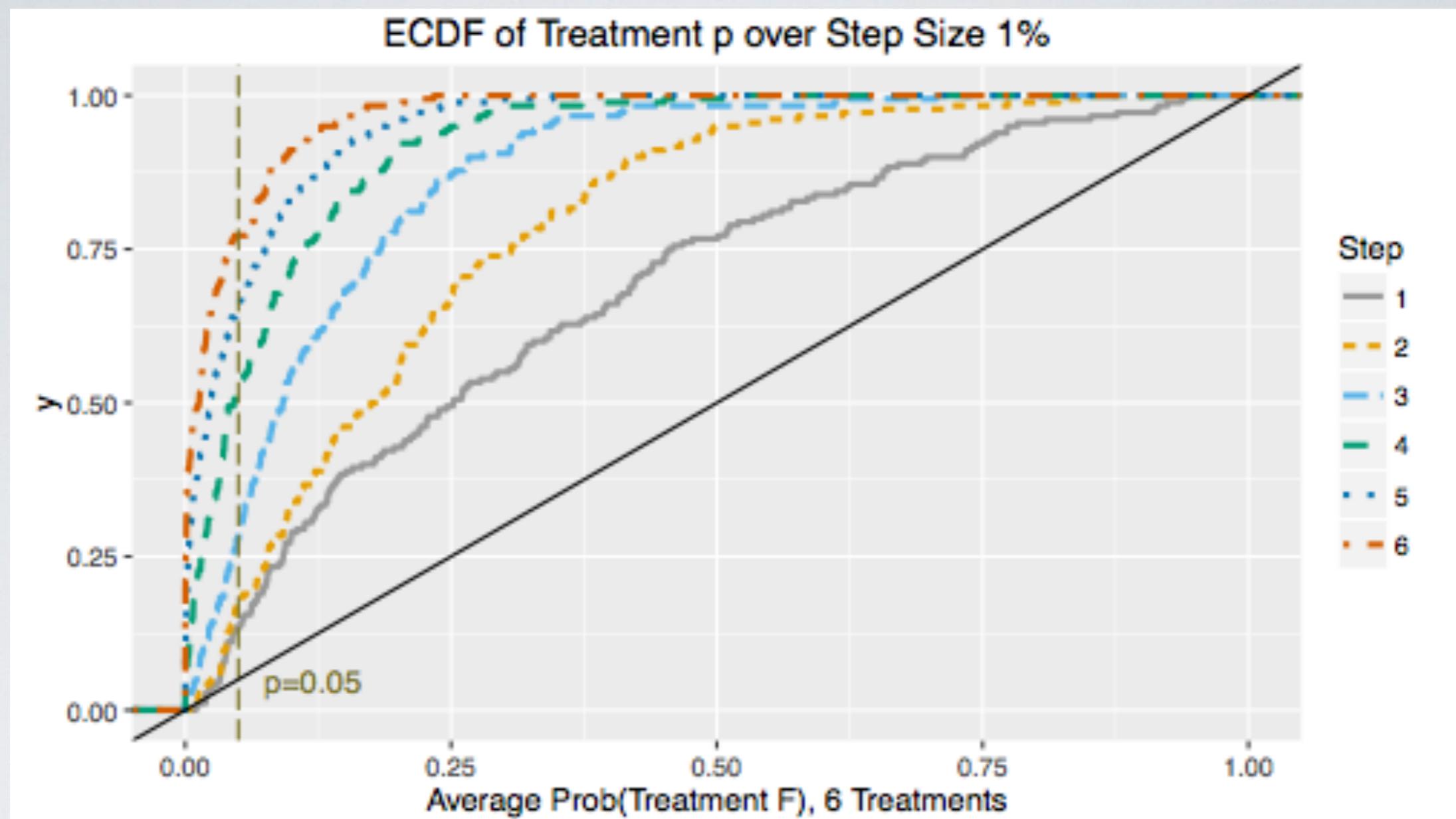
- Different layouts may produce achieved Type I error rates that are much lower than nominal error.
- However, planning experiments requires a compromise between Type I rates (detecting significance where none is present) and Type II error rates (overlooking a true treatment difference).
- We can also attempt to simulate Type II error and compare classes of restricted randomization.

# Simulating Type II Error Rates

- Simulating Type I Error rates using uniformity data is straight forward. Since there is no treatment effect, any trial detecting significance can be counted as an error.
- To determine Type II error rates, we need to add a “true” effect, and count the number of trials that fail to detect significance.
- But what is a true effect?

