Visualizing Effect Sizes Across the Full Distribution

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Background

- Effect sizes generally defined by standardized mean differences
  - Cohen's *d*
  - Hedges' *g*
- Particularly in non-experimental settings, interest may lie at other locations of the scale
  - Achievement gaps at proficiency cut scores on statewide tests
- Depending on the shape of each distribution, magnitude of group differences may depend upon scale location

Cohen's *d* & Hedges' *g*

$$d = \frac{\bar{X}_{foc} - \bar{X}_{ref}}{\sqrt{\frac{(n_{foc}-1)Var_{foc}+(n_{ref}-1)Var_{ref}}{n_{foc}+n_{ref}-2}}}$$

$$g = d\left(1 - \frac{3}{4(n_{foc} + n_{ref}) - 9}\right)$$

Percentage above the cut effect sizes

Percentage Above the Cut

$$d^{pac} = PAC_{ref} - PAC_{foc}$$

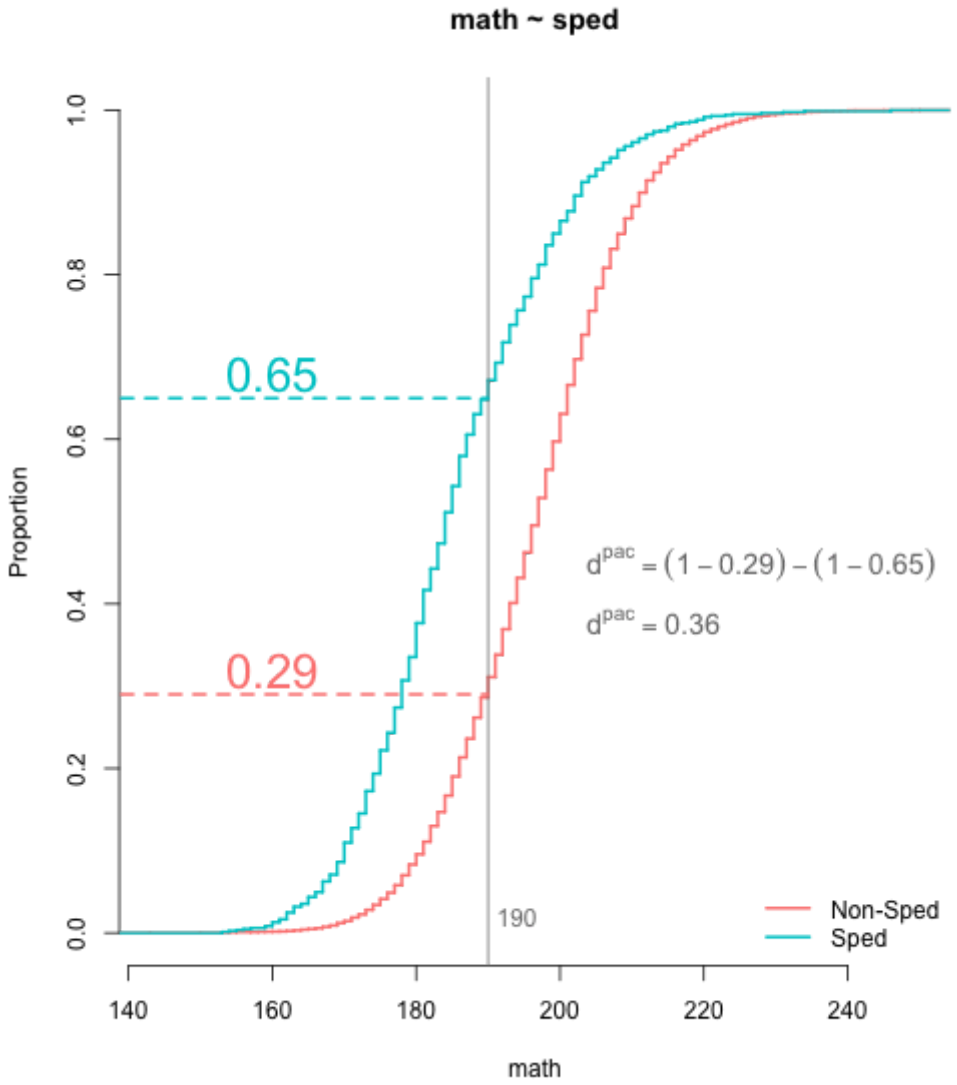
- Highly dependent on scale location

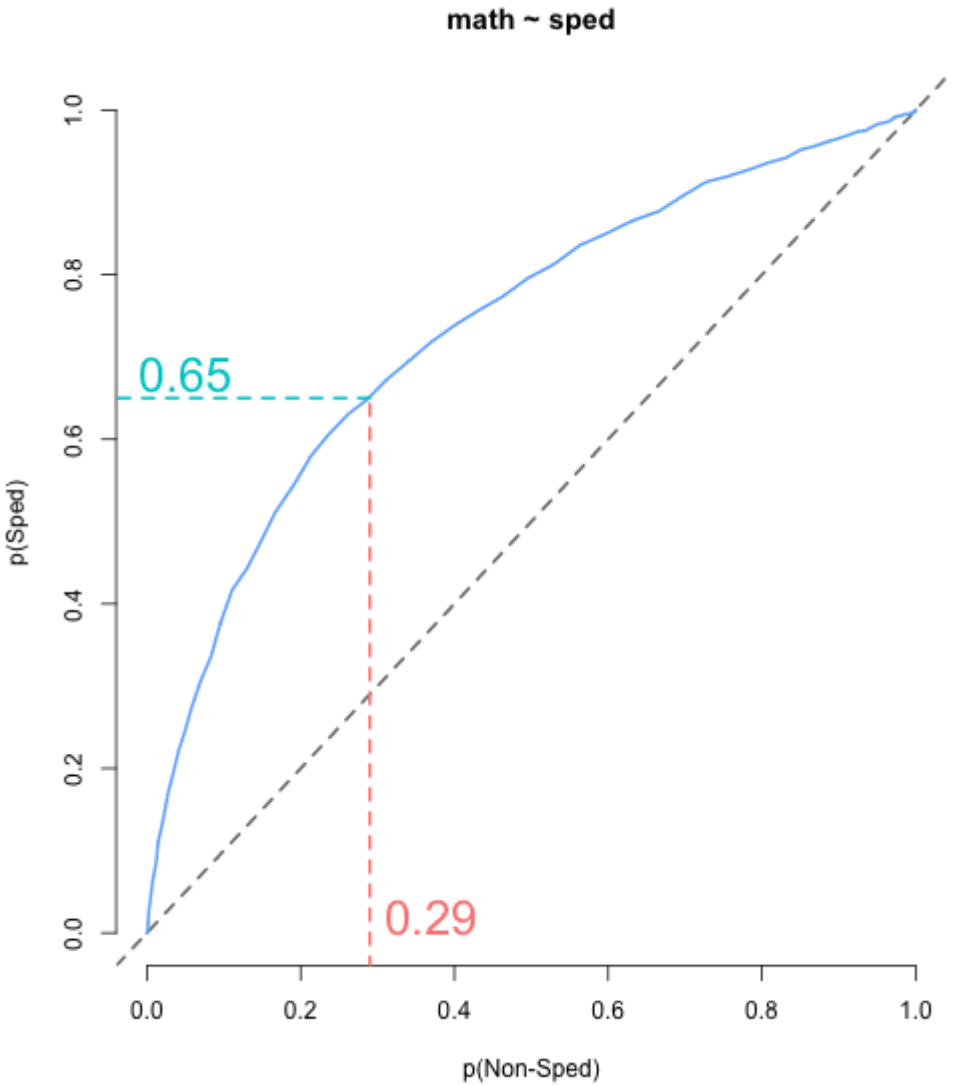
