Consequences of Correcting Measurement Errors in Value-Added Models

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CRESST Games, Technology, and Assessment Conference

Los Angeles, CA – April 29-30, 2004

National Center for Research on Evaluation, Standards, & Student Testing

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Background

- Value-added models (VAM) as a component for teacher evaluation
- 43 states requires annual teacher evaluation
- 32 incorporate student performance measures
- Identification of “effective” and “ineffective” teachers
- Validity, reliability, and intertemporality
- Measurement errors of student test scores

Study Goals

- Overview two measurement error correction methods: Error in Variable Regression and Latent Variable approach
- Comparison of value-added estimates (VAE) with and without measurement error correction
- Who and Why are the teachers benefiting most with measurement error correction?
- Policy implications of implementing measurement error correction

Measurement Errors

- Test scores contain measurement errors
- .85 to .92 reliability in state assessments
- Measurement errors in prior test score(s) attenuate regression coefficients
- It potentially causes biases in VAEs

Correction of Measurement Errors

- Errors in Variables Regression (EiVReg; Fuller, 1987; 2006; Guarino et.al, 2013), instrumental variable approach, latent variable approach (Lookwood & McCaffrey, 2012)
- EiVreg was implemented in NYC (2010) and FL (2013)
- EiVreg uses known measurement error variance to alter regression cross product (X’X) matrix
- Subtract measurement error variance from the matrix element corresponding to prior test score(s)
- Then, what is wrong with this?

Errors in Variables Regression

$$Y_{1i} = \beta_0 + \beta_1 Y_{0i}^* + u_i, \textit{ where } Y_{0i}^* = Y_{0i} + e_i,\, e_i \sim N(0, CSEM^2(Y_{0i}))$$

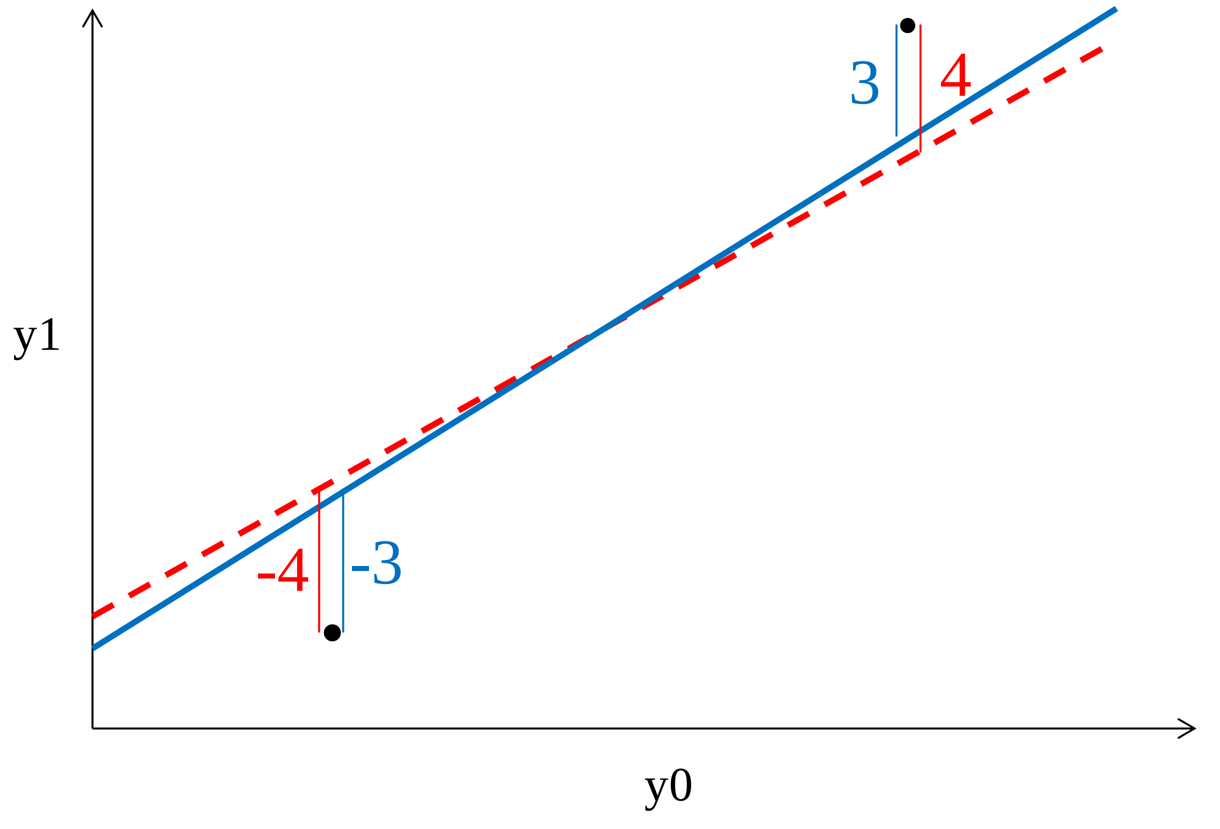
$$\textit{OLS regression}: \boldsymbol{\beta} = (X'X)^{-1} X'Y_1$$