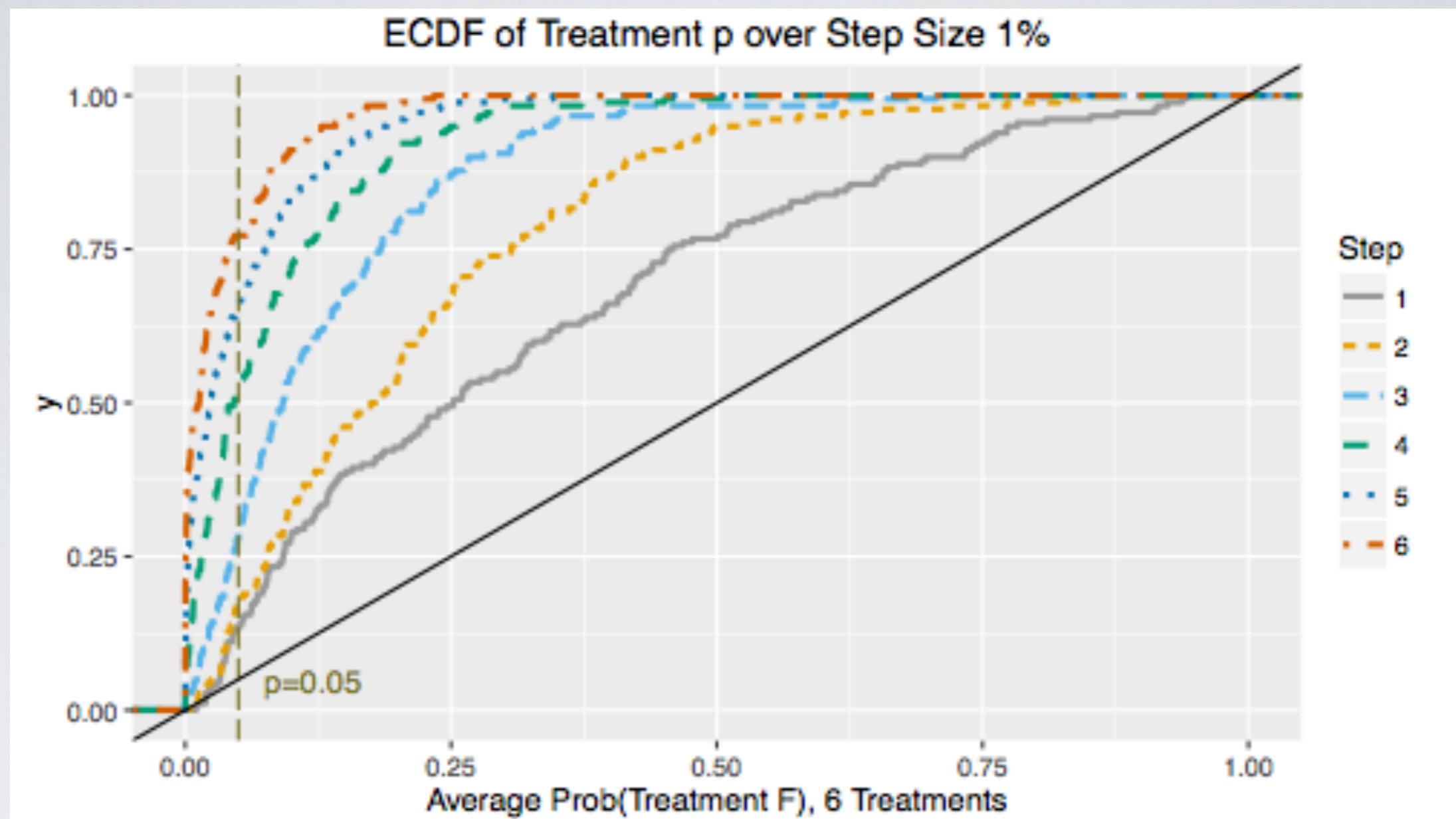
# Simulating Type II Error Rates

- To determine a true effect, we start with a small value,  $\sim 1\%$  of the grand mean, add this value to a single treatment, perform AOV and check treatment p.
- Do this for each treatment (of 6), and each location (of 180) in our field.
- If we haven't detected significance in at least 864 trials (80% of  $180 \times 6$ ), increment our effect value and repeat.
- This gives an estimate of effect size required to achieve 80% power.



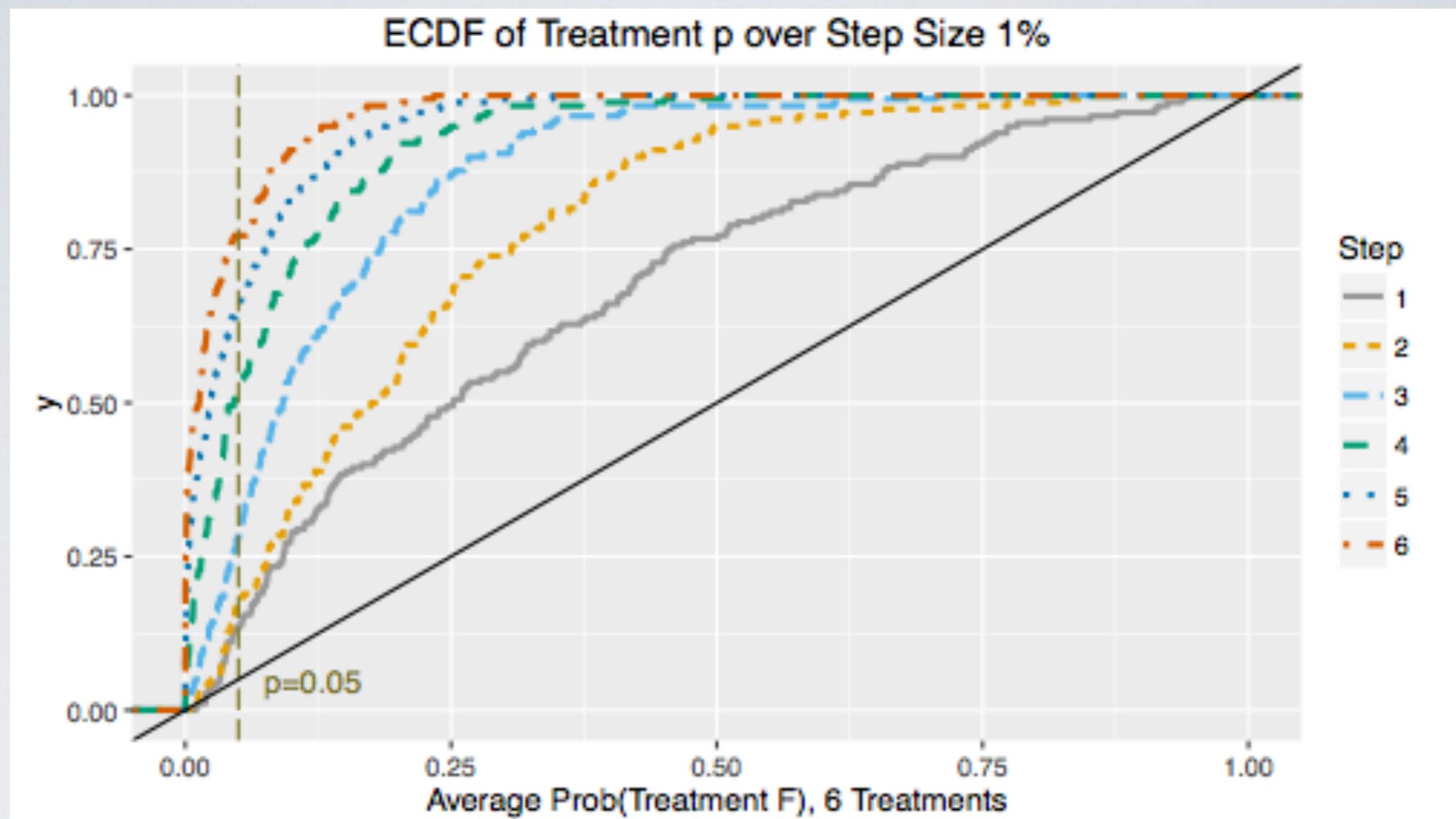
# Incrementing Effect Size

As we increment effect size for a single RCB trial, we see the Treatment p distribution shifted toward the left.