Transformed Percentage Above the Cut

$$d^{tpac} = \Phi^{-1}(PAC_{ref}) - \Phi^{-1}(PAC_{foc})$$

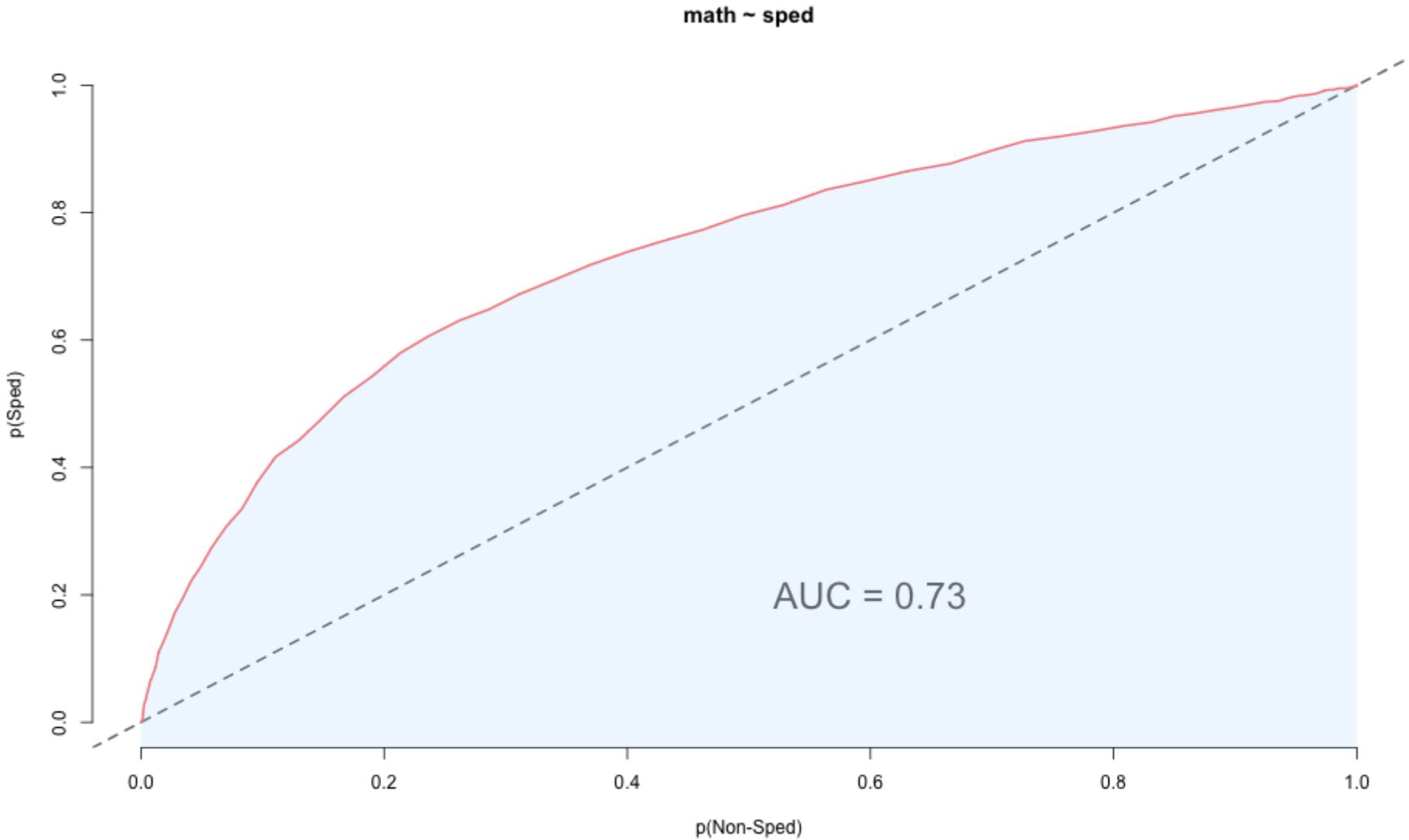
- Assumes both distributions are normally distributed with equal variance

Probability-Probability Plots





Area Under the PP Curve



Putting AUC in SD units

Ho and colleagues

$$V = \sqrt{2}\Phi^{-1}(AUC)$$

- Scale invariant
- Assumes respective normality
    - Normal with respect to each other under a shared transformation

- *AUC* and *V* make fewer assumptions about the data, but are nonetheless summary measures.
- May miss nuances in the data that can be picked up by visualizations - particularly if the magnitude of the effect depends on scale location.

Implementation in `esvis`

R package actively in development

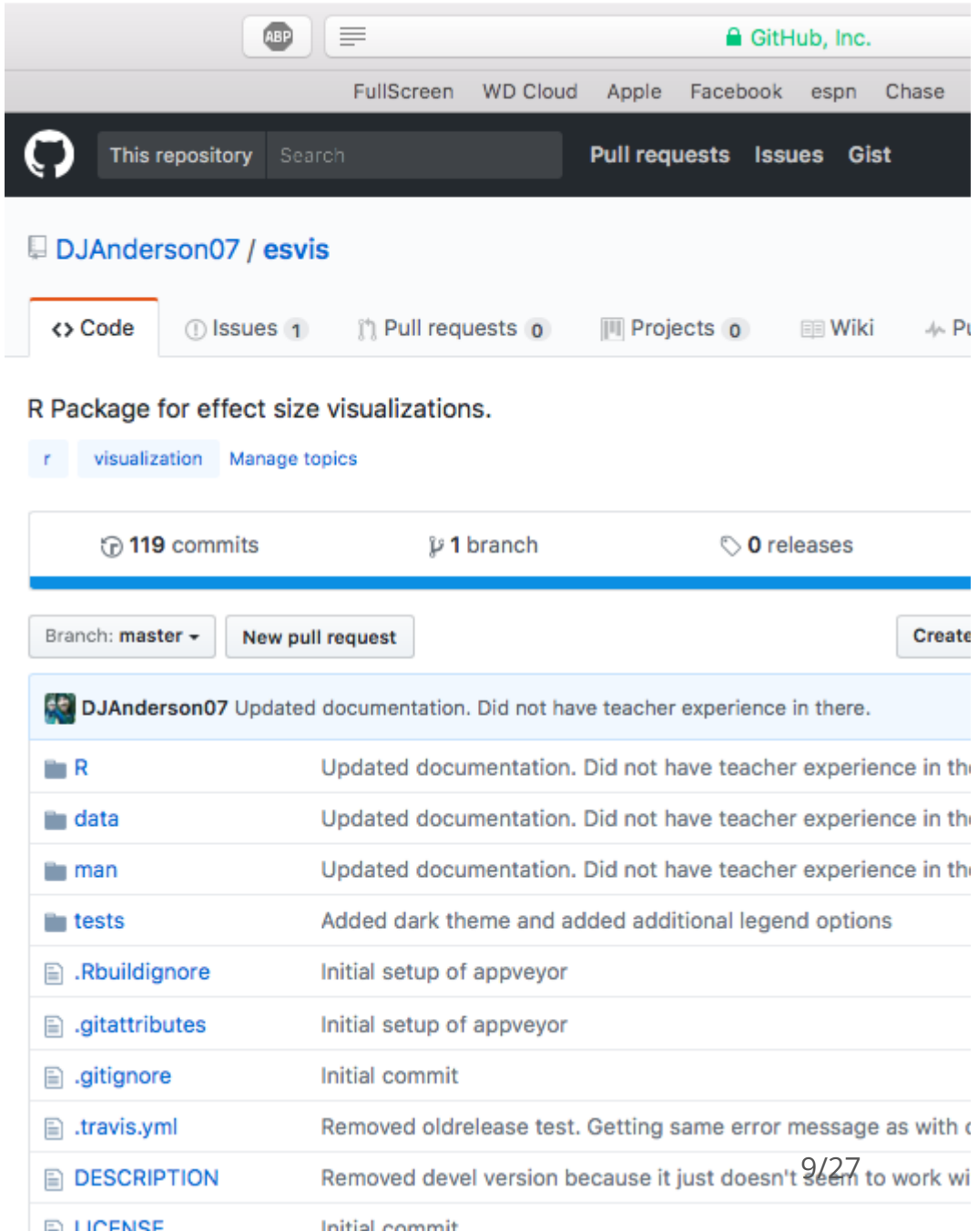
- Install using the *devtools* package

```
install.packages("devtools")
library(devtools)
install_github("DJAnderson07/esvis")
```