$$Growth_i = Y_{1i} - \hat{Y}_{1i} = (\beta_0 + \beta_1 Y_{0i}^* + u_i) - (\beta_0 + \beta_1 Y_{0i}^*) = u_i$$

$$\textit{EiV regression}: \boldsymbol{\beta} = (X'X - \sum CSEM^2(Y_{0i}))^{-1} X'Y_1$$

$$Growth_i = Y_{1i} - \hat{Y}_{1i} = (\beta_0 + \beta_1 Y_{0i}^* + u_i) - (\beta_0' + \beta_1' Y_{0i}^*) = u_i'$$

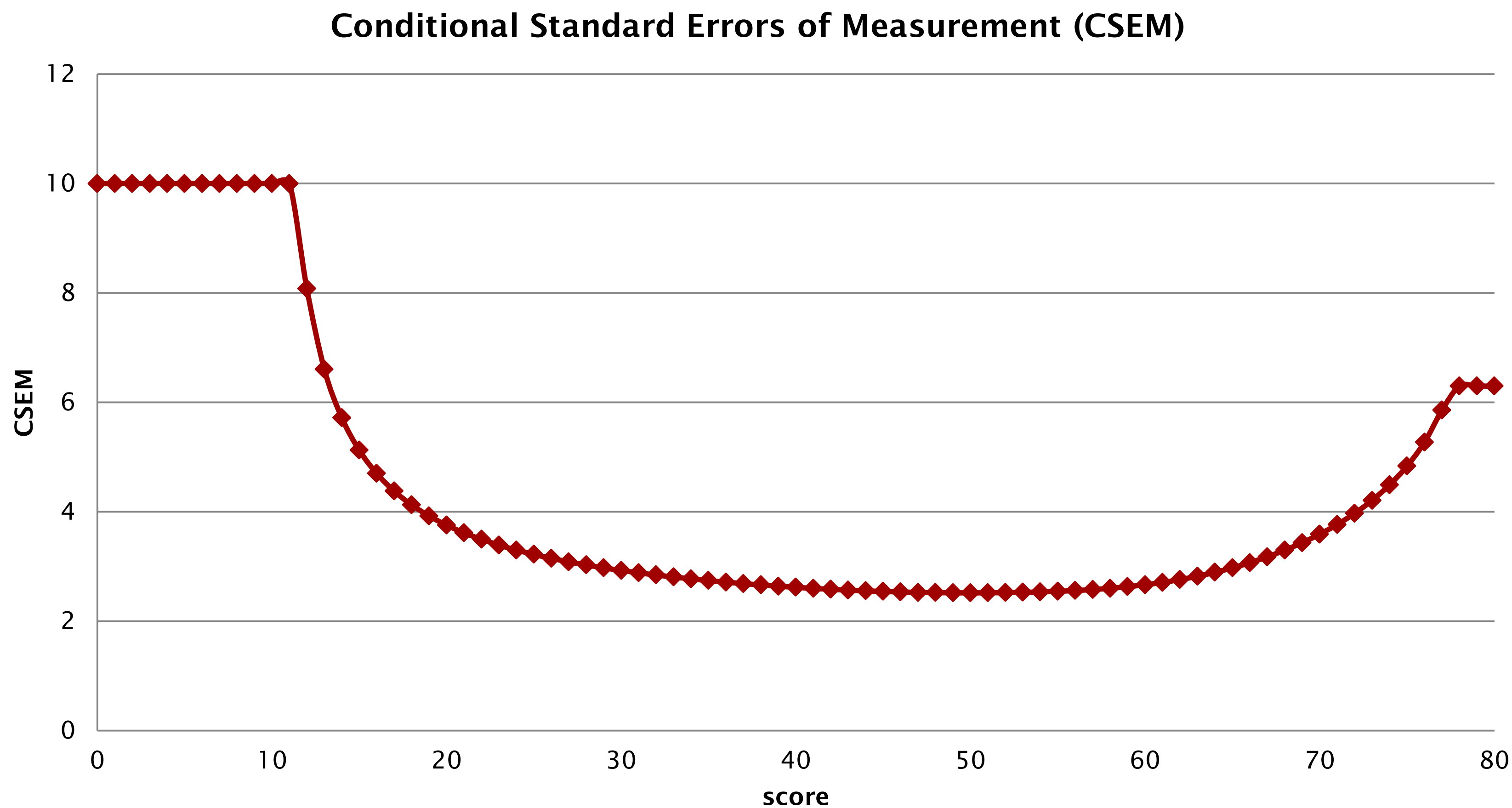
Student Growth with Correction