# Incrementing Effect Size

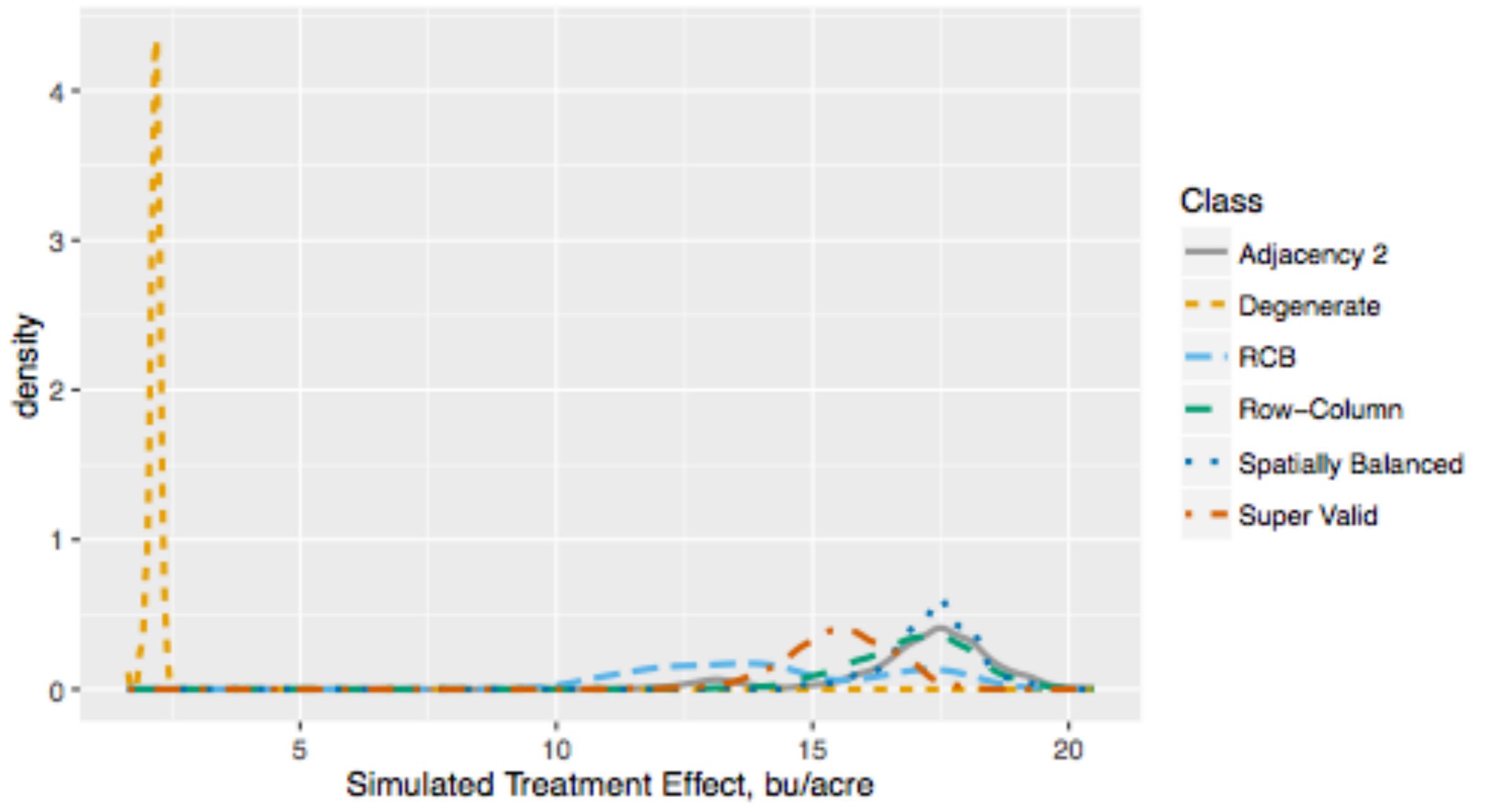
True effects shift treatment p distribution to the left.



# Incrementing Effect Size

Remember, null treatment effects confounded with spatial effects also shifted treatment p distributions to the left.

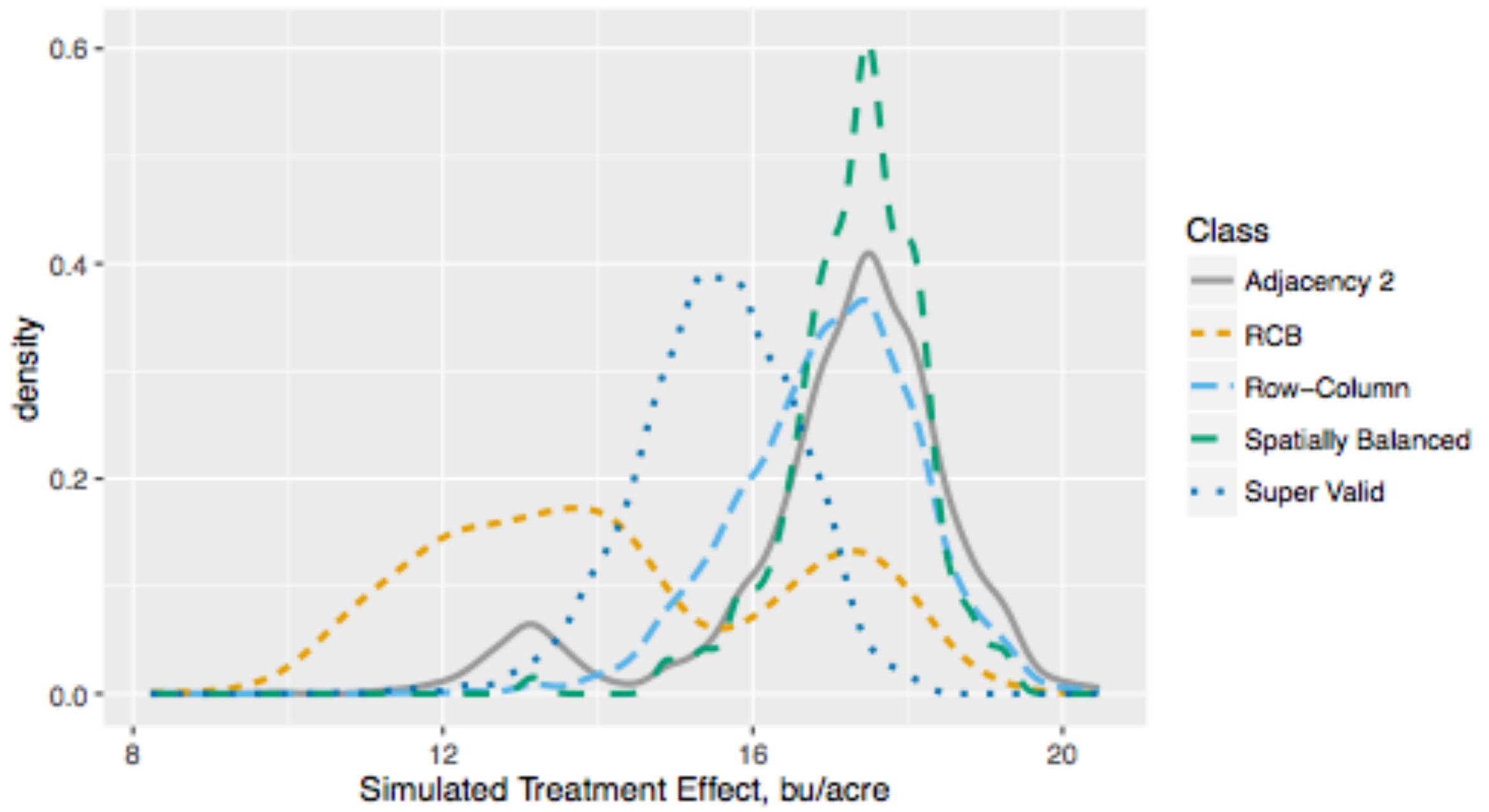
## Distribution of Effects to Achieve 80% Significance



# Pooled Power Analysis

An unrandomized layout is almost certain to detect very small treatment effects as significant.