- Release to CRAN planned for summer
- Has many useful features currently

See current development at

https://github.com/DJAnderson07/esvis



Example data

I have stored a dataset in an object called `d`. Below are the first six rows of these data.

```
##         sid cohort     sped  ethnicity frl     ell season reading math
## 2873 332347      1 Non-Sped   Hispanic FRL  Active Spring     167  192
## 162  400047      1 Non-Sped Native Am. FRL Non-ELL Spring     191  191
## 355  400047      1 Non-Sped Native Am. FRL Non-ELL   Fall     183  182
## 387  400047      1 Non-Sped Native Am. FRL Non-ELL Winter     178  179
## 230  400277      1 Non-Sped Native Am. FRL Non-ELL Winter     199  197
## 648  400277      1 Non-Sped Native Am. FRL Non-ELL   Fall     203  196
```

Standard argument structure

- All functions in *esvis* take a common argument structure, as follows

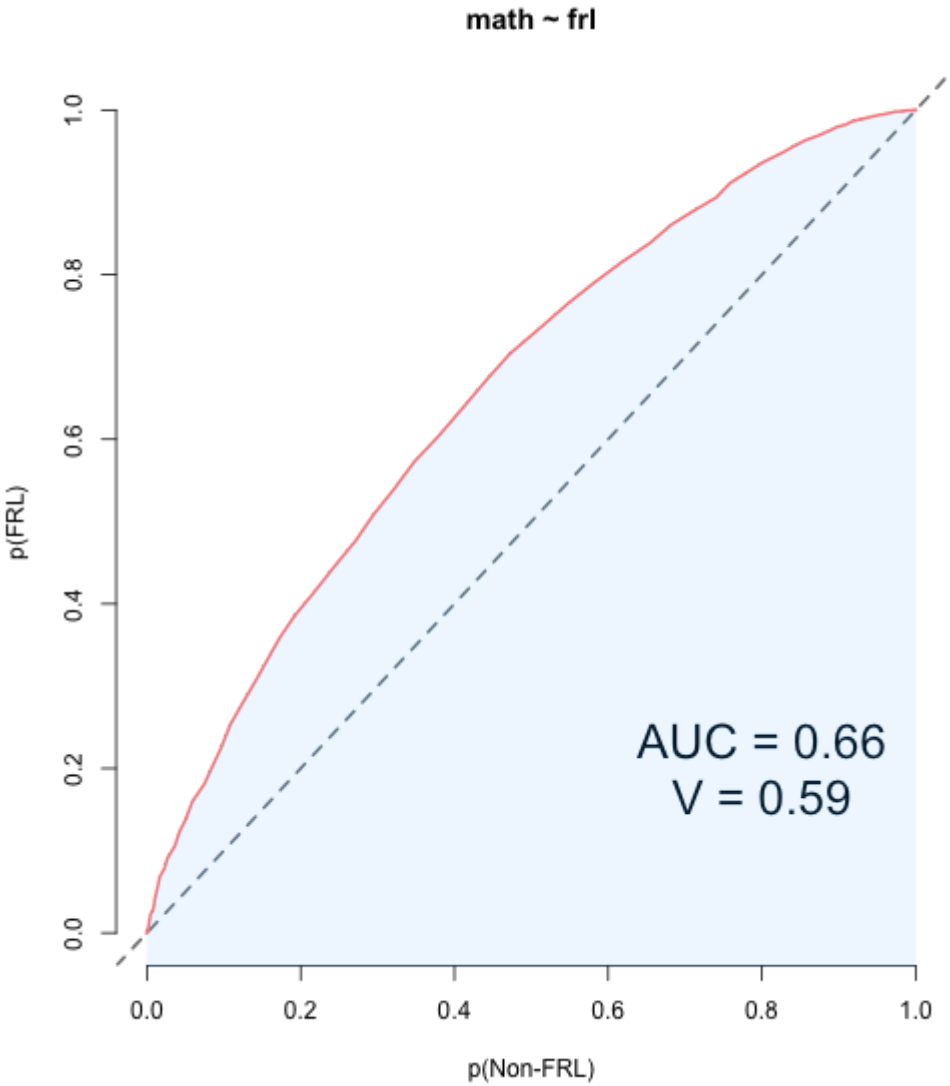
```
fun_name(outcome ~ group, data, additional_optional_args)
```

PP Plots

- Examine math differences by free or reduced lunch status

```
pp_plot(math ~ frl, d)
```

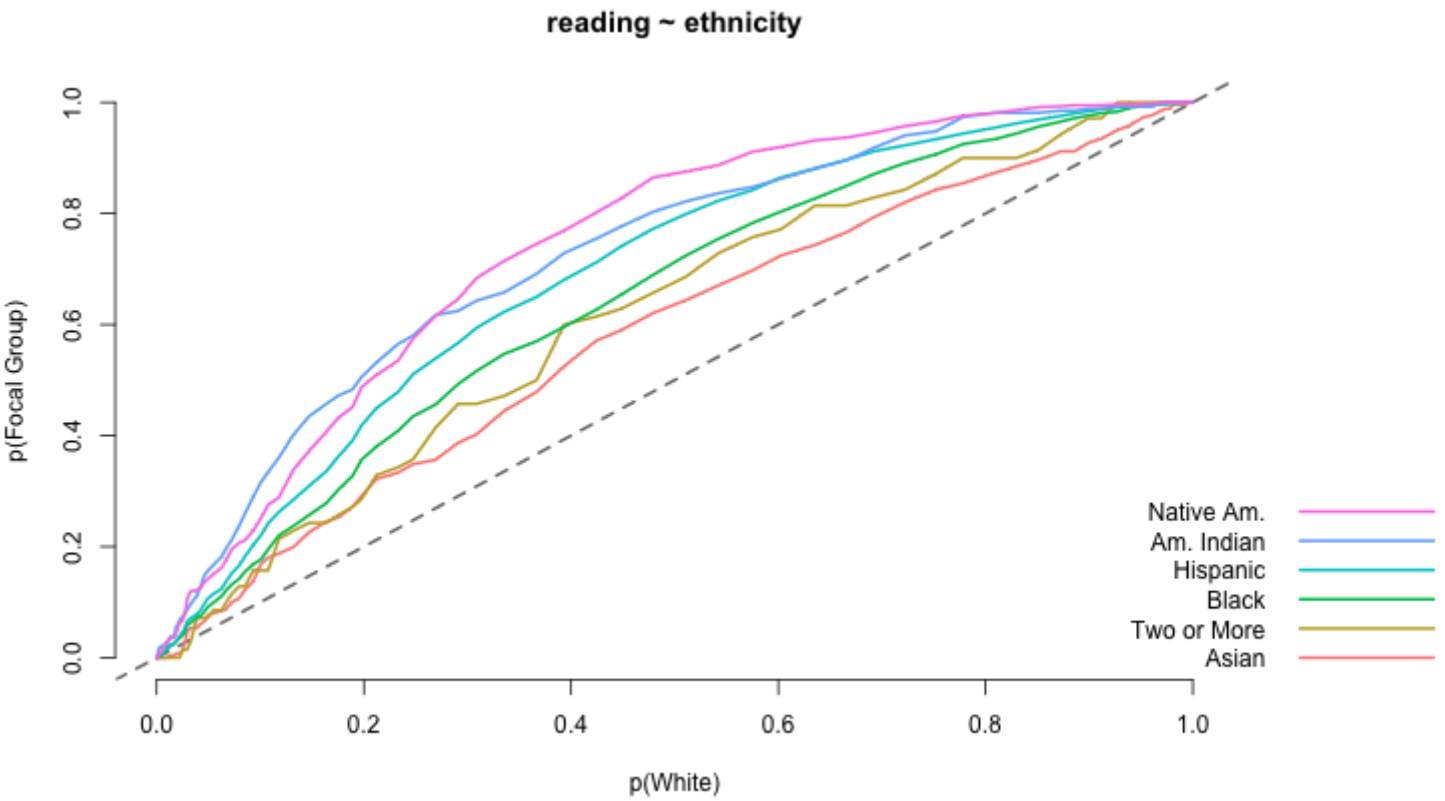
- Notice shading by default when only two groups are compared.
- *AUC* and *V* annotated to the plot, by default
- Plot is fully customizable with calls to base plotting functions (e.g., `main`, `col`, etc.)