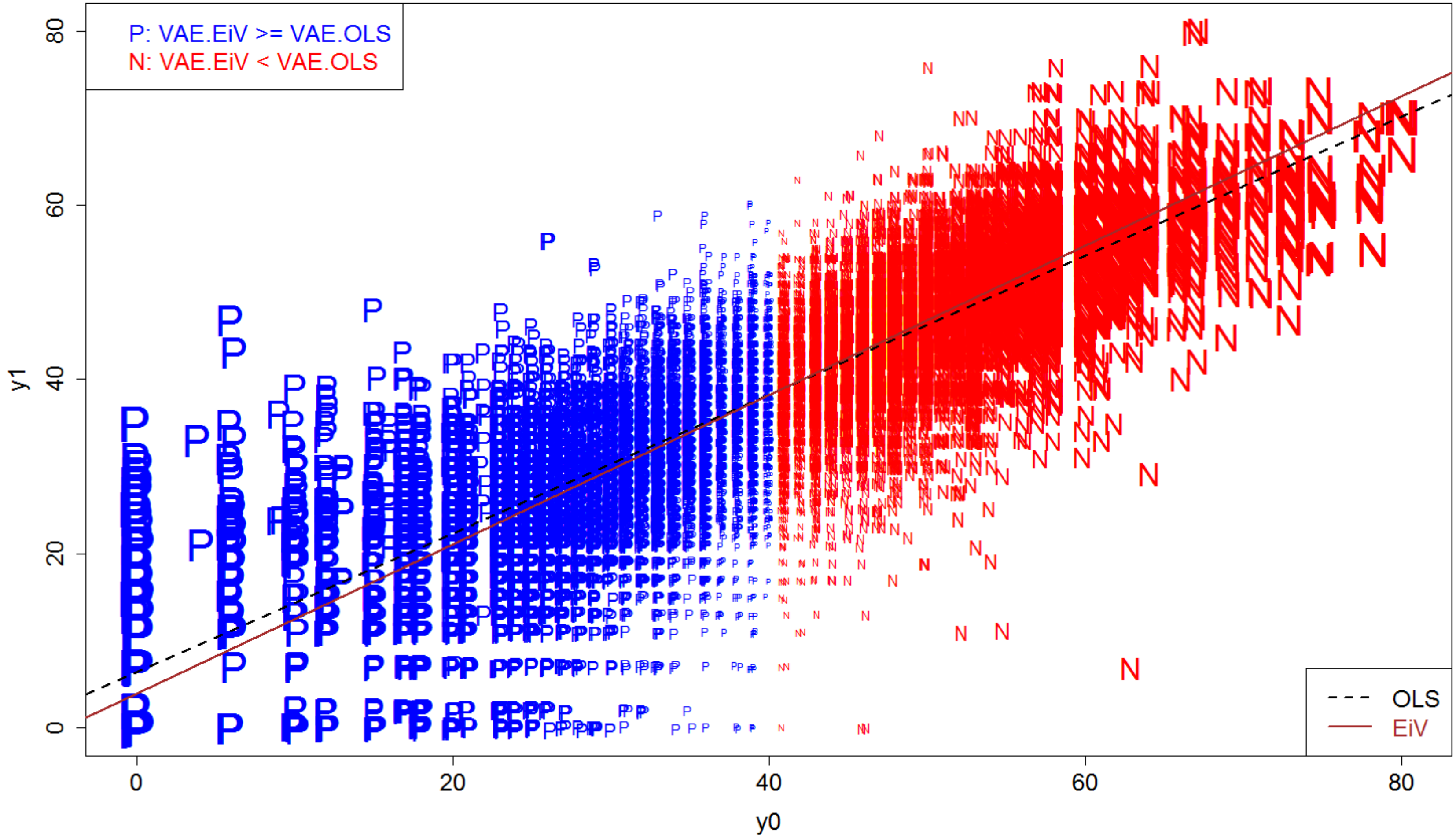
Illustrative Example

1. A state-wide achievement data
2. Math scores for Grade 4 students in 2012 and their 3rd grade math score in 2011
    1. *1,212 teachers*
    2. *24,738 students*
    3. *Score scale range: 0-80*
3. Conditional standard errors of measurement
    1. *Ranges from 2.5 to 10*
    2. *Much larger at the extremely low or high scores*
    3. *Unsymmetric U shape*