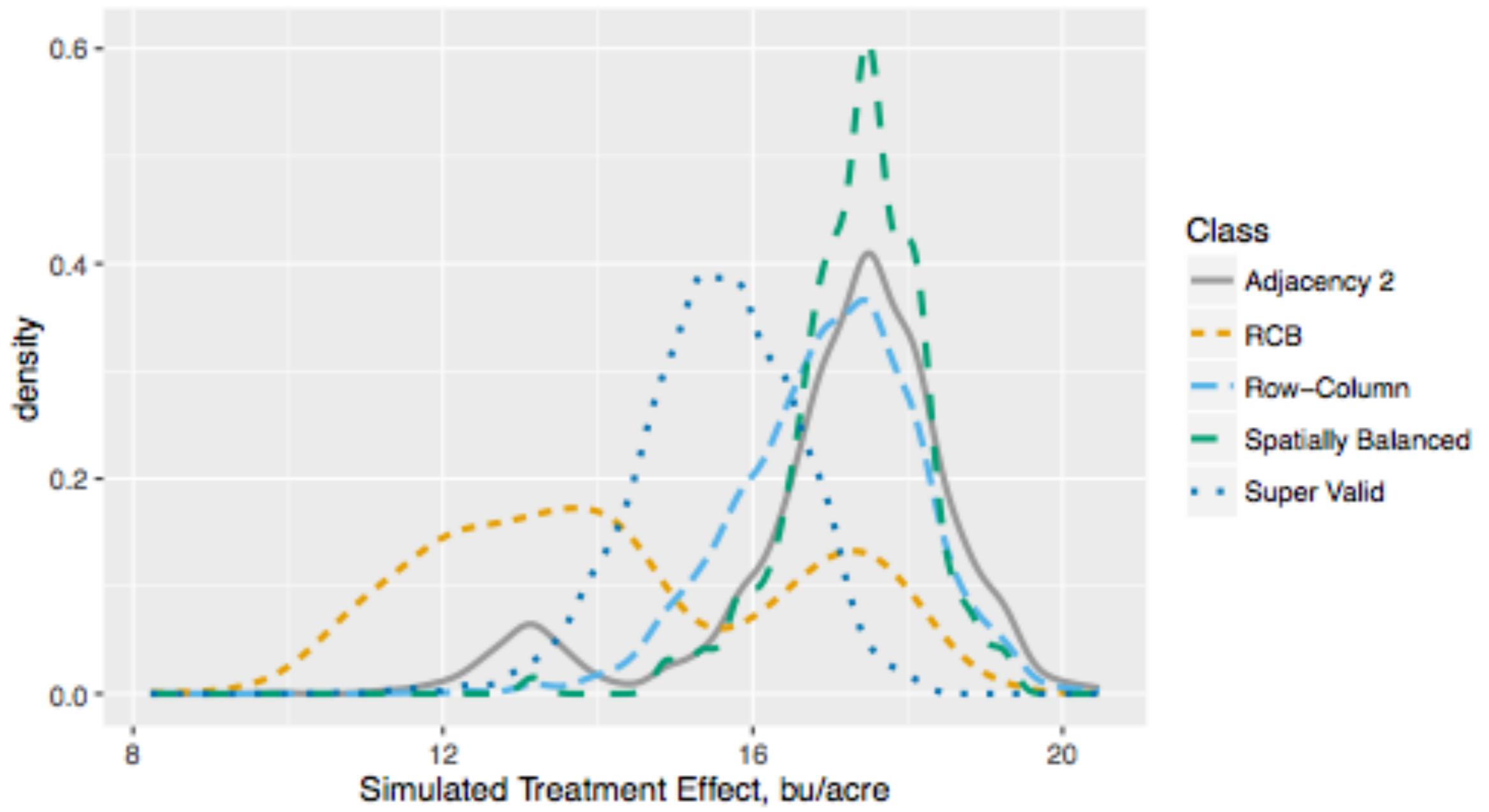
### Distribution of Effects to Achieve 80% Significance



## Pooled Power Analysis

Layouts that tend toward lower Type I error rates require larger absolute treatment effects ( $\sim 17$  bu/acre) to achieve a desired power.

## Distribution of Effects to Achieve 80% Significance

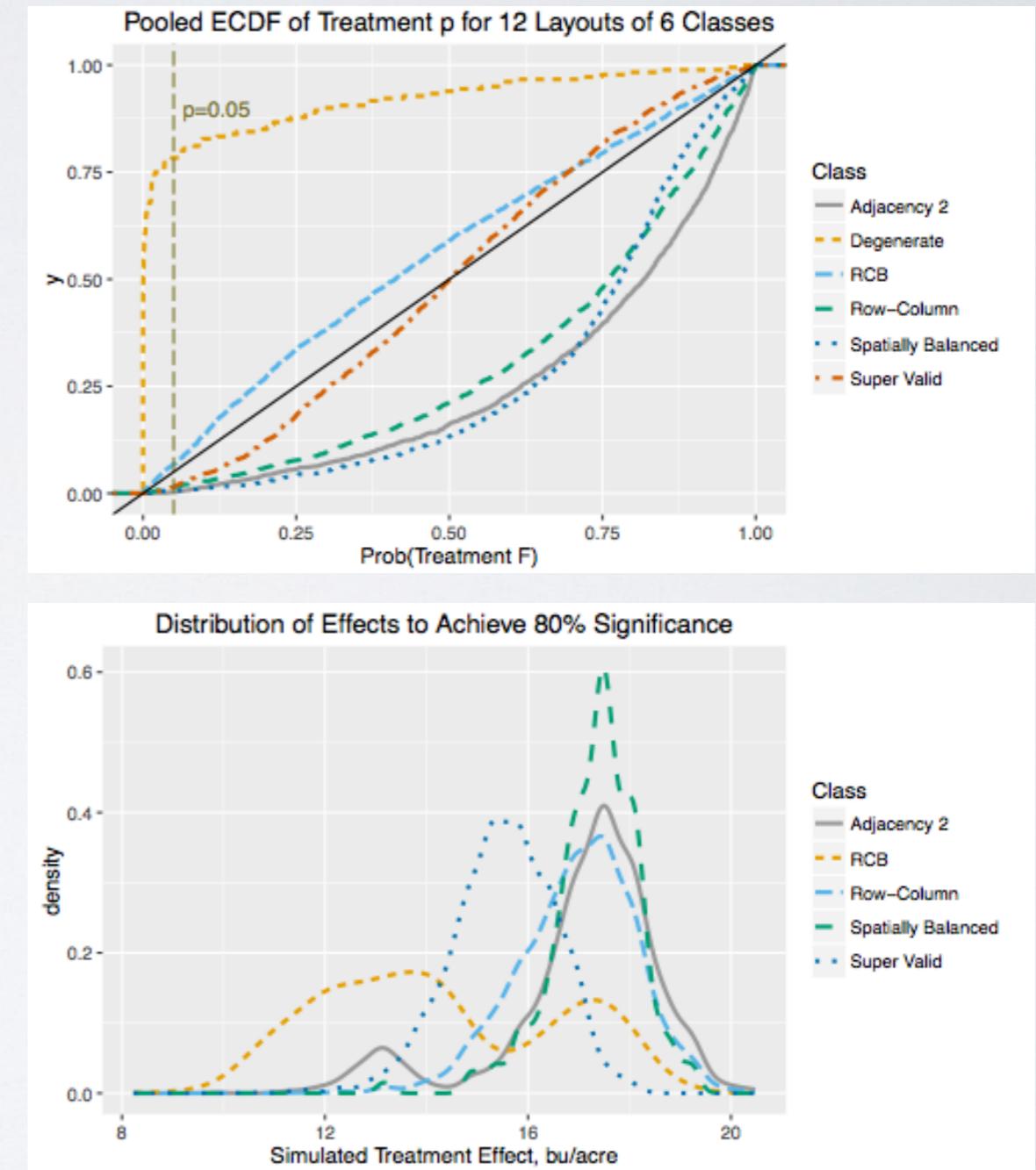


# Pooled Power Analysis

Super valid layouts offer a compromise between Type I and Type II error rates.