More than one group?

- Highest performing group selected by default

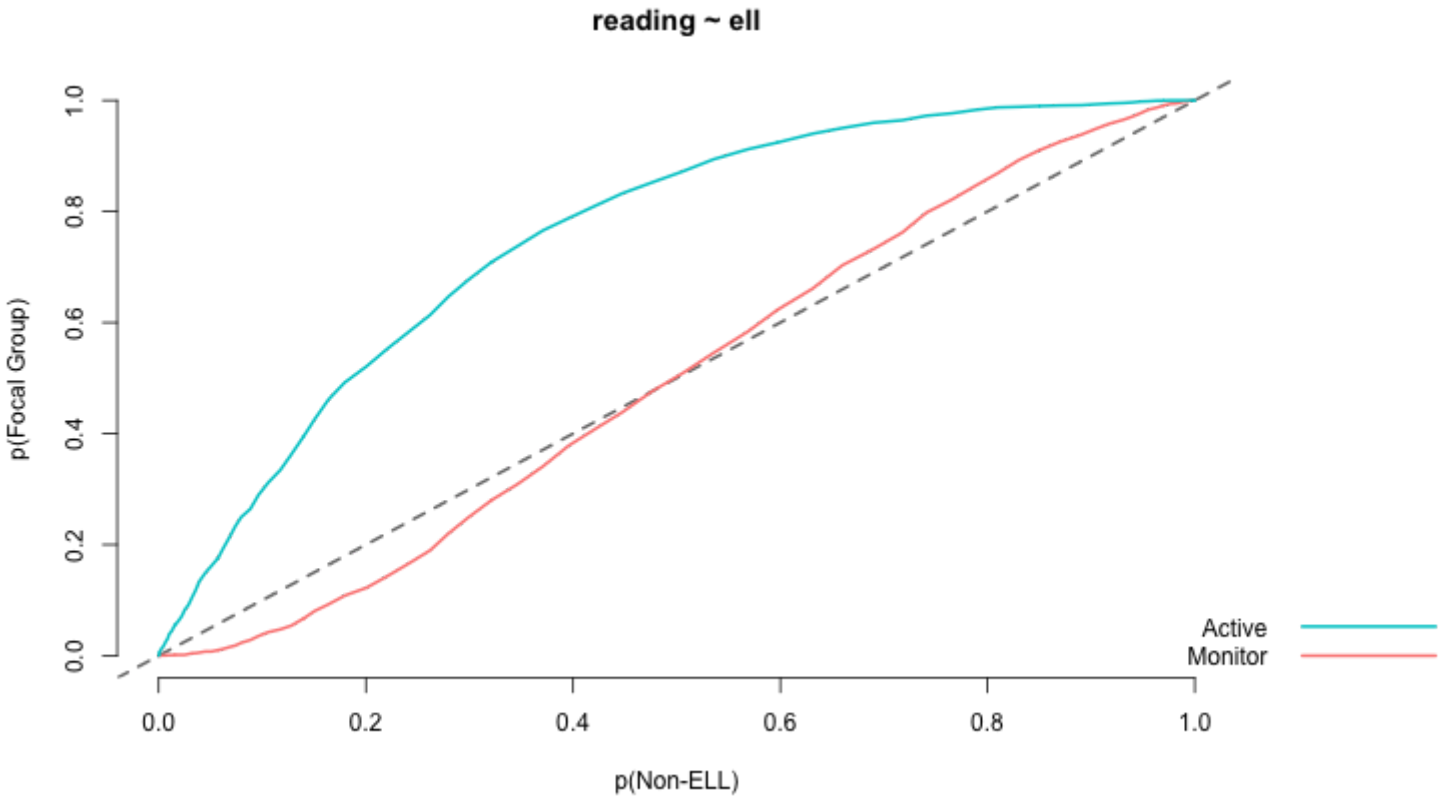
```
pp_plot(reading ~ ethnicity, d)
```



Change reference group

- Investigate differences by ELL Classification

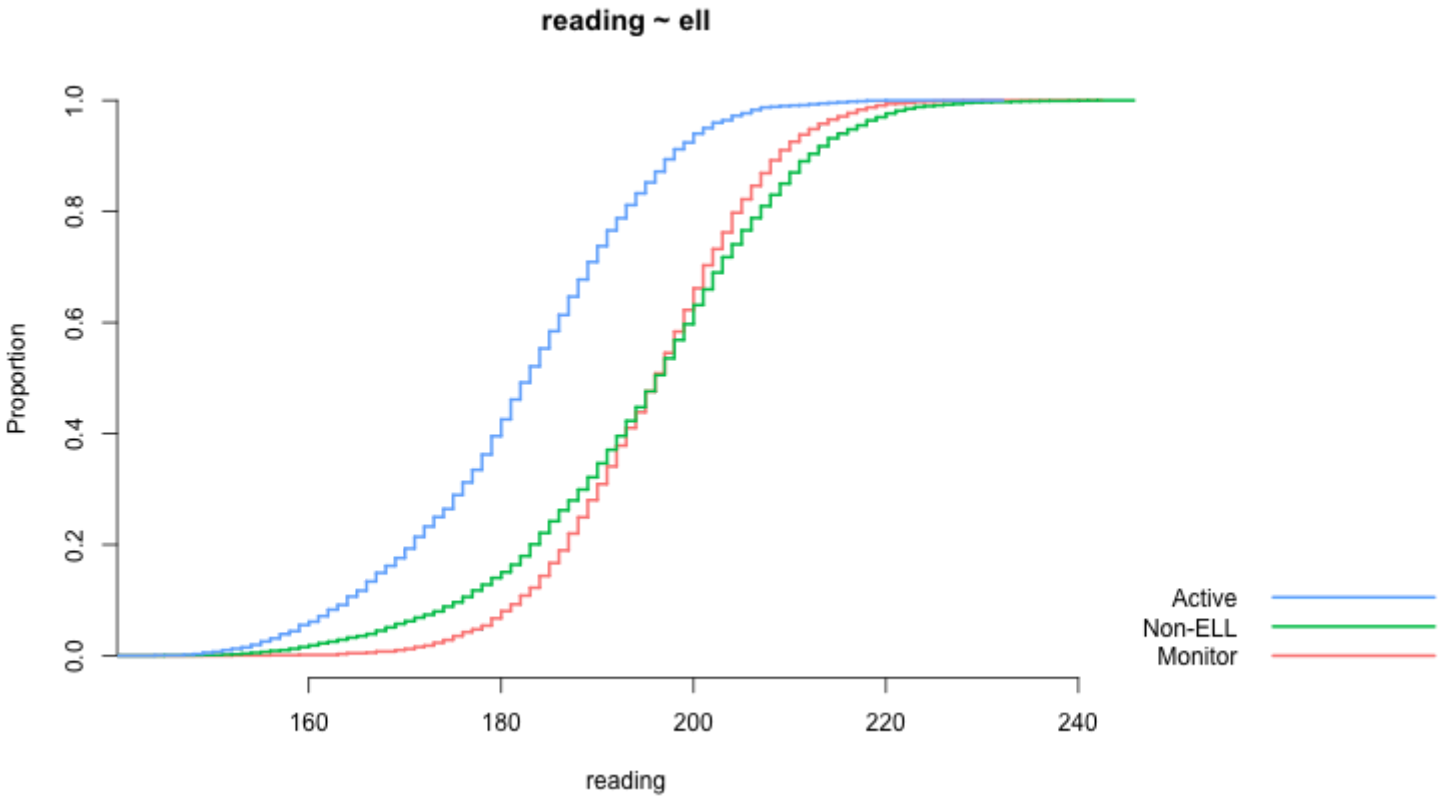
```
pp_plot(reading ~ ell, d, ref_group = "Non-ELL")
```