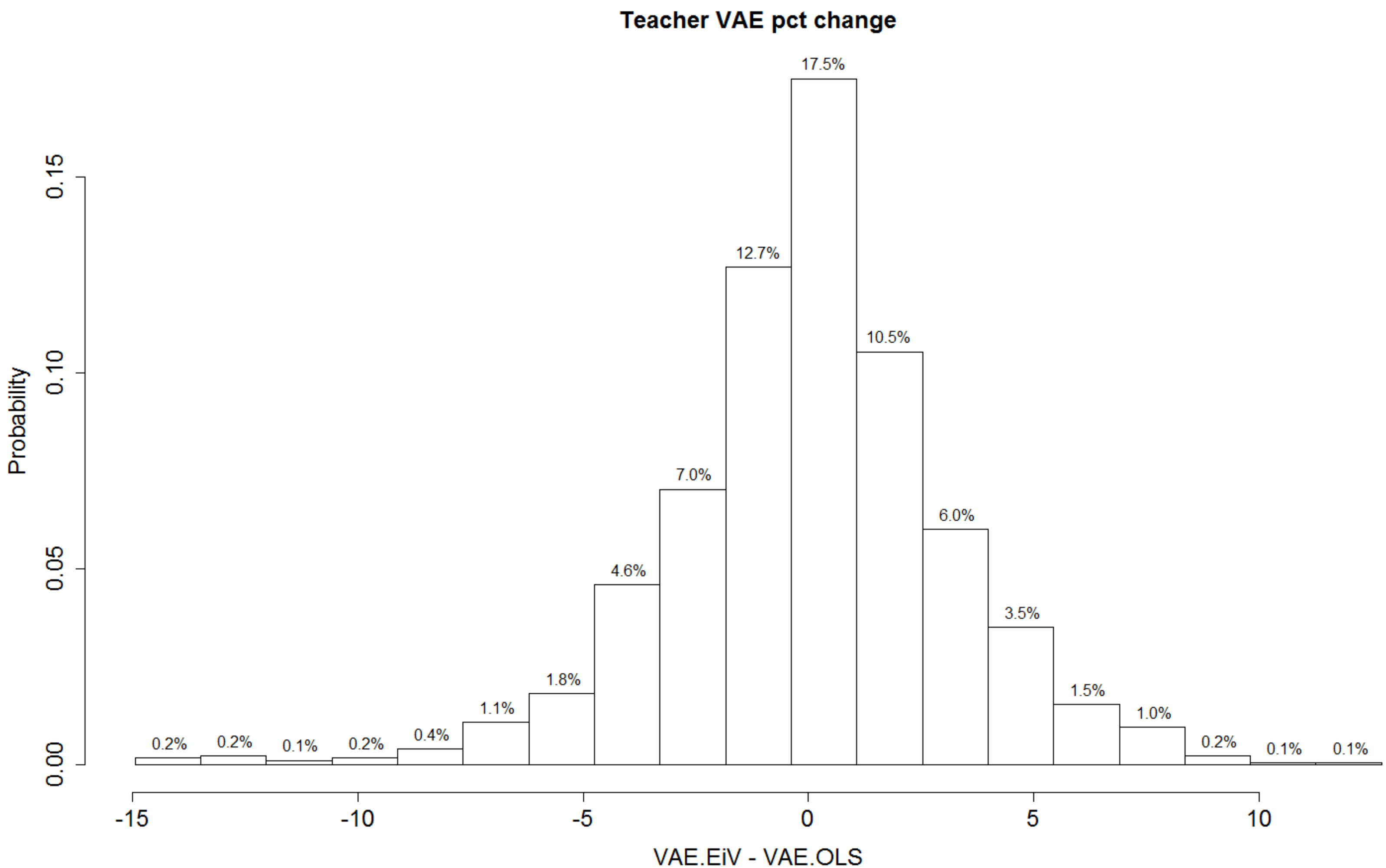
Conditional Standard Errors of Measurement