# Recommended Replicates

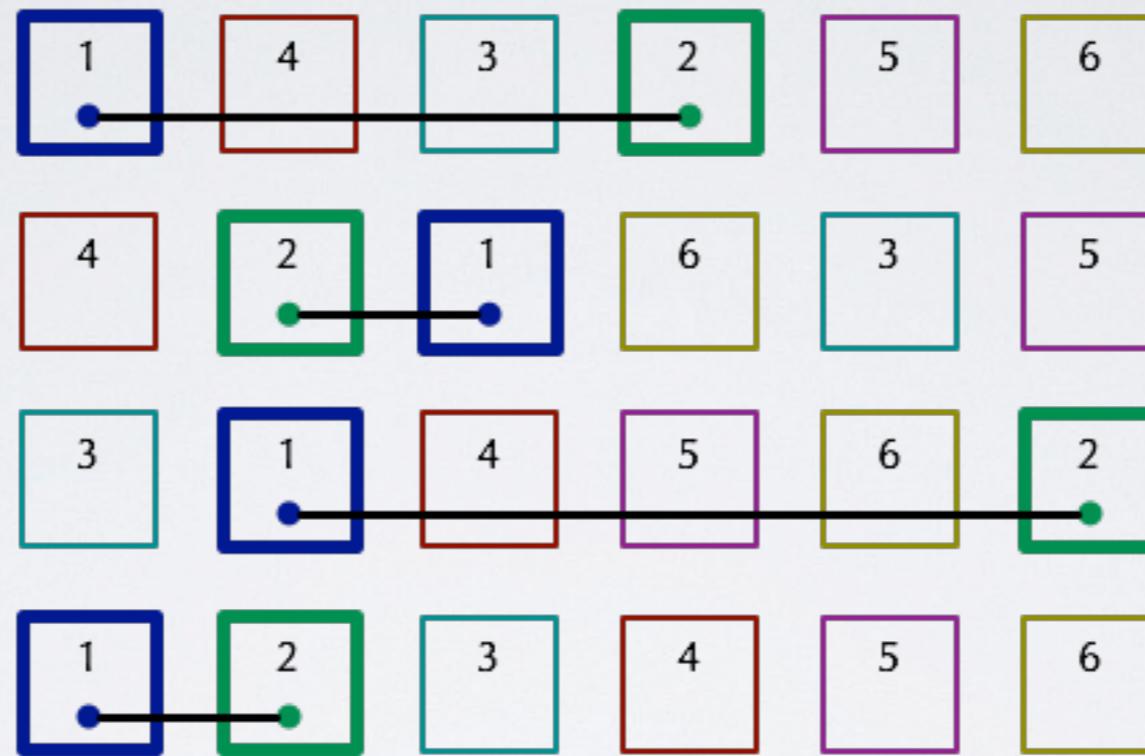
- If we suspect that a layout has a tendency to low p-values, would we use the same number of replicates?
- If we suspect that a layout has a tendency to require larger treatment effects, would we use the same number of replicates?
- Given an arbitrary layout, can we predict these tendencies?



# Average Distance of Treatment Comparison

- van Es and van Es, "Spatial Nature of Randomization and Its Effect on the Outcome of Field Experiments", Agron J, 85:420-428 (1993).
- Comparison between treatments 1 and 2 is made from data taken from 4 plots for each treatment.
- Measure the plot-to-plot distance for each plot containing treatment 1 to the paired plot, within replicates, containing treatment 2, for a total of 4 distances.
- ADTC for the treatment pair 1-2 is the average of the 4 distances.

# Distances, Treatments I-2



The average distance for the contrast between treatments I and 2 is computed by averaging the linear distances between plot centers, including plot width (4m) and buffer space (0.5m)

# Average Dispersion

- To provide an estimate of how well a treatment is dispersed relative all other treatments, compute the average of ADTC for all comparisons including that treatment.
- Contrasts including Treatment I
  - $\text{ADTC I-2} = 10.125$        $\text{ADTC I-3} = 7.875$        $\text{ADTC I-4} = 7.875$
  - $\text{ADTC I-5} = 14.625$        $\text{ADTC I-6} = 15.75$
- Average Distance, Treatment I Contrasts = 11.25
- Standard Deviation, Treatment I Contrasts = 3.73

# Summarizing ADTC

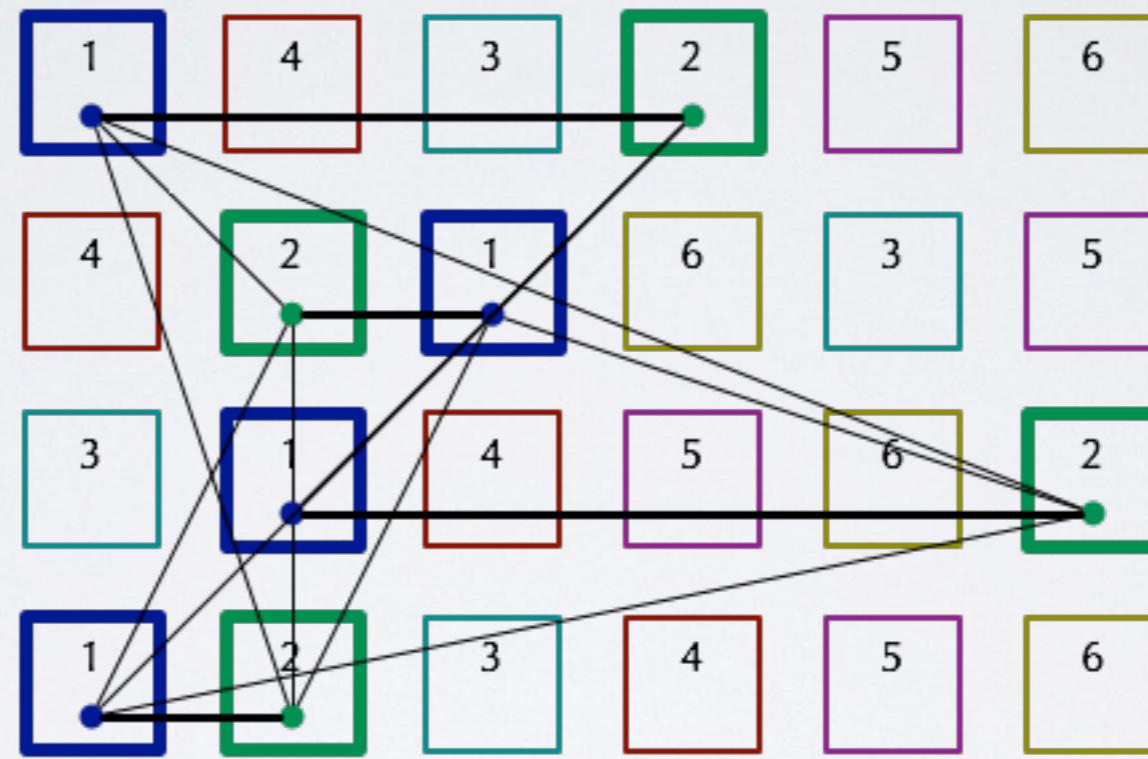
Standard Deviation of Average Distances = 0.61