ECDFs

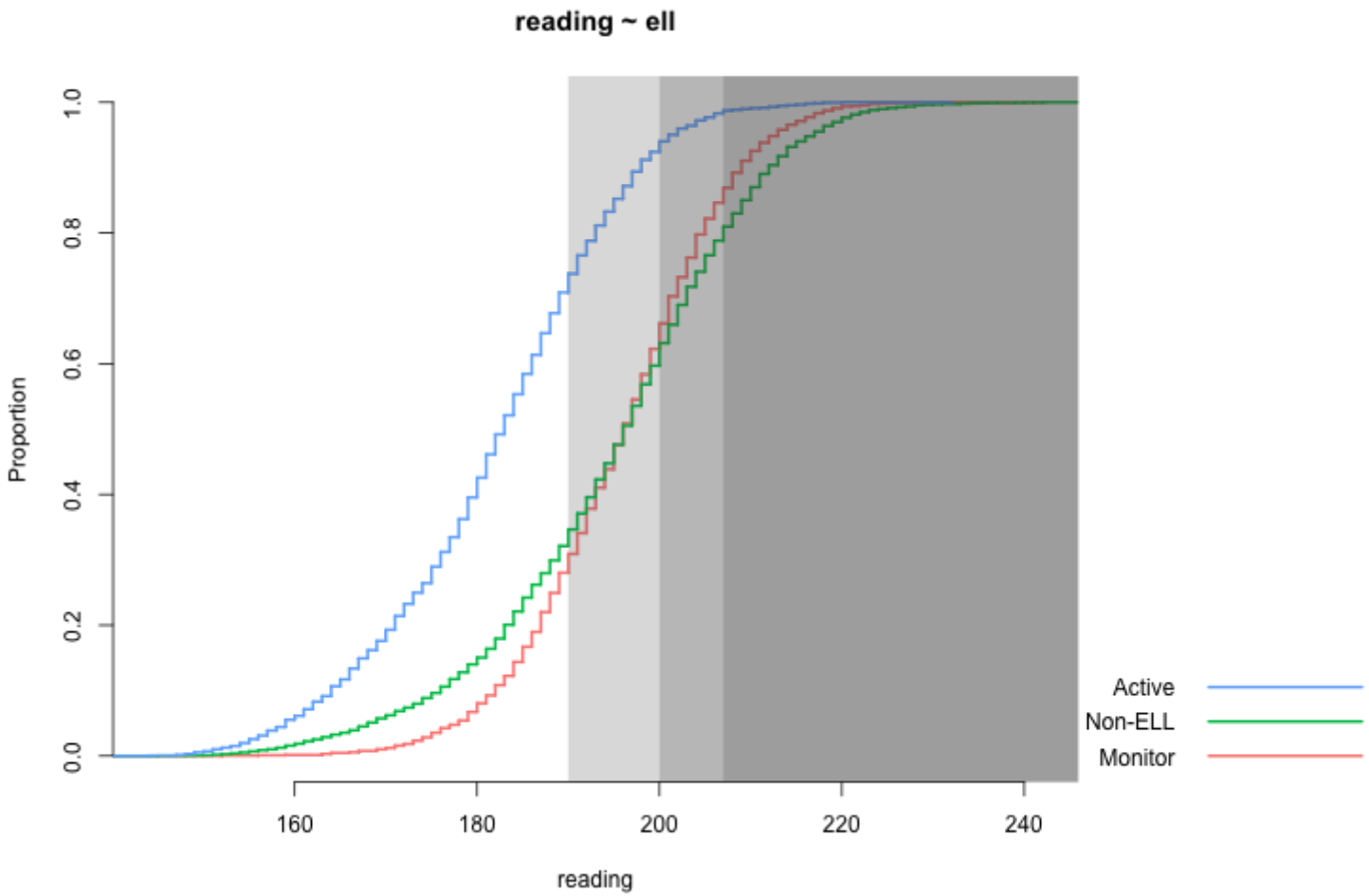
- Produced equivalently

```
ecdf_plot(reading ~ ell, d)
```



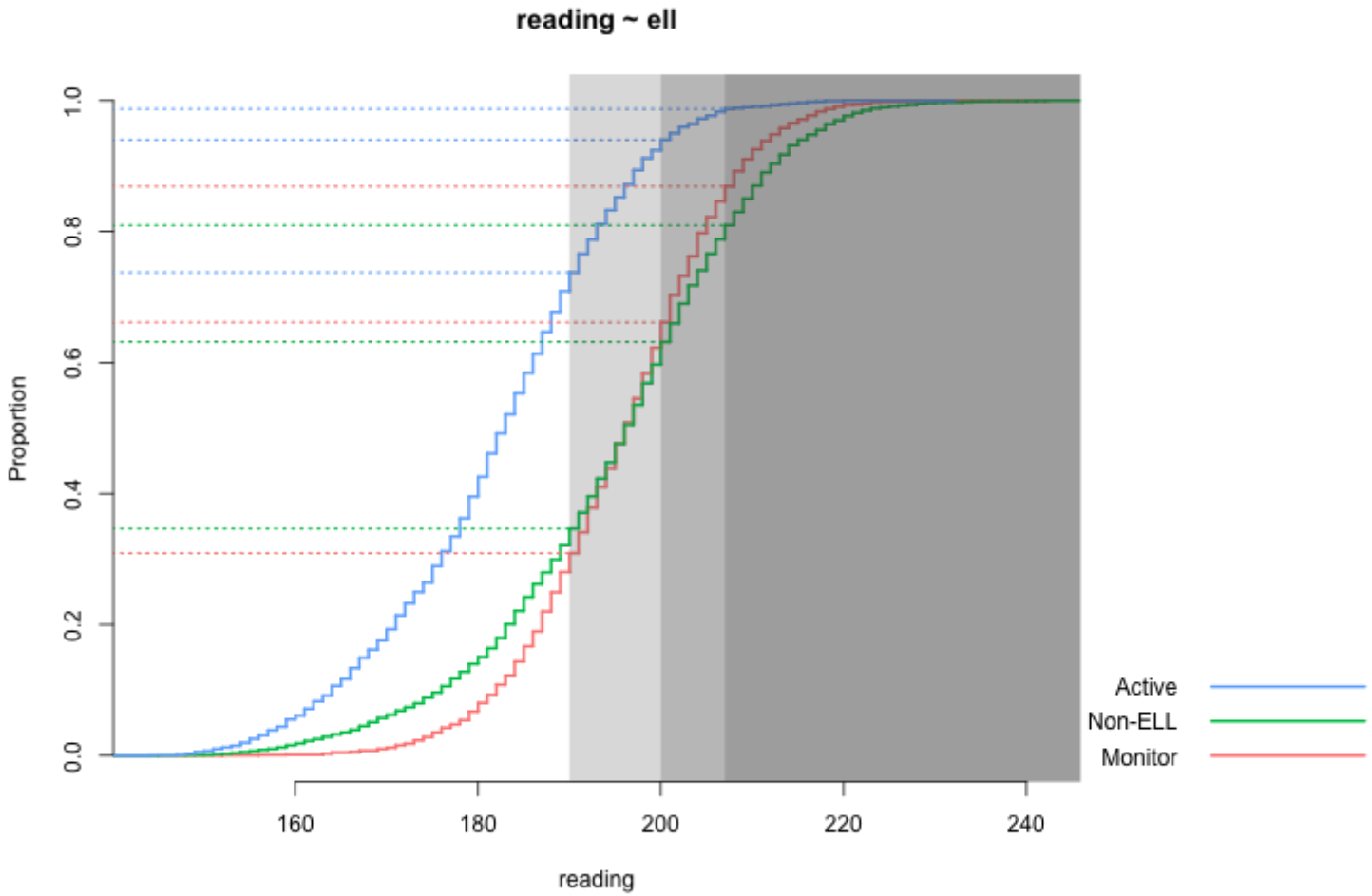
Cut-point?

```
ecdf_plot(reading ~ ell, d, ref_cut = c(190, 200, 207))
```