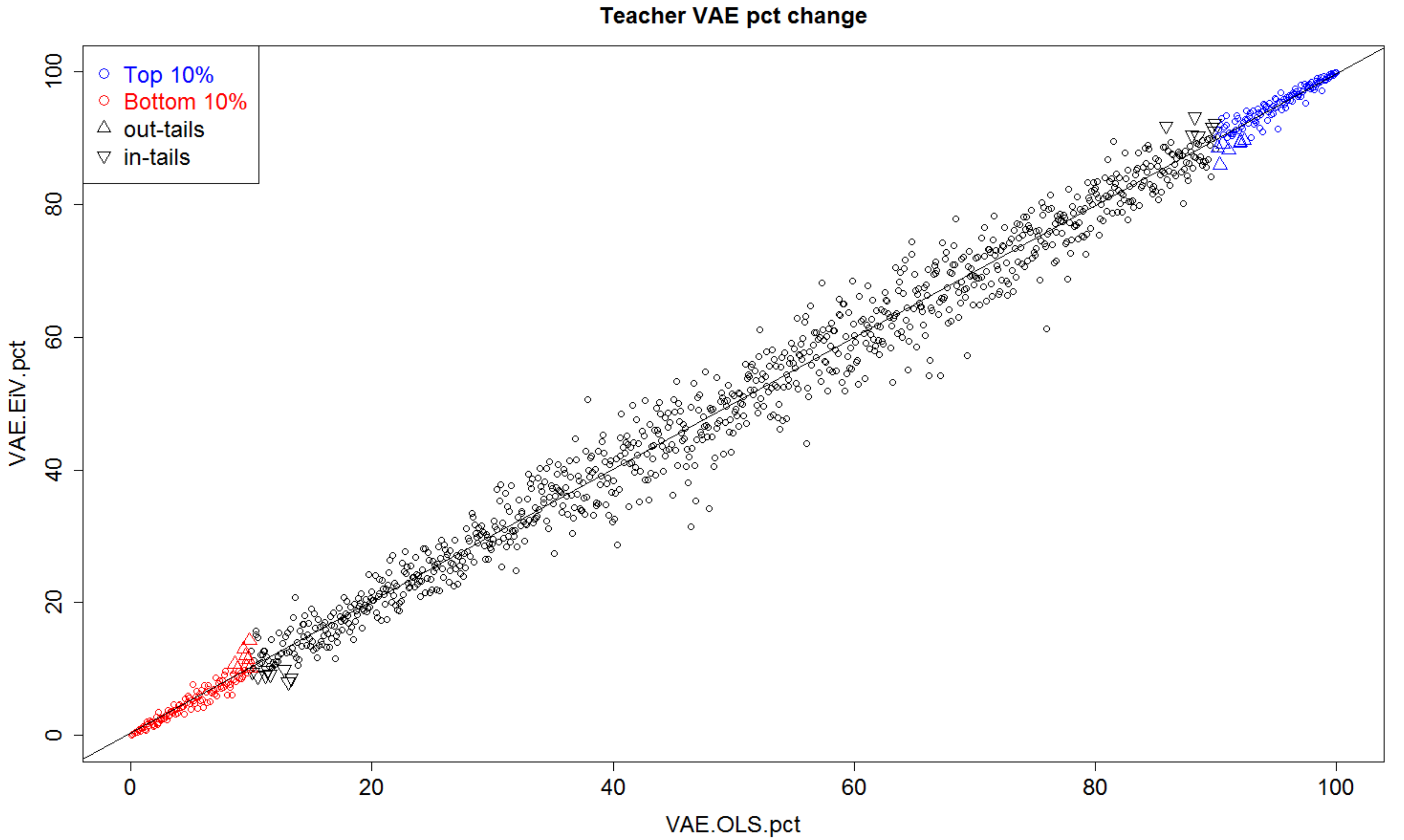
Student Growth with EiV correction



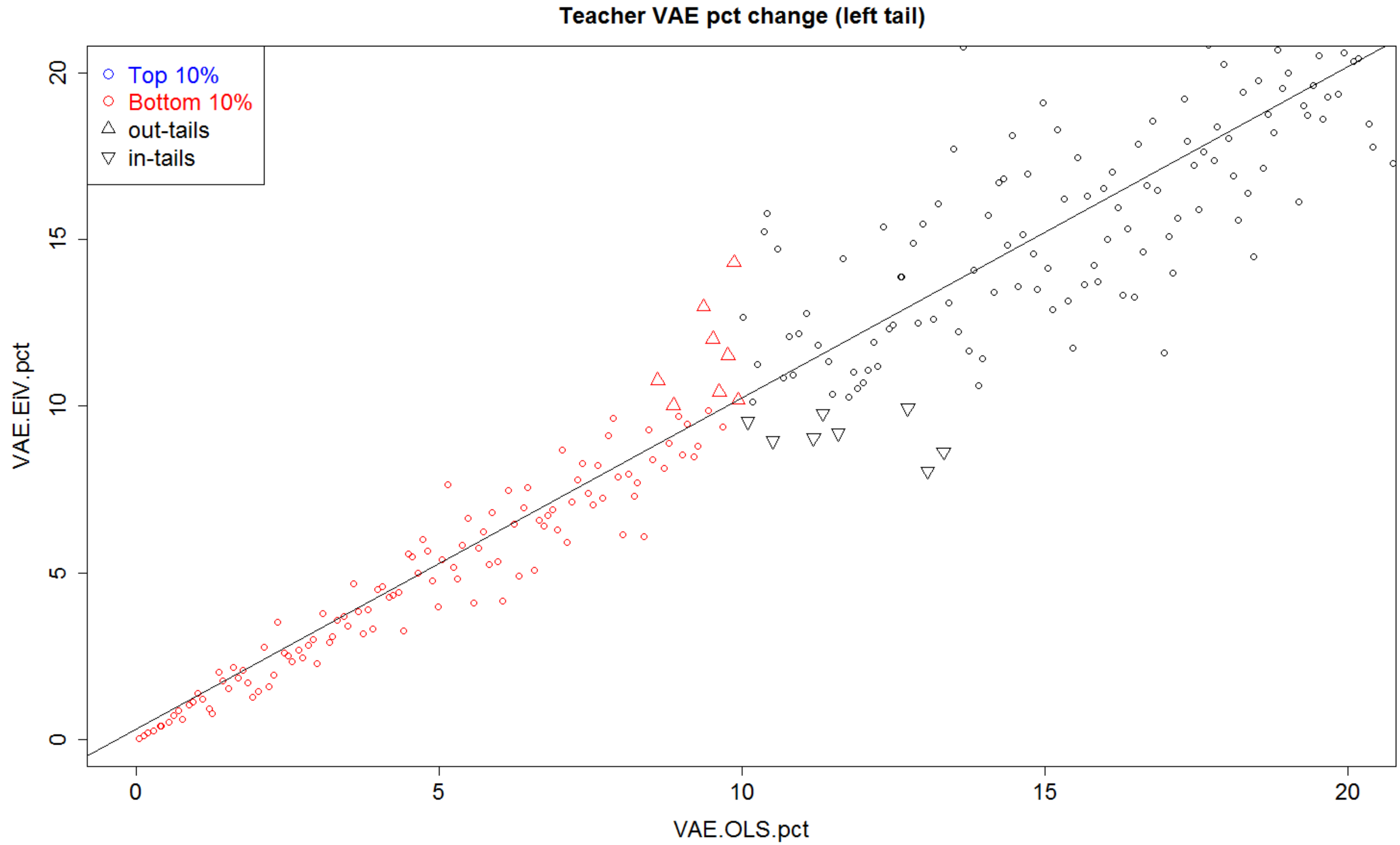
Teacher VAE percentile change with EiV correction



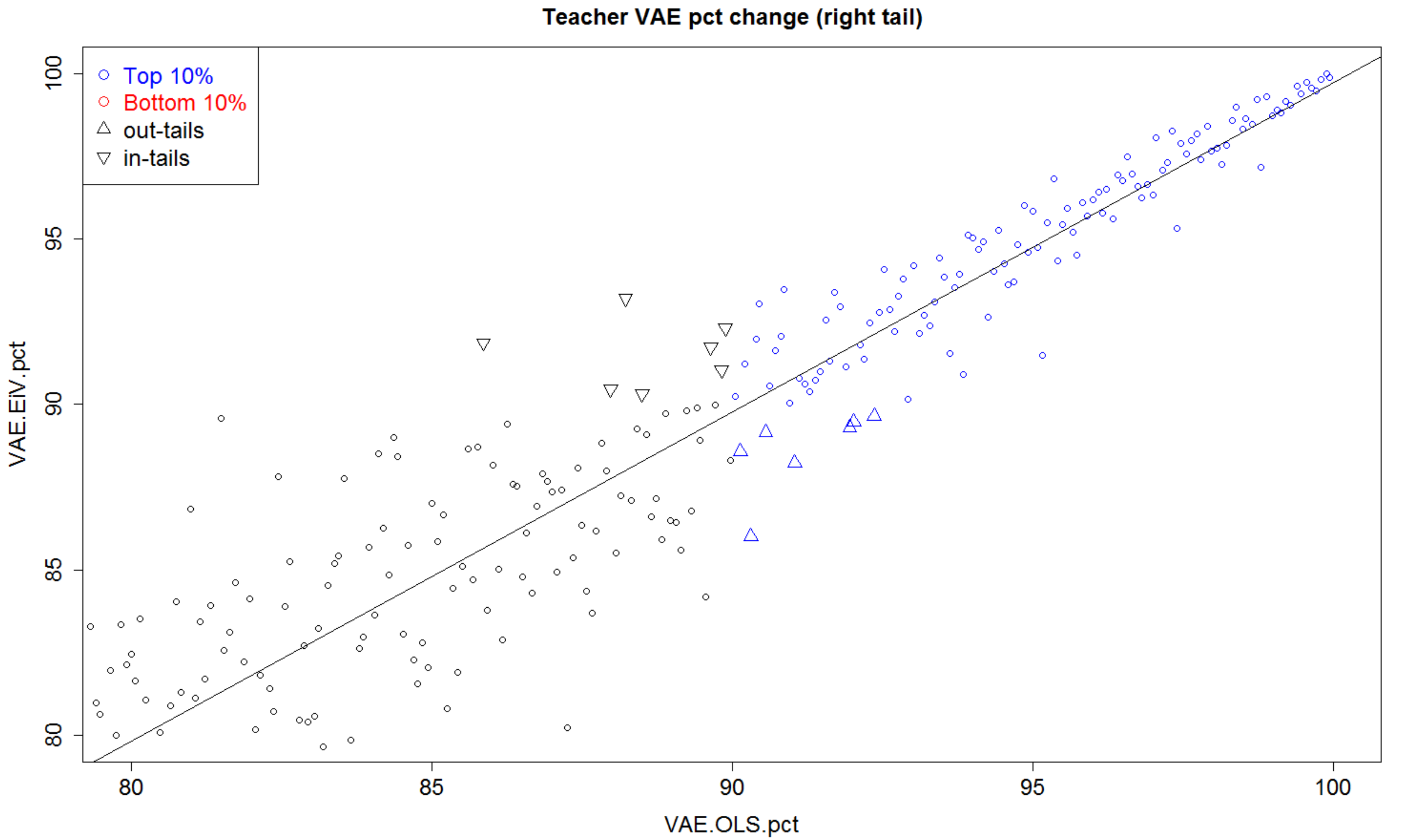
Teacher VAE percentile change with EiV correction