Treatment						
Trt	Code	At Edge	Ave Dist.	StDev	Min	Max
1		2	11.3	3.73	7.9	15.8
2		3	10.4	0.94	9	11.3
3		3	9.9	1.85	7.9	12.4
4		3	9.9	1.85	7.9	12.4
5		3	10.4	3.32	5.6	14.6
6		2	11.3	3.73	5.6	15.8
Average		2.7	10.5	2.57	7.3	13.7

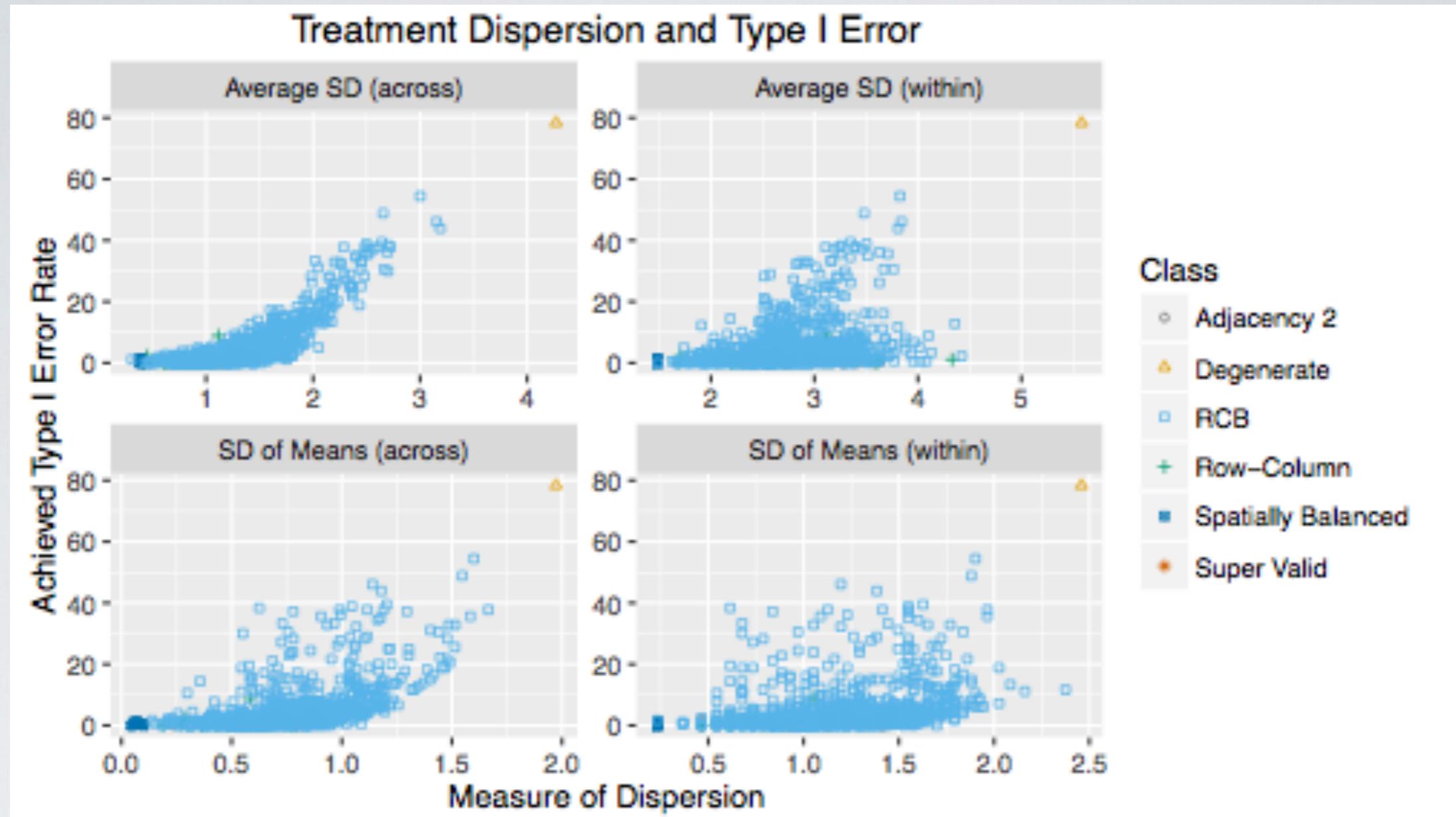
Average of Standard Deviations

Two choices for a single value summarizing ADTC

# Distances, Treatments 1-2, Across Replicates

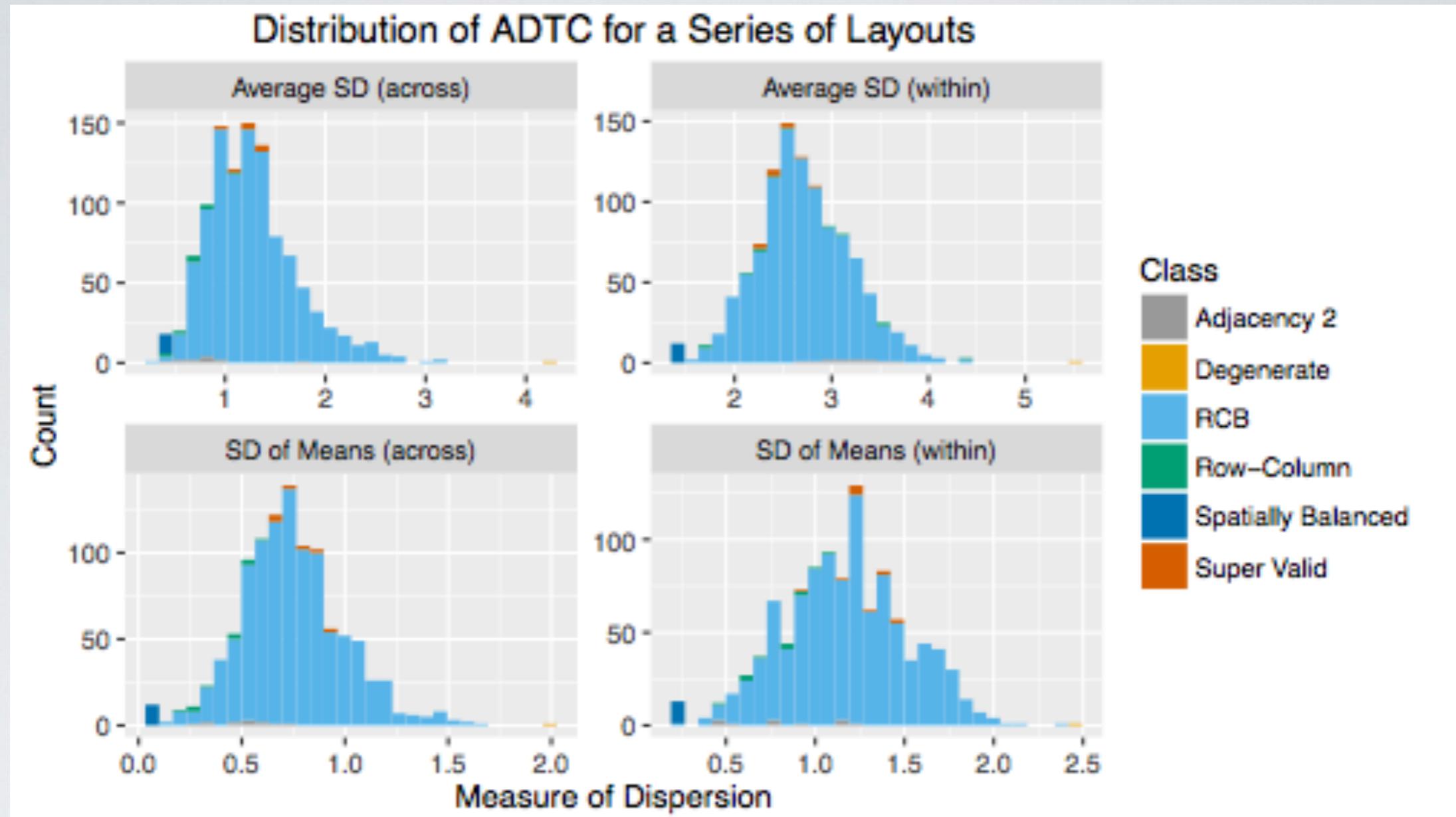


