Detecting DIF between Conventional and Computerized Adaptive Testing: A Monte Carlo Study

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## Introduction

- Instruments are being transitioned from paper-and-pencil (P&P) to computerized adaptive modes of administration.
- Problems arise when item parameters used by CAT are estimated from P&P.
- Mode effects can diminish measurement reliability and validity and increase error in trait estimates (Pommerich, 2007).

## Problem

- Differential item functioning (DIF) refers to differences in level of item endorsement between two or more groups after controlling for differences in ability.
- Most DIF methods are designed for use within mode but not between mode of administration.
- Differences in level of missing item responses between modes.

## **Purpose and Rationale**

- Develop and evaluate approaches to assessing item-level mode effects.
- Bayesian methods can provide more accurate results compared to conventional approaches.
  - Take into account uncertainty in trait and item parameter estimates.

## **DIF** Procedure

- 1. Estimate  $\theta$  using item response data pooled across administration modes (CAT and P&P).
- 2. Using  $\theta_i$  obtained in Step 1, estimate the posterior distributions of mode-specific item parameters.
- 3. For each item common across modes, assess the difference in the posterior distributions of the item parameters (i.e., between  $\beta j^{CAT}$  and  $\beta j^{P&P}$ ).

#### **Comparing Posterior Distributions**

- Two approaches.
  - Modified robust Z statistic (Huynh & Meyer, 2010).
  - 95% Credible Interval for mean difference between  $\beta_i^{CAT}$  and  $\beta_i^{P&P}$ .

## Modified Robust Z

Robust 
$$Z_j = \frac{Med(\beta_j^{CAT} - \beta_j^{P\&P})}{0.74(IQR[\beta_j^{CAT} - \beta_j^{P\&P}])}$$

- Med = median of the differences in the CAT and P&P item parameters based on their posterior distributions.
- *IQR* = interquartile range of the difference.

#### **Priors and Generated Parameters**

Parameter	Prior	Generated
Discrimination	<i>LN</i> (0.0,0.5)	1PLM: 1.0
		2PLM: <i>LN</i> (0.0,0.5)
Difficulty	Normal(0.0,2.0)	Uniform(-3.0,3.0)
Ability	Normal(0.0,1.0)	<i>Normal</i> (0.0,1.0)

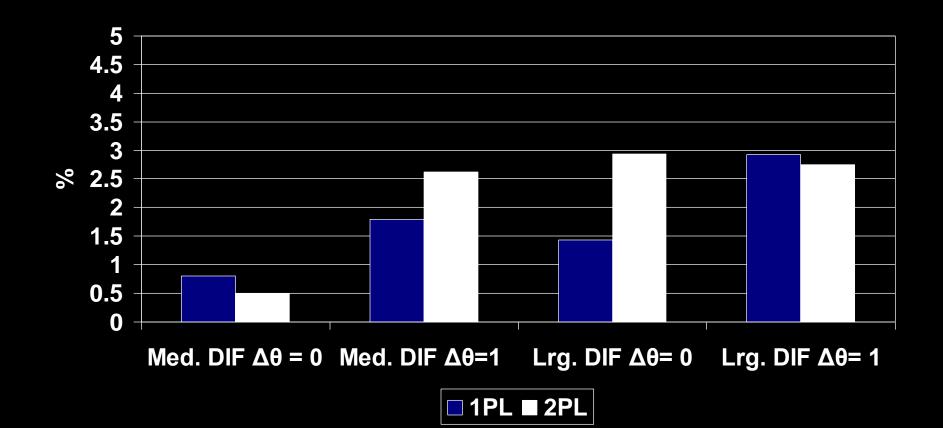
# Monte Carlo Study

- Two sets of P&P item parameters generated using previous criteria fitting one- (1PLM) and two-parameter (2PLM) IRT models.
- Item response data generated using each set of parameters.
- Parameters then estimated using maximum likelihood (Mplus).

