Item Characteristic Curves generated from common CTT Item Statistics

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Introduction

Item characteristic curves are frequently referenced by psychometricians as visual indicators of important attributes of assessment items - most frequently *difficulty* and *discrimination*. This information is conveyed through item characteristic curves (see 1 for reference). Assessment specialists who examine ICC's usually do so from within the psychometric framework of either Item Response Theory (IRT) or Rasch modeling. We previously provided an extension of this tradition of item characteristic visualization within the more commonly leveraged Classical Test Theory (CTT) framework. This current study builds on the first and focuses on placing the CTT p-value on the IRT b-parameter metric.
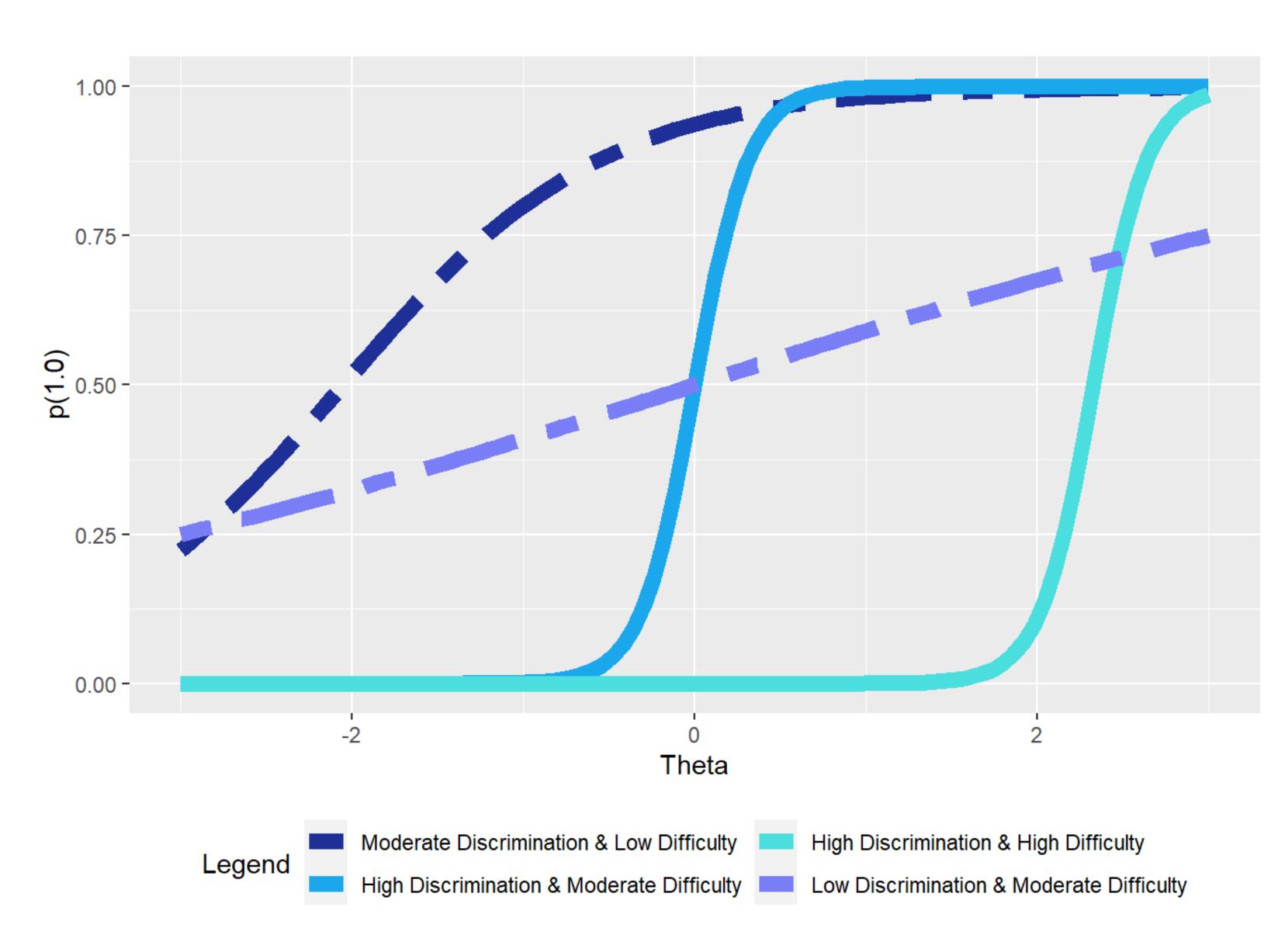

Figure 1: Item characteristic curves reflecting visual differences in difficulty and discrimination.