Measure dispersion by computing ADTC with distances across replicates as well as within replicates.



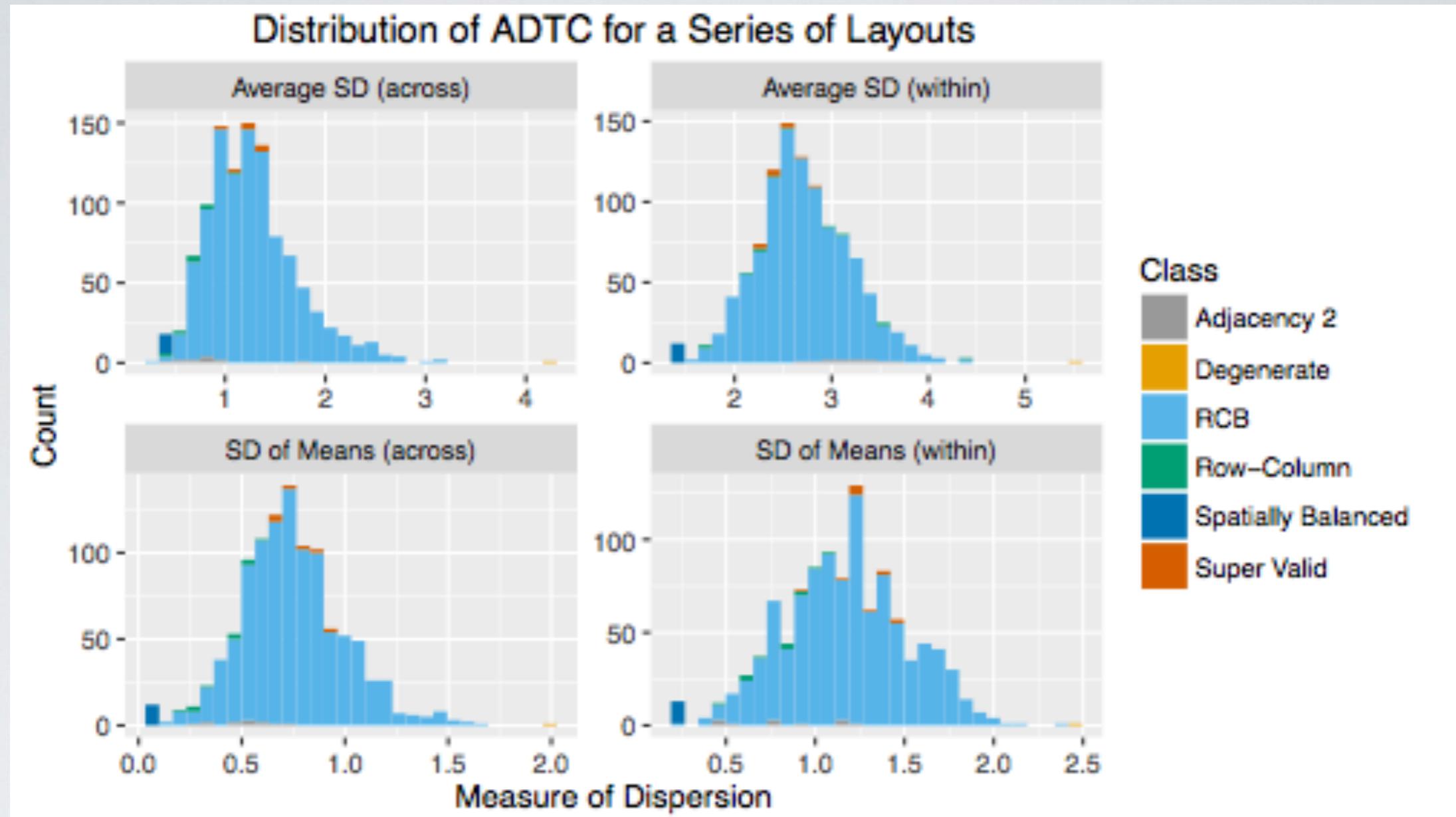
## ADTC as a Predictor of Type I Error

12 trials of each class of restricted randomizations, along with 1000 unrestricted RCB layouts



# Distribution of ADTC

Adjacency, row-column and spatially balanced randomizations tend toward low ADTC



# Distribution of ADTC

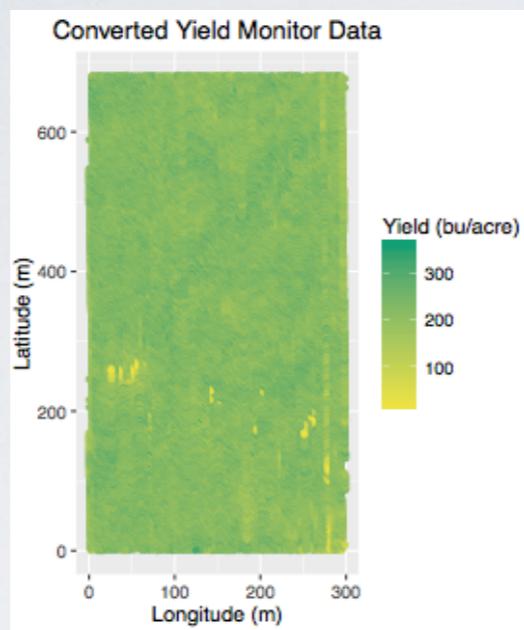
Super valid layouts tend toward mean ADTC