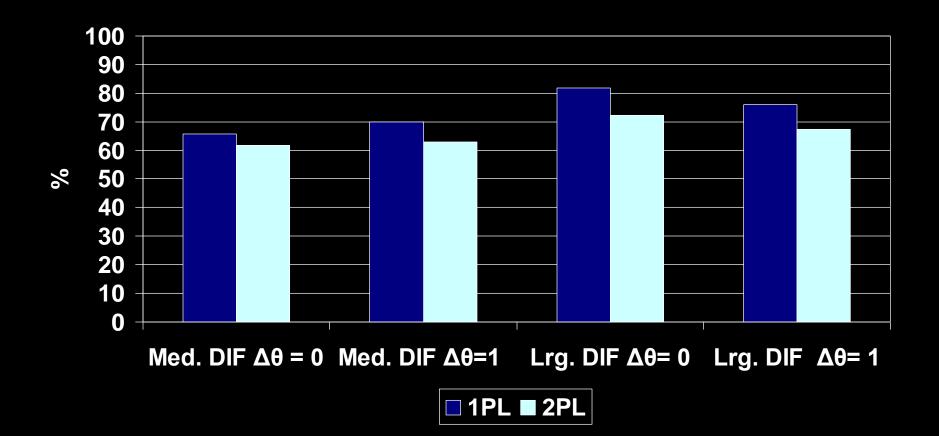
# Monte Carlo Study cont.

- CAT item response data were generated using the following variables:
  - % of DIF items (10% vs. 30%).
  - Magnitude of DIF  $|\beta_i^{CAT} \beta_i^{P\&P}| = 0.42 \text{ vs. } 0.63.$
  - Mean difference in  $\theta$  between CAT and P&P samples (0 vs. 1 logit).
  - Direction of DIF was randomized.
  - 10 datasets generated per condition.
- CAT simulations: Firestar 1.33 (Choi, 2009).
- Bayesian Analysis: WinBUGS 1.43 (Spiegelhalter et al., 2007).
- Sample Size:
  - P&P Data: N = 1,000.
  - CAT Data: N = 3,000.