Teacher VAE percentile change with EiV correction (bottom 10 percentile)



Teacher VAE percentile change with EiV correction (top 10 percentile)



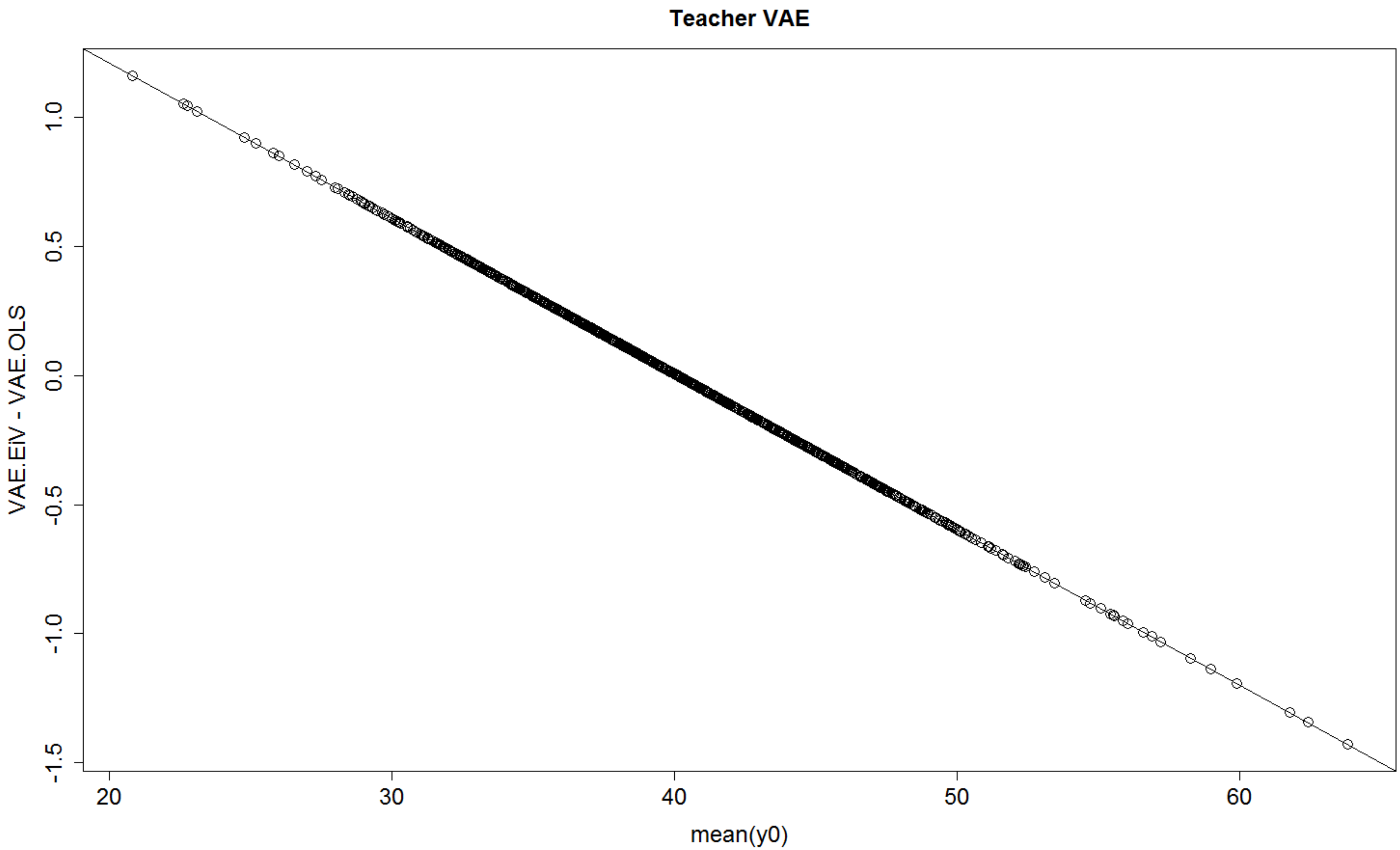
Who’s in and who’s out of top 10%tile with EiV correction

Tch ID	y0 mean	y1 mean	VAE_OLS	VAE_EiV	Prop. "P"	Prop. "N"	%tile_OLS	%tile_EiV	%tile_diff	top10% In or Out
360	24.8	29.7	3.61	4.54	1.00	0.00	86	92	6	in
828	23.1	28.6	3.84	4.87	1.00	0.00	88	93	5	in
1108	22.6	27.4	2.97	4.03	0.91	0.09	82	90	8	in
1181	33.7	37.0	3.84	4.23	0.85	0.15	88	91	3	in
585	34.7	37.9	3.88	4.21	0.82	0.18	89	90	1	in
191	37.8	40.4	3.91	4.05	0.65	0.35	89	90	1	in
484	38.2	40.7	3.95	4.06	0.60	0.40	89	90	1	in
431	38.8	41.2	3.99	4.07	0.54	0.46	89	90	1	in
3	44.7	46.1	4.14	3.86	0.40	0.60	90	88	-2	out
113	41.1	43.1	4.00	3.94	0.36	0.64	90	89	-1	out
1006	44.7	46.2	4.18	3.90	0.35	0.65	90	89	-1	out
669	45.6	47.0	4.30	3.97	0.25	0.75	91	89	-2	out
813	48.5	49.4	4.37	3.86	0.19	0.81	91	88	-3	out
157	49.4	50.3	4.56	4.00	0.13	0.88	92	89	-3	out
406	51.6	51.5	4.01	3.31	0.07	0.93	90	84	-6	out
150	51.6	51.7	4.23	3.54	0.04	0.96	90	86	-4	out

Who's in and who's out of bottom 10%tile with EiV correction

Tch ID	y0 mean	y1 mean	VAE_OLS	VAE_EiV	Prop. "P"	Prop. "N"	%tile_OLS	%tile_EiV	%tile_diff	top10% In or Out
242	41.6	35.3	-4.18	-4.27	0.39	0.61	12	10	-2	in
246	47.1	39.7	-4.25	-4.67	0.13	0.87	11	9	-2	in
288	44.9	38.1	-4.05	-4.34	0.35	0.65	13	10	-3	in
291	46.1	38.8	-4.31	-4.67	0.22	0.78	11	9	-2	in
494	53.5	45.0	-3.98	-4.79	0.15	0.85	13	9	-4	in
505	42.2	35.8	-4.24	-4.36	0.47	0.53	11	10	-1	in
612	54.7	45.9	-4.01	-4.89	0.05	0.95	13	8	-5	in
708	46.3	39.0	-4.21	-4.58	0.20	0.80	12	9	-3	in
775	41.0	34.8	-4.22	-4.27	0.52	0.48	12	10	-2	in
79	31.4	26.9	-4.44	-3.92	0.79	0.21	10	13	3	out
108	28.3	24.3	-4.60	-3.89	0.95	0.05	9	13	4	out
149	32.1	27.3	-4.57	-4.09	0.78	0.22	10	12	2	out
456	28.0	24.3	-4.33	-3.60	0.89	0.11	10	15	5	out
666	27.0	23.5	-4.32	-3.53	1.00	0.00	10	16	6	out
844	37.4	31.8	-4.36	-4.20	0.48	0.52	10	11	1	out
1005	27.5	23.8	-4.46	-3.70	0.96	0.04	10	14	4	out
1077	32.1	27.2	-4.71	-4.23	0.94	0.06	9	11	2	out
1142	35.0	29.8	-4.49	-4.18	0.75	0.25	10	12	2	out

Teacher VAE change vs. Y0 mean : EiV correction



Consequences of EiV correction

- EiV sets the higher growth expectation for higher performing students, whereas the lower growth expectation for lower performing students.
- Student’s growth is calculated based on the steeper regression slope yet with measurement error prone observed prior year score(s).
- Teacher’s VAE is systematically downward for teachers with higher prior year test scores but upward for those with lower prior year test scores.
- Teachers’ VAE percentiles are changed with fair amount, especially for “effective” or “ineffective” teachers.

Latent Variable Approach