Add horizontal reference lines

```
ecdf_plot(reading ~ ell, d, ref_cut = c(190, 200, 207), hor_ref = TRUE)
```



Binned ES Plot

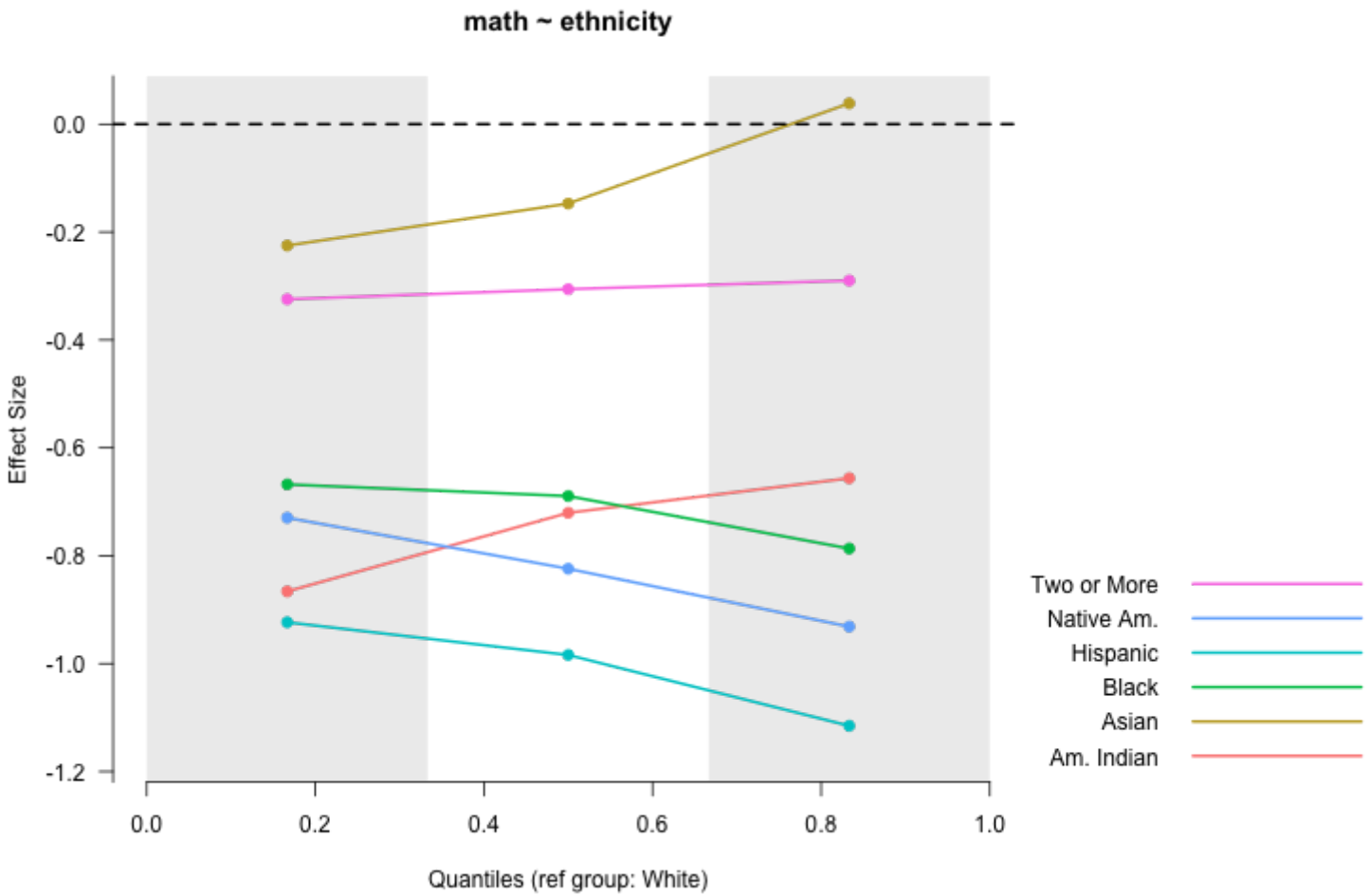
- Split each distribution into arbitrary (even) quantile bins
- Calculate mean difference within each bin
- Divide by overall pooled standard deviation

$$d_{[i]} = \frac{\bar{X}_{foc_{[i]}} - \bar{X}_{ref_{[i]}}}{\sqrt{\frac{(n_{foc}-1)Var_{foc}+(n_{ref}-1)Var_{ref}}{n_{foc}+n_{ref}-2}}}$$

- In this case, essentially equivalent to Cohen's *d*, except that there are multiple mean differences (one for each bin)

Ethnicity differences

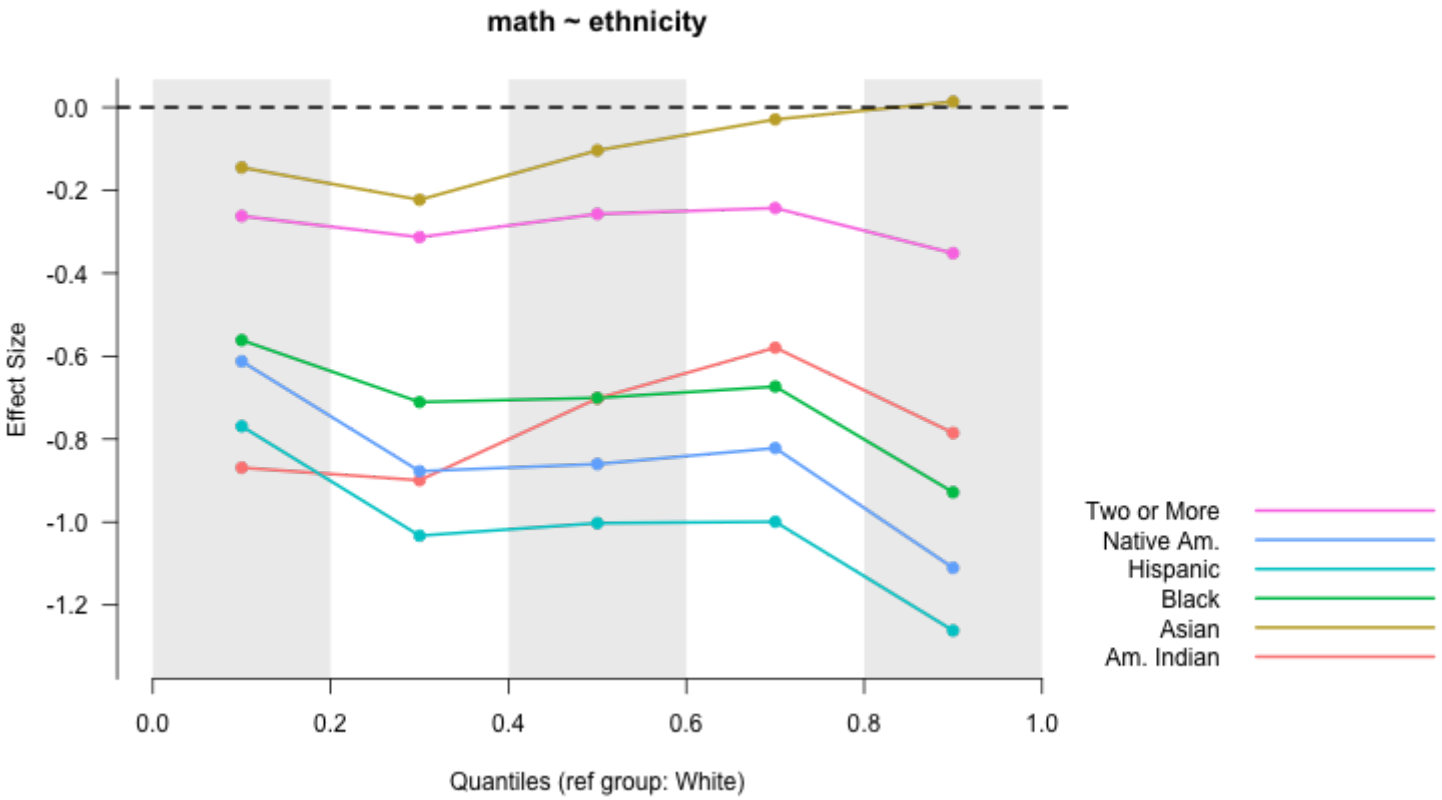
```
binned_plot(math ~ ethnicity, d)
```



Change binning

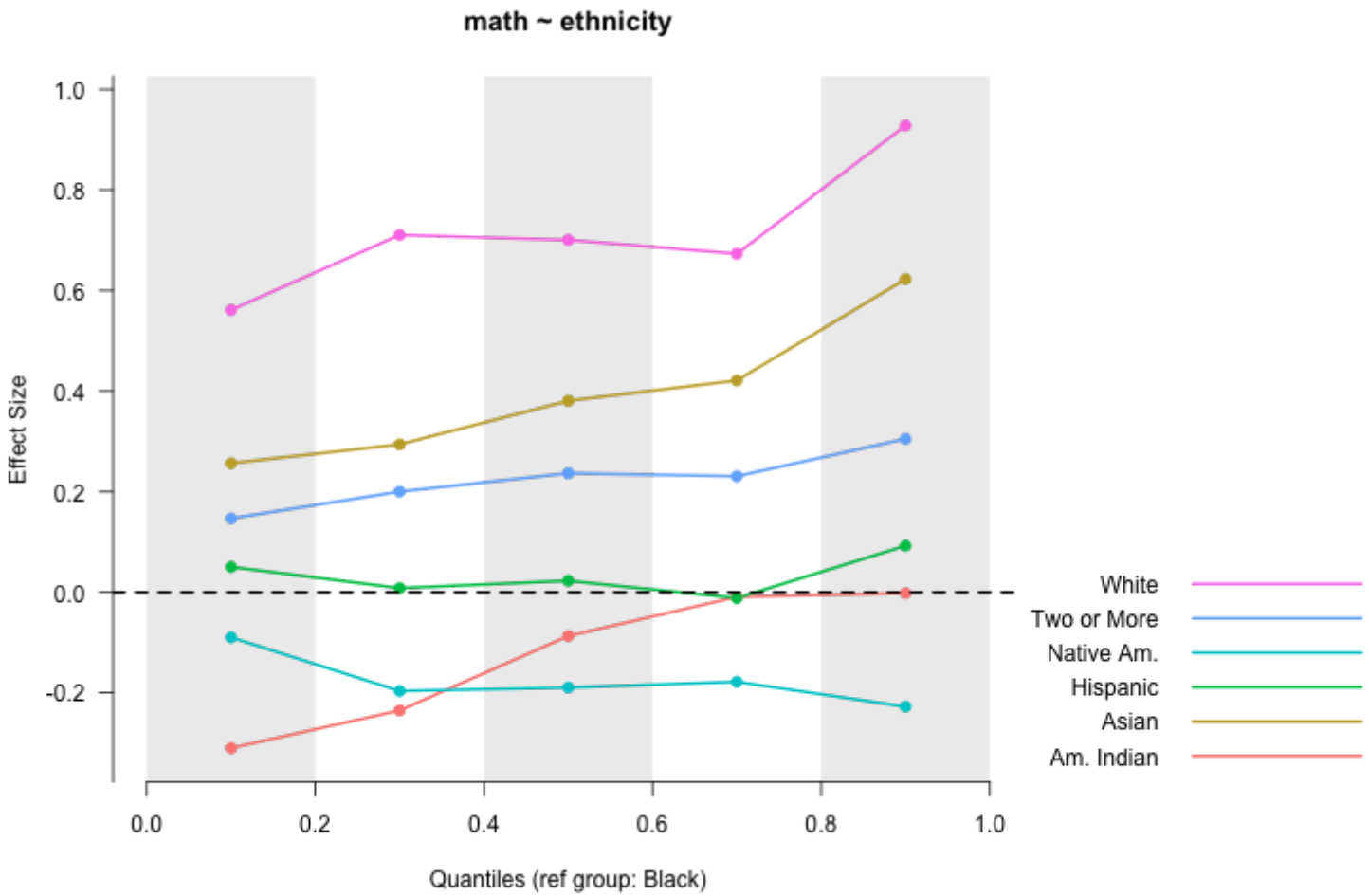
Quintile binning

```
binned_plot(math ~ ethnicity, d, qtiles = seq(0, 1, .2))
```



