

Sending Value-Added into Tailspin: A Simulation Study of Measurement Error and Nonrandom Sorting

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Oct 11, 2013

Acknowledgment: This work was supported in part by a Pre-Doctoral Training Grant from the Institute for Education Sciences, U.S. Department of Education (Award #R305B090011) to Michigan State University and an IES Statistical Research and Methodology Grant (Award #R305100028). The opinions expressed are those of the authors and do not represent views of the IES or the U.S. Department of Education.

Introduction

- ▶ Accurate teacher value-added measures in high demand
- ▶ Bias caused by measurement error increasingly a concern
- ▶ Some districts and states moving toward estimators that try to correct for measurement error

Research Questions:

1. How does measurement error affect teacher evaluation measures?
2. Which teachers most affected by bias ?
3. Do measurement error corrections reduce bias in VAMs?

Findings:

- ▶ Measurement error can generate noticeable bias, particularly for teachers with students in tails
- ▶ Measurement error correction techniques work well when assignment based on true scores
- ▶ Work less well when assignment based on observed scores
- ▶ Test score ceilings and floors are a less important issue

Background on Measurement Error in Test Scores

- ▶ Measurement Error
 - ▶ State achievement tests composed of finite number of test items (40-50 questions)
 - ▶ With small number of test items, have imperfect measures of student ability
 - ▶ There are other sources of measurement error as well
- ▶ This measurement error can cause bias in value-added estimates

Data Generating Process

$$A_{i3}^* = \lambda A_{i2}^* + \beta_{i3} + c_i + u_{i3}$$

- ▶ DGP based on true scores
- ▶ A_{ig}^* - true achievement level of student i in grade g
- ▶ β_{ig} - teacher effect
- ▶ c_i - student learning heterogeneity
- ▶ u_{ig} - idiosyncratic error term independent across students and time

Model and Empirical Approach

Value-Added Model and Estimators

Considering Model:

$$A_{ig} = \lambda A_{ig-1} + T_{ig}\beta + c_i + u_{ig} + v_{ig} - \lambda v_{ig-1}$$

Examine Performance of:

- ▶ DOLS: OLS estimation
- ▶ EIVReg: Errors in Variables Regression - uses average measurement error variance
- ▶ Colorado Growth Model