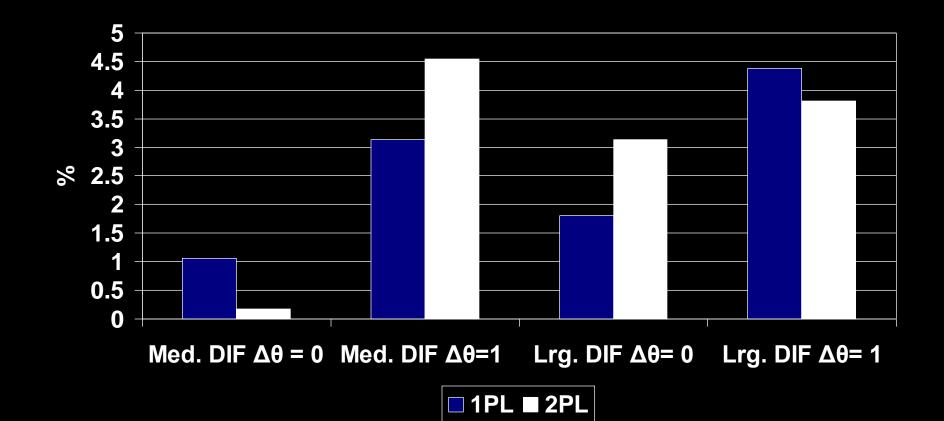
#### Robust Z: False Positive Rate



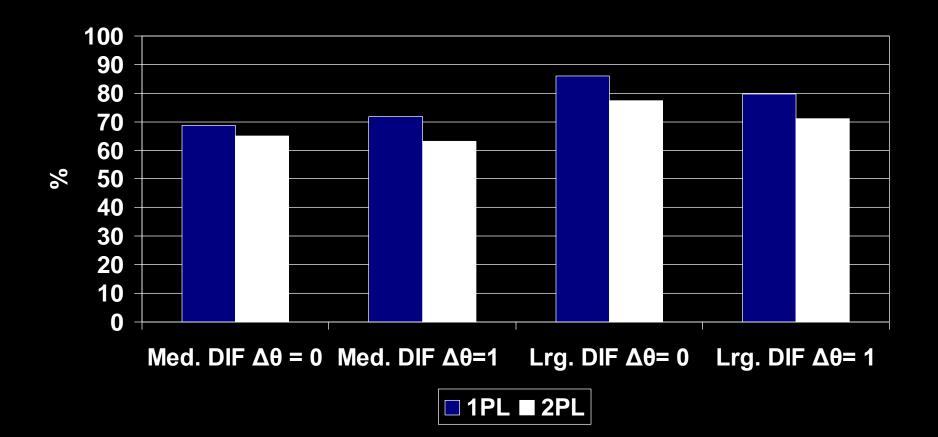
#### Robust Z: True Positive Rate



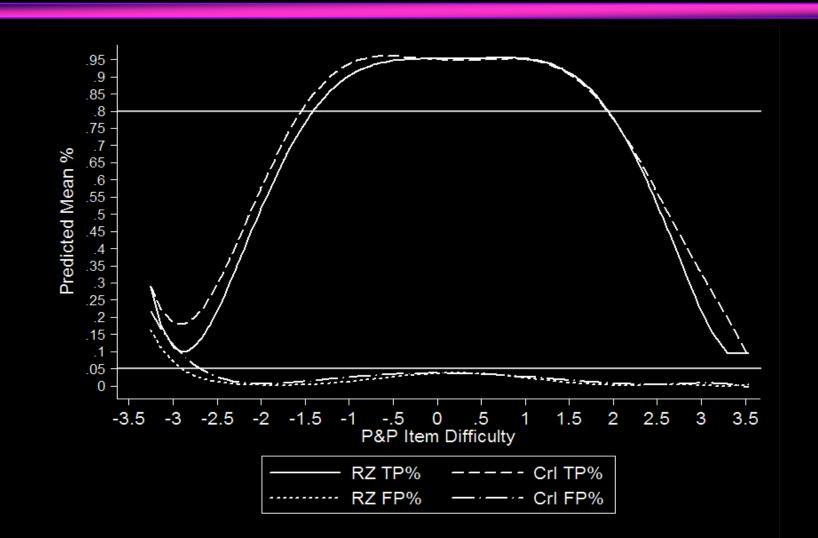
#### **Crl: False Positive Rate**



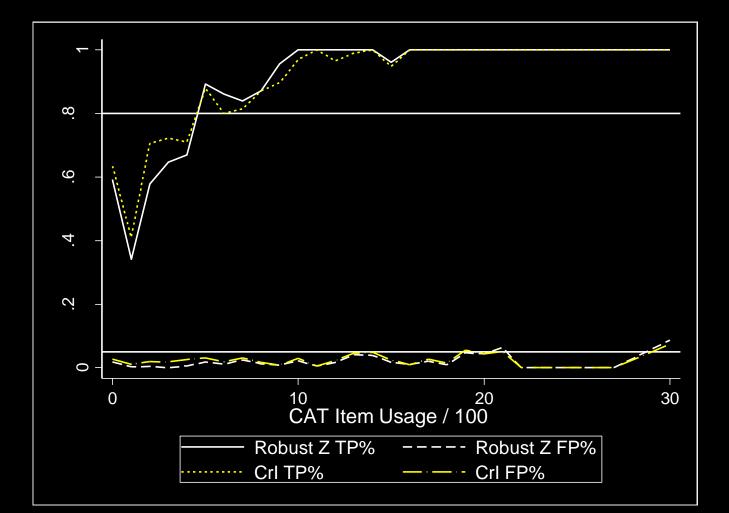
#### Crl: True Positive Rate



#### Performance by Item Difficulty



#### True & False Positive Rates by CAT Item Usage



## Conclusions

- Both procedures evidenced adequate control of false positive DIF results.
  - Exception: low difficulty items (< -2.5 logits).
  - Not significantly affected by % of DIF items.
  - Was affected by mean trait level difference.
- Crl evidenced slightly higher power to detect DIF, but also higher false positive rate.

## Conclusions cont.

- Power to detect DIF varied considerably, and was affected by several factors, including:
  - Item usage.
  - DIF size.
  - IRT model.
  - Mean difference in trait estimates.
  - Item difficulty.

#### **Future Research**

- Test robustness of procedures to data that do not conform to prior assumptions.
  - Skewed ability and item parameter distributions.
- Detecting non-uniform DIF.

#### References

Choi SW: Firestar: Computerized adaptive testing simulation program for polytomous IRT models. Applied Psychological Measurement 2009, 33(8):644-645. Huynh H, Meyer P: Use of robust z in detecting unstable items in item response theory models. In Practical Assessment Research & Evaluation. Volume 15. 2010. Pommerich M: The effect of using item parameters calibrated from paper administrations in computer adaptive test administrations. Journal of Technology, Learning, and Assessment 2007, **5**(7):1-29. Spiegelhalter D, Thomas A, Best N, Lunn D: WinBUGS version 1.4. 3 user manual. Cambridge, United Kingdom: MRC Biostatistics Unit; 2007.

## Thank You

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