# References and Related Work

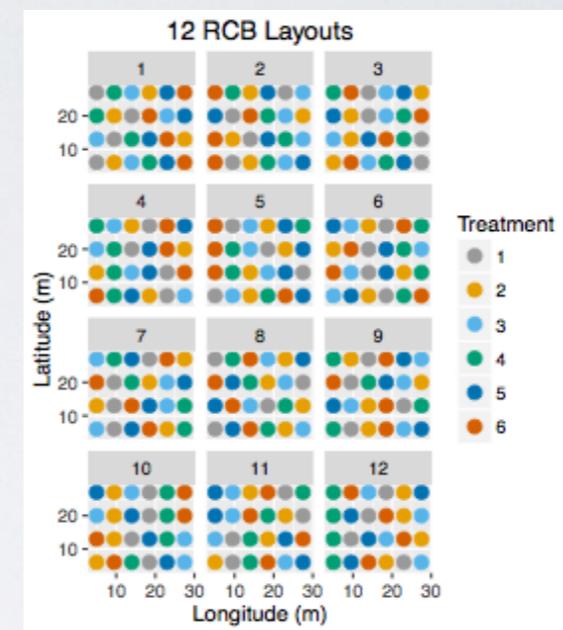
- Bailey, R. A. "Experiments in rectangular areas: design and randomization." *Journal of Agricultural, Biological, and Environmental Statistics* 17.2 (2012): 176-191.
- van Es, H. M., and C. L. van Es. "Spatial nature of randomization and its effect on the outcome of field experiments." *Agronomy Journal* 85.2 (1993): 420-428.
- van Es, H. M., et al. "Spatially-balanced complete block designs for field experiments." *Geoderma* 140.4 (2007): 346-352.
- Williams, Emlyn R., and Hans-Peter Piepho. "An evaluation of super-valid restricted randomization." *Journal of Agricultural, Biological, and Environmental Statistics* 19.4 (2014): 470-478.
- Forkman, Johannes. "A comparison of super-valid restricted and row–column Randomization." *Journal of Agricultural, Biological, and Environmental Statistics* 21.2 (2016): 243-260.
- Piepho, Hans-Peter, Emlyn R. Williams, and Volker Michel. "Beyond Latin squares: A brief tour of row-column Designs." *Agronomy Journal* 107.6 (2015): 2263-2270.

# TL; DR

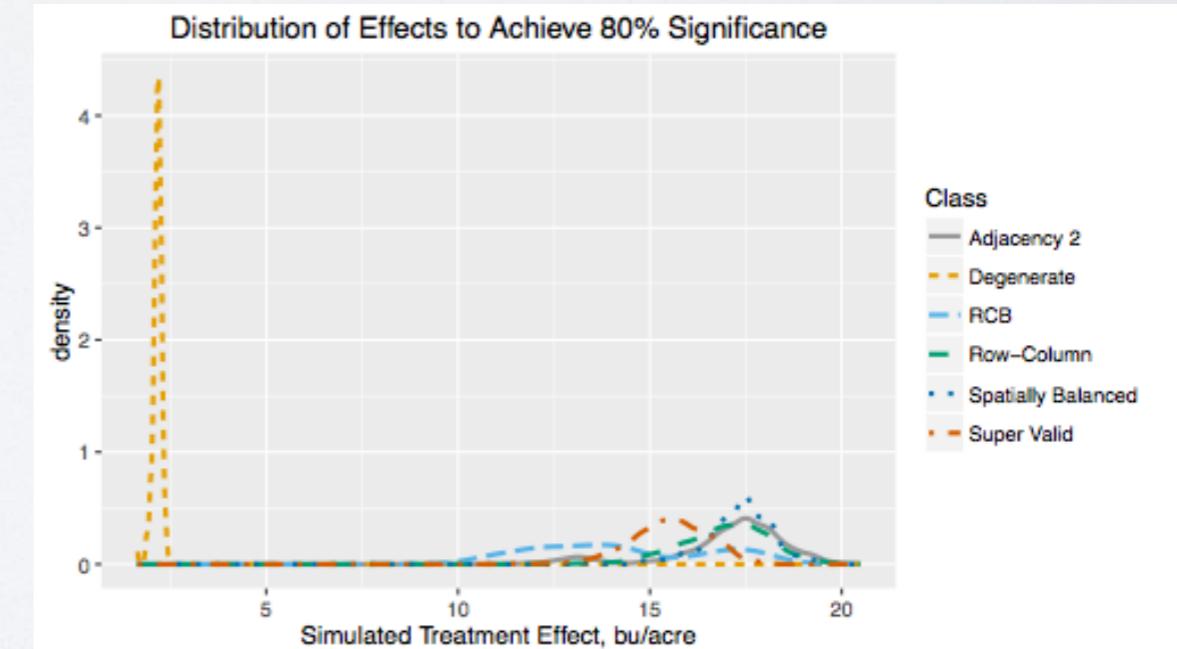
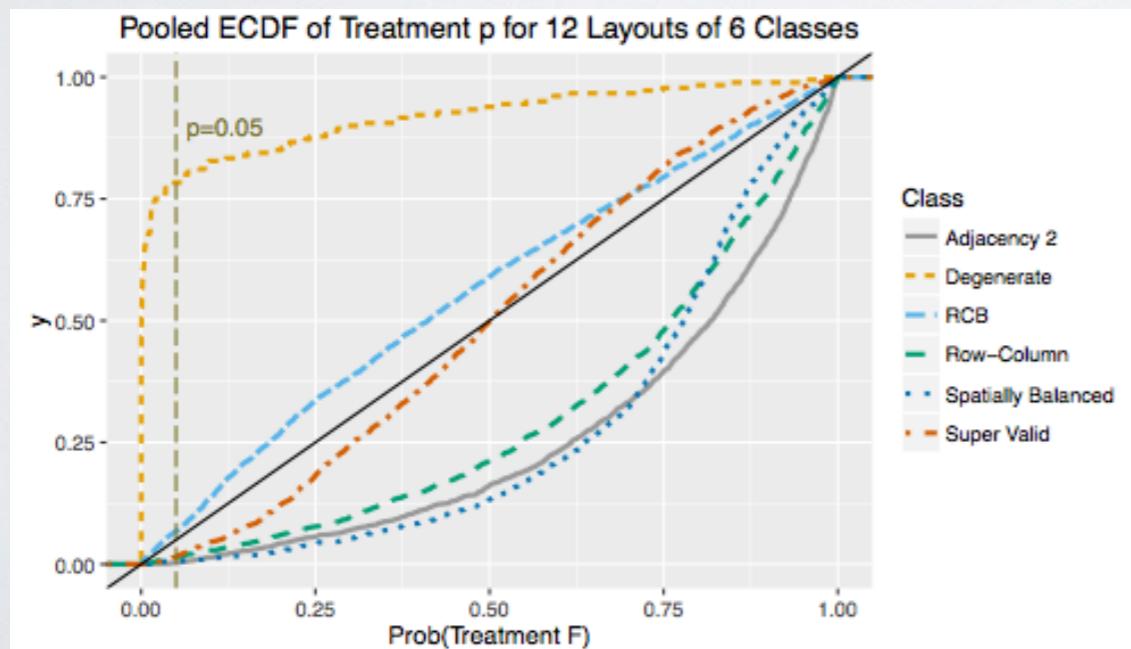
How do



and



combine to produce



?