Simulation Design

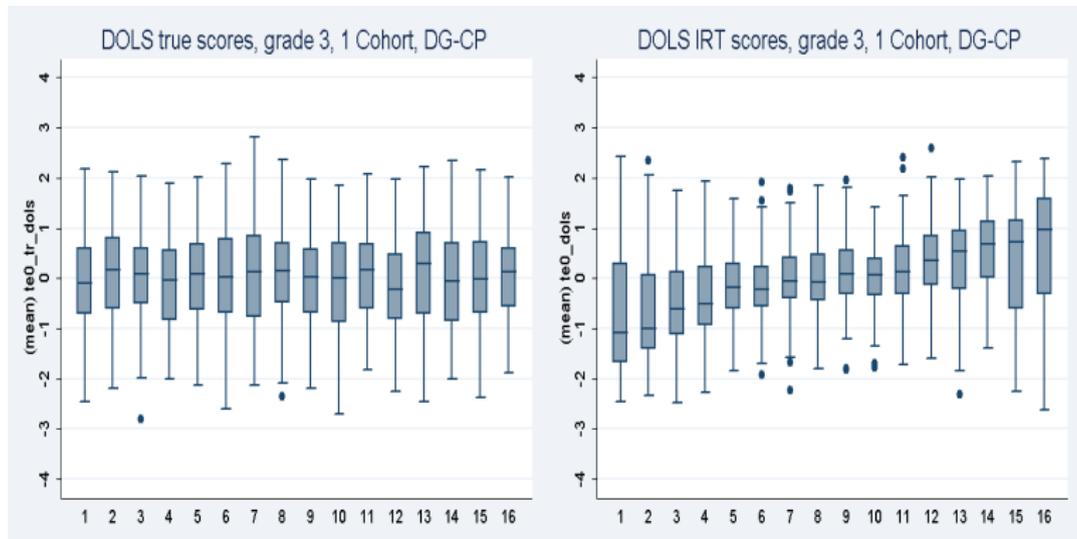
Simulation Parameters

- ▶ Grade 3 plus a base year
- ▶ 320 Students
- ▶ 16 teachers
- ▶ 1 School
- ▶ Class size fixed at 20
- ▶ 100 Simulation Reps

Test Score Generation

- ▶ Test scores generated based on 3 parameter Logistic IRT model
- ▶ Item parameters come from large, diverse southern state's test
- ▶ Estimate A_{ig} by MLE

DOLS

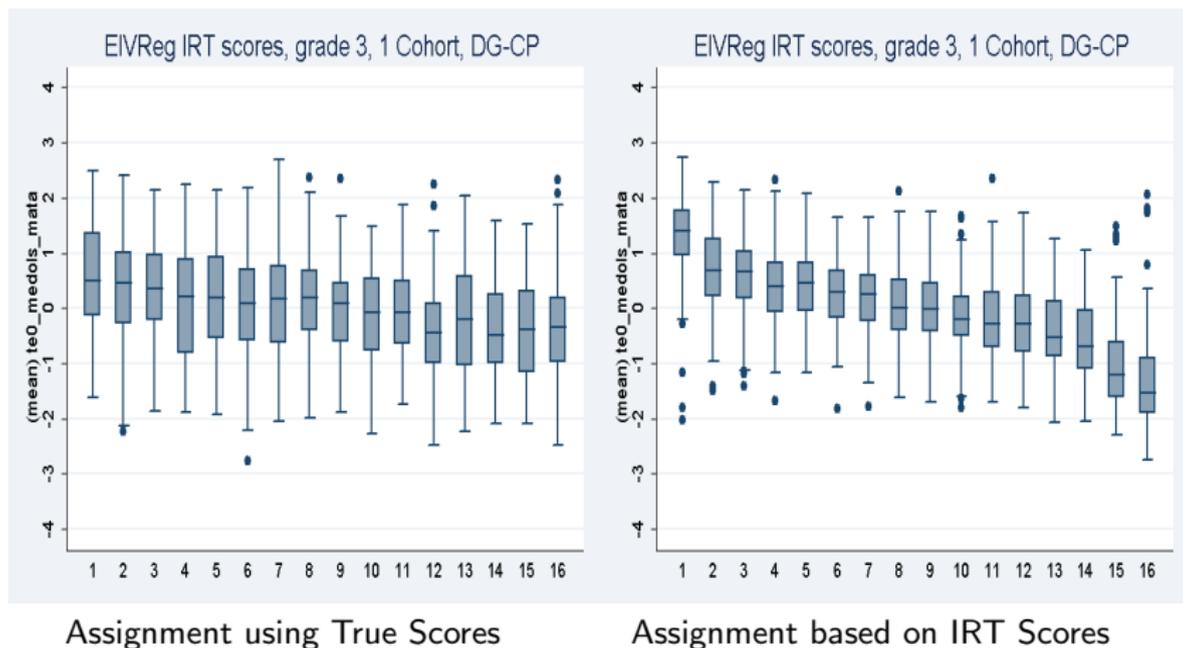


- ▶ Box and Whisker Plots:
 - ▶ Middle of Box - Median from 100 reps
 - ▶ Lower Part of Box - 25th Percentile
 - ▶ Top of Box- 75th Percentile
- ▶ For additional simplicity, we assume every teacher has identical effect of 0
- ▶ Classes sorted by prior year true achievement level or test score
- ▶ Teacher on left side of graph receive class with lowest prior score