Change reference group

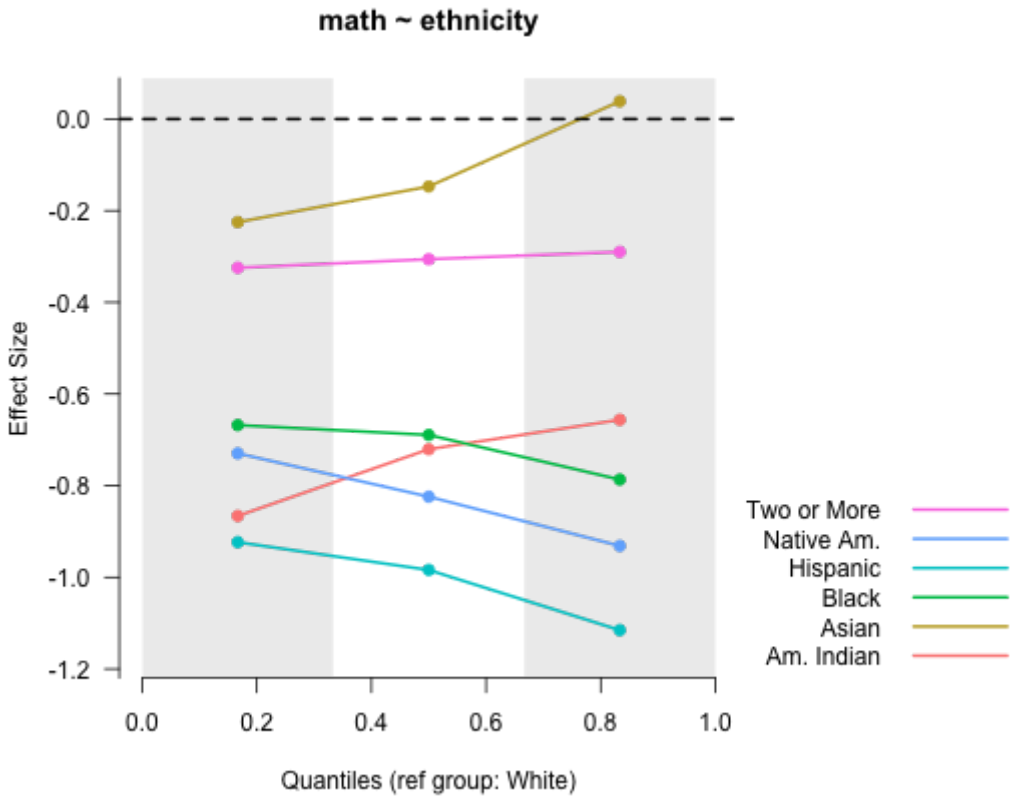
```
binned_plot(math ~ ethnicity, d, ref_group = "Black", qtiles = seq(0, 1, .2))
```



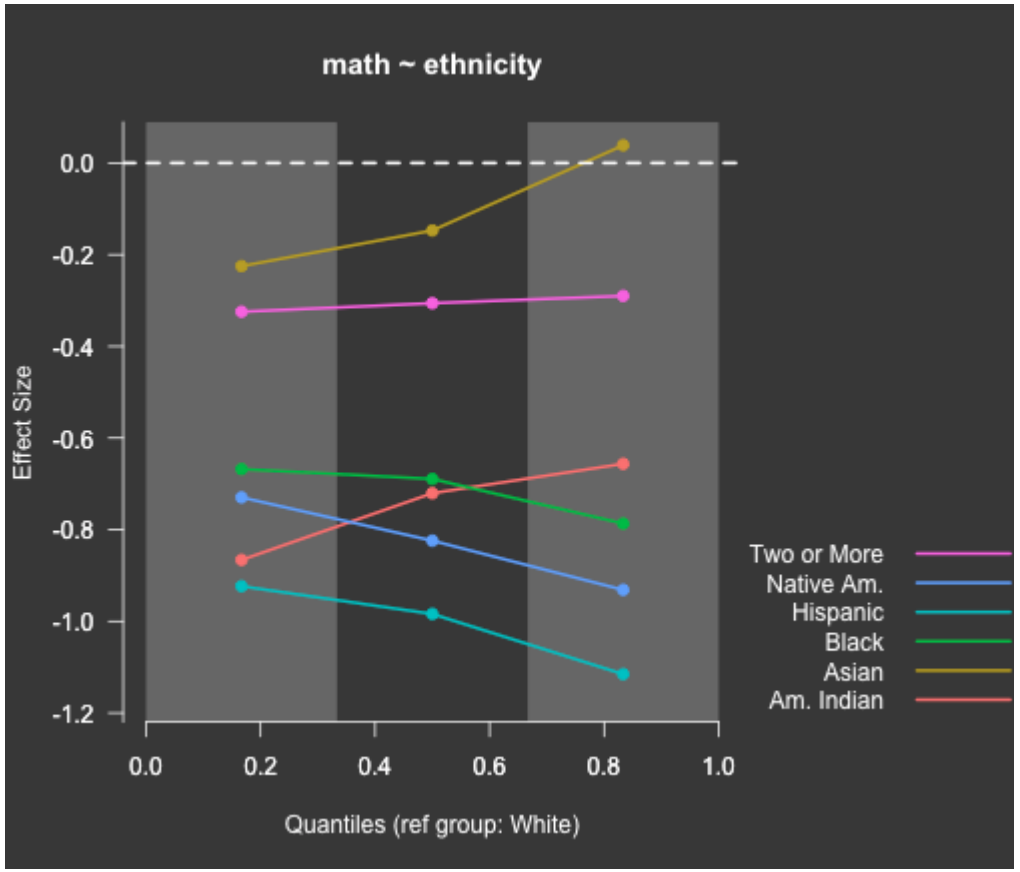
Themes (last note on plots)

- Currently standard and dark themes implemented

```
binned_plot(math ~ ethnicity, d)
```




```
binned_plot(math ~ ethnicity, d, theme = "dark"
```



Estimation (quickly)

`esvis` will also calculate a number of effect sizes using the same argument structure, including:

- Cohen's *d*
- Hedges' *g*
- *AUC*
- *V*
- *PAC* with **any set** of cut scores
- *TPAC* with **one** cut score (currently)

By default, effect sizes are produced for all possible pairwise comparisons, but reference groups can be selected as well.

```
coh_d(math ~ ethnicity, d)
```

```
##      ref_group   foc_group    estimate
## 1        White       Asian  0.10689571
## 2        White Two or More  0.30281232
## 3        White    Hispanic  1.03147010
## 4        White       Black  0.72127040
## 5        White  Am. Indian  0.76483392
## 6        White  Native Am.  0.84185433
## 7        Asian Two or More  0.07471180
## 8        Asian    Hispanic  0.72590767
## 9        Asian       Black  0.39210777
## 10       Asian  Am. Indian  0.29878405
## 11       Asian  Native Am.  0.39455423
## 12 Two or More    Hispanic  0.40811606
## 13 Two or More       Black  0.21475724
## 14 Two or More  Am. Indian  0.16297587
## 15 Two or More  Native Am.  0.24174797
## 16    Hispanic       Black  0.02423883
## 17    Hispanic  Am. Indian  0.25579261
## 18    Hispanic  Native Am.  0.30800593
## 19       Black  Am. Indian  0.12256685
## 20       Black  Native Am.  0.15962973
```

```
coh_d(math ~ ethnicity, d, "White")
```

```
##   ref_group   foc_group  estimate
## 1     White       Asian 0.1068957
## 2     White Two or More 0.3028123
## 3     White    Hispanic 1.0314701
## 4     White       Black 0.7212704
## 5     White  Am. Indian 0.7648339
## 6     White  Native Am. 0.8418543
```

```
pac(math ~ ethnicity, d, cut = c(190, 200, 207), ref_group = "White")
```

```
##    ref_group   foc_group cut    estimate
## 1      White       Asian 190 0.091192628
## 2      White Two or More 190 0.105914547
## 3      White    Hispanic 190 0.204674477
## 4      White       Black 190 0.194817998
## 5      White  Am. Indian 190 0.281166804
## 6      White  Native Am. 190 0.293704535
## 22     White       Asian 200 0.067726906
## 23     White Two or More 200 0.138174016
## 24     White    Hispanic 200 0.265801628
## 25     White       Black 200 0.258117222
## 26     White  Am. Indian 200 0.262496905
## 27     White  Native Am. 200 0.328528106
## 43     White       Asian 207 0.006063335
## 44     White Two or More 207 0.085670751
## 45     White    Hispanic 207 0.183788361
## 46     White       Black 207 0.182983988
## 47     White  Am. Indian 207 0.180997357
## 48     White  Native Am. 207 0.241836807
```

Summary and future developments

- Visualizing group differences across the full scale, or at particular points of the scale, is important for interpretation and communication.
- `esvis` provides a simple interface to produce powerful visualizations

Future development

- Interactions with `:`
- Interactions via panel plotting
- Others?

Slides available at: https://djanderson07.github.io/ncme_2017/

Thanks!