Method

We built six simulations of binary data, each with different shapes and p-values, as can be seen in 2. Each simulation consisted of 10,000 observations and 100 items. Simulation 1 was uniform, with p-values ranging from 0 to 1. Simulation 2 was a normal distribution with p-values centered around 0.5. Simulation 3 was an inverted U-shaped distribution, with p-values ranging from 0 to 1. Simulation 4 was a left skewed distribution with p-values centered around 0.5, and simulation 5 was a right skewed distribution with p-values centered around 0.5.

We regressed b-parameters onto z_g indices of all simulations, and used the average slope and intercept to rescale *p-values* on a psuedo-θ scale for graphing purposes.
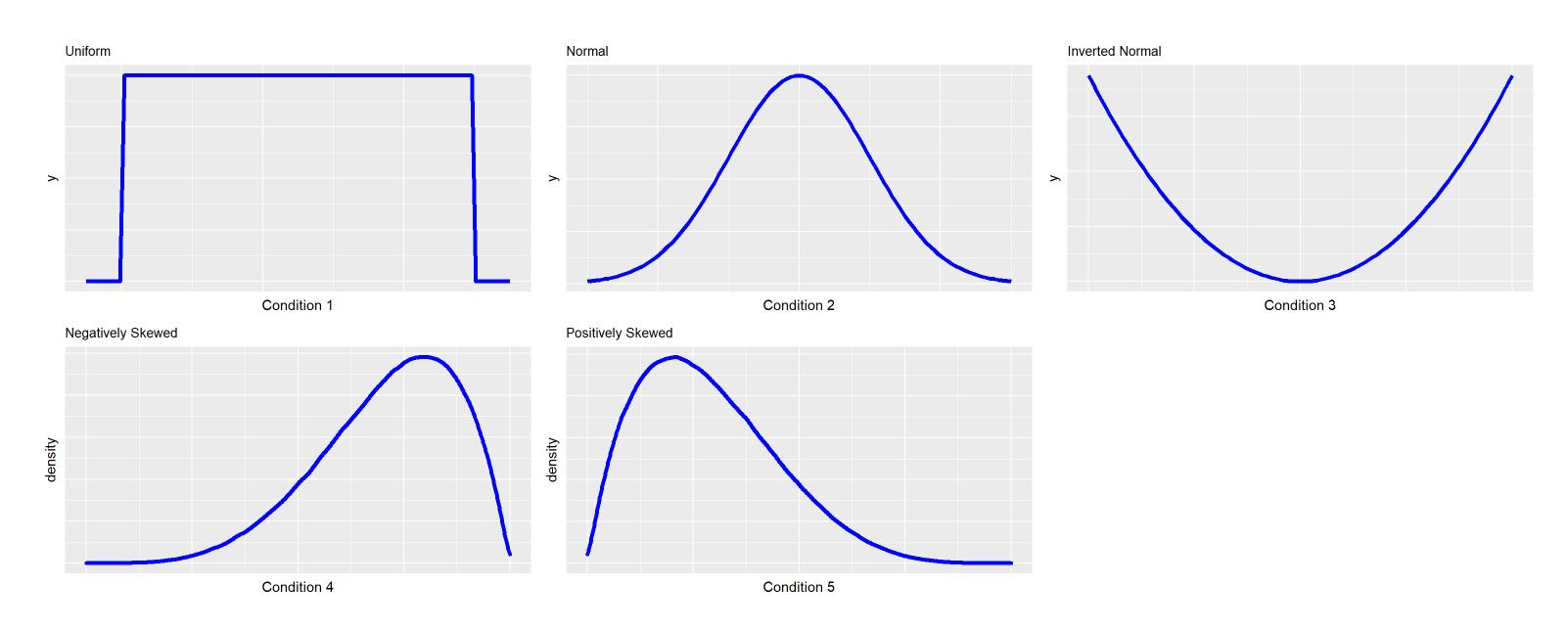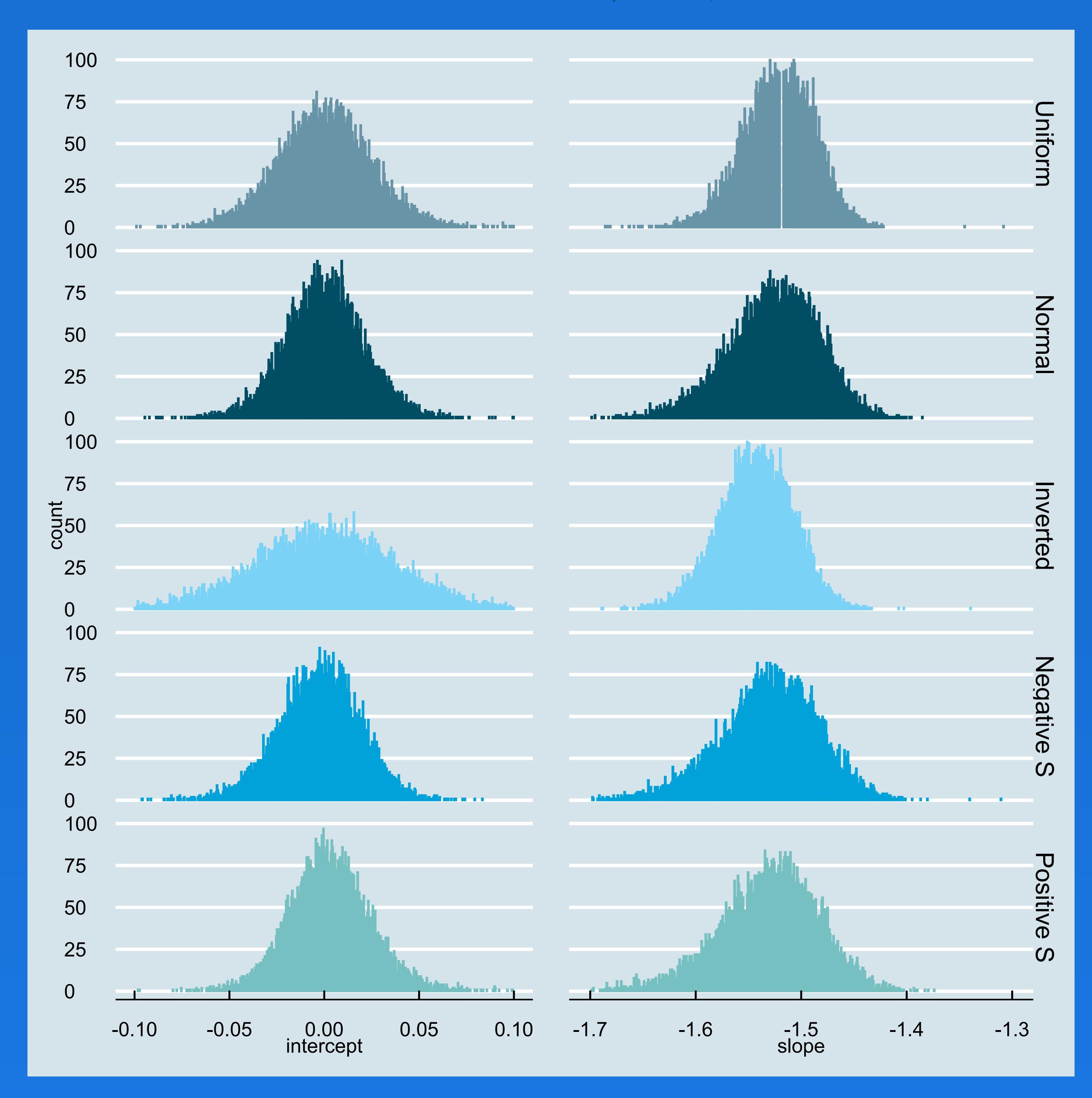

Figure 2: Shape of prescribed distributions of p-values across Study 1 conditions.

Results

The resulting regression coefficients for all 5 simulations was an average intercept of approximately 0 and an average slope of -1.53. *note: include the actual statistics A hierarchical regression showed no interaction effect between the different simulated

conditions, indicating that our scaling was not sample dependent, as can be seen in **??**. In this graph we report the distribution of slopes for all 1,000 simulations per simulation condition. They are all centered at about -1.53, with very little deviance in terms of shape, kurtosis, or spread. There were 3383 cases removed from the overall 500000 simulated items due to extreme b-estimates. The area between ICC's was calculated between CTT-derived and IRT-derived ICC's. The average difference for all 100 curves was 0.214. As we can see in **??**, most of the data is skewed towards the lower end, indicating that out of the 100 items, most of them have areas between the curves of less than 0.21. This diff was computed after scaling our Zg using the coefficients estimated with our simulations. Without the regression coefficient modifier the average area under the curves were 0.80, as we can see in **??**. We ran a test of significance between these two means. Our results are t(99) = 11.72, p < .001.

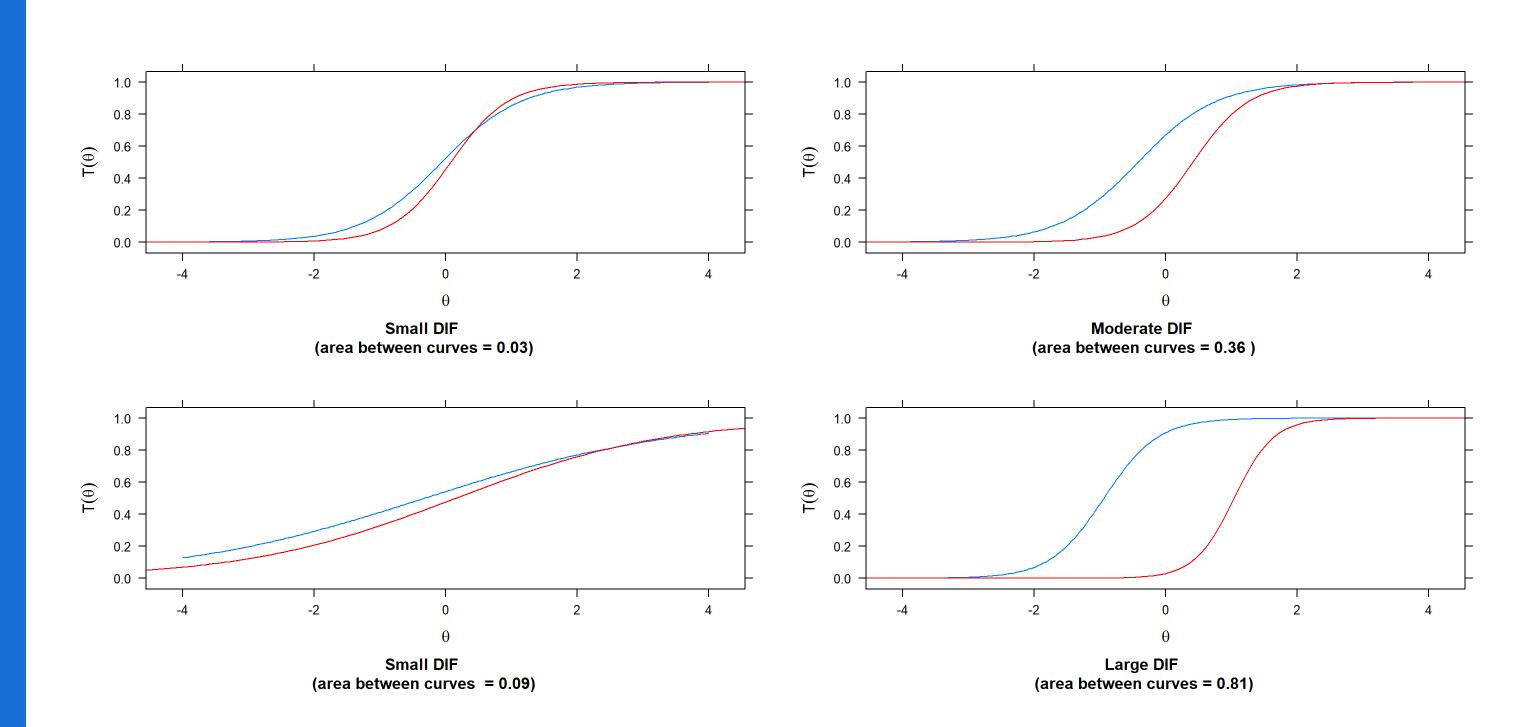
Figure 3: Four ICCs highlighting the difference between CTT and IRT-derived ICCs at different levels of DIF.
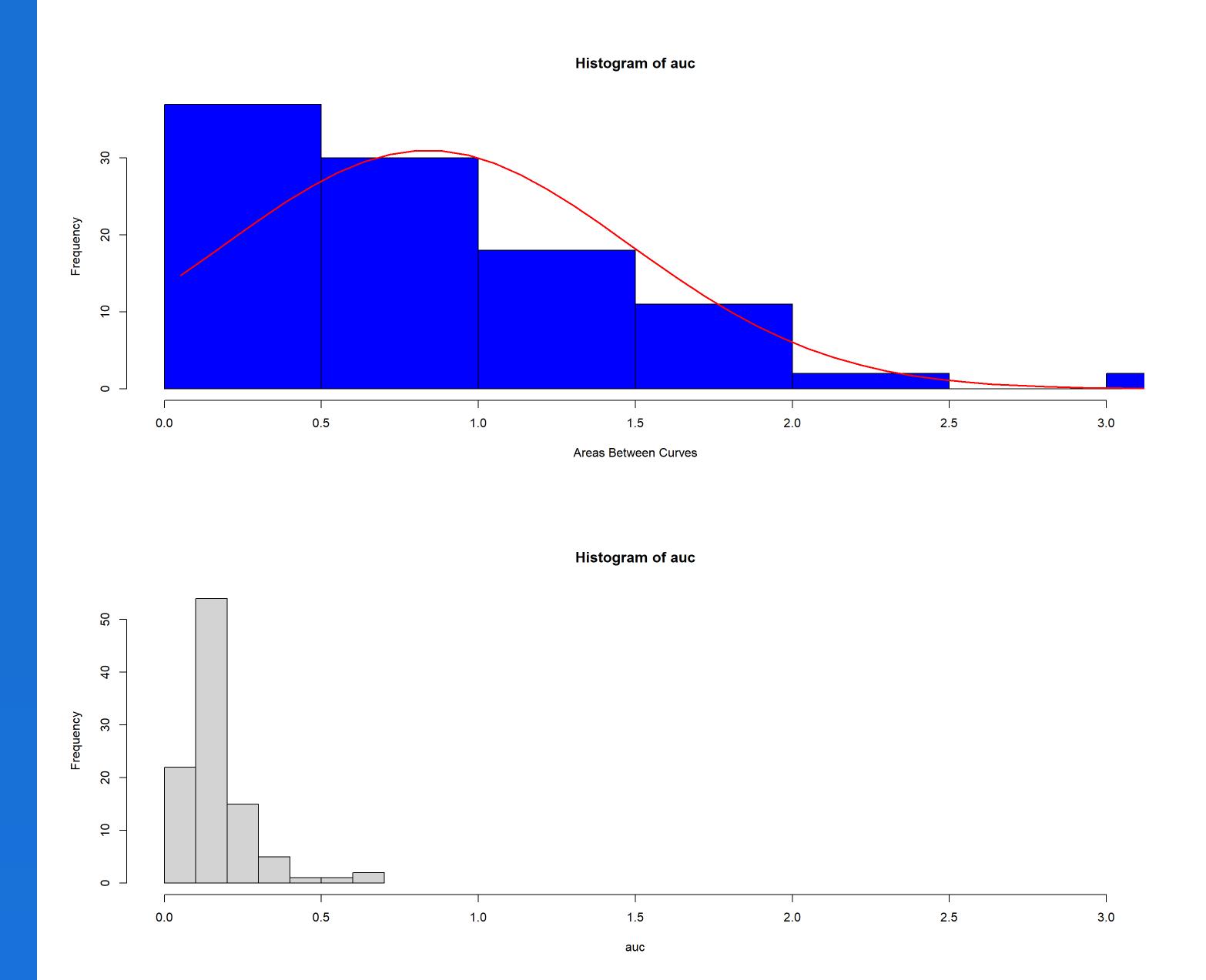

Figure 4: Histogram of all areas between ICCs plotted using IRT parameters vs ICCs plotted using CTT parameters.

Discussion

Although invariance is a property historically associated exclusively for IRT applications, large scale data, truly random sampling, and large range items can also yield stable CTT item and person statistics (Fan, 1998; Kulas et al., 2017). The current investigation scaled the CTT p-value to the IRT b-parameter. The linking equation was relatively invariant across simulations. Our most relevant finding was that there was no interaction effect between simulated conditions. We are currently working on using real world data to cross-validate the findings from these simulations. We created an R package that generates these CTT-derived ICCs (https://github.com/MontclairML/ctticc). This poster was crafted via posterdown (Thorne, 2019).