Measurement Error Corrections

- ▶ Measurement error corrections can give bias free estimates if some assumptions are met
 - ▶ Use information on measurement error variances to adjust estimates for bias
 - ▶ Requires that measurement error uncorrelated with true scores and other covariates
 - ▶ Not true when assignment based on observed scores or with test ceilings and floors
 - ▶ Plausible cause of violation is if principals assign observed scores
 - ▶ Then non-random assignment of classrooms to teachers creates correlation between teacher assignment and measurement error

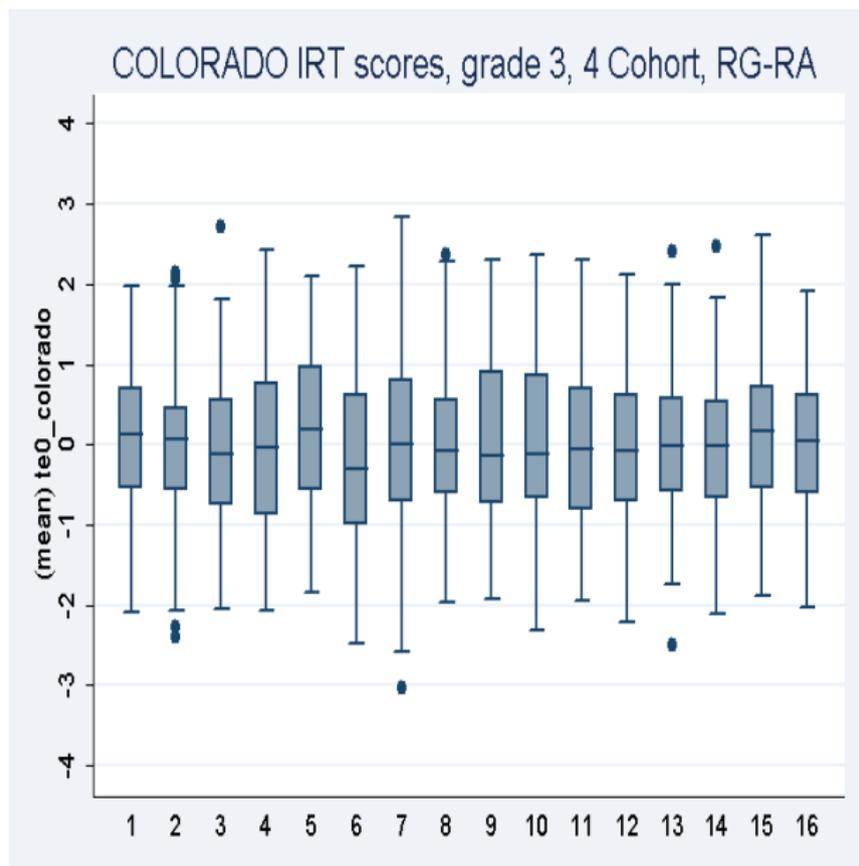
EIVReg Estimator



Colorado Growth Model

- ▶ With measurement error, Colorado growth model approach may be problematic
 - ▶ Difficult to make measurement error adjustments in quantile regression
 - ▶ Heteroskedastic measurement error in dependent variable can cause bias in quantile regression

CGM Boxplots



Conclusion

Conclusions

- ▶ Under some conditions of non-random assignment and measurement error, VAMs can mischaracterize teachers
- ▶ Estimators that correct for measurement error don't work when assignment based on observed score
- ▶ Colorado Growth Model looks surprisingly good, but we need to study more
- ▶ Test score floors and ceilings can add even more potential for bias, although in simulations did not see big differences

END

Assignment and Grouping Based on Observed Scores

- ▶ Principals could group students on observed scores
- ▶ Then non-random assignment of classrooms to teachers creates correlation between teacher assignment and measurement error
- ▶ Can create bias even for EIVReg and other measurement error corrected estimators
- ▶ No longer theoretically clear whether bias greater or less than VAMs that ignore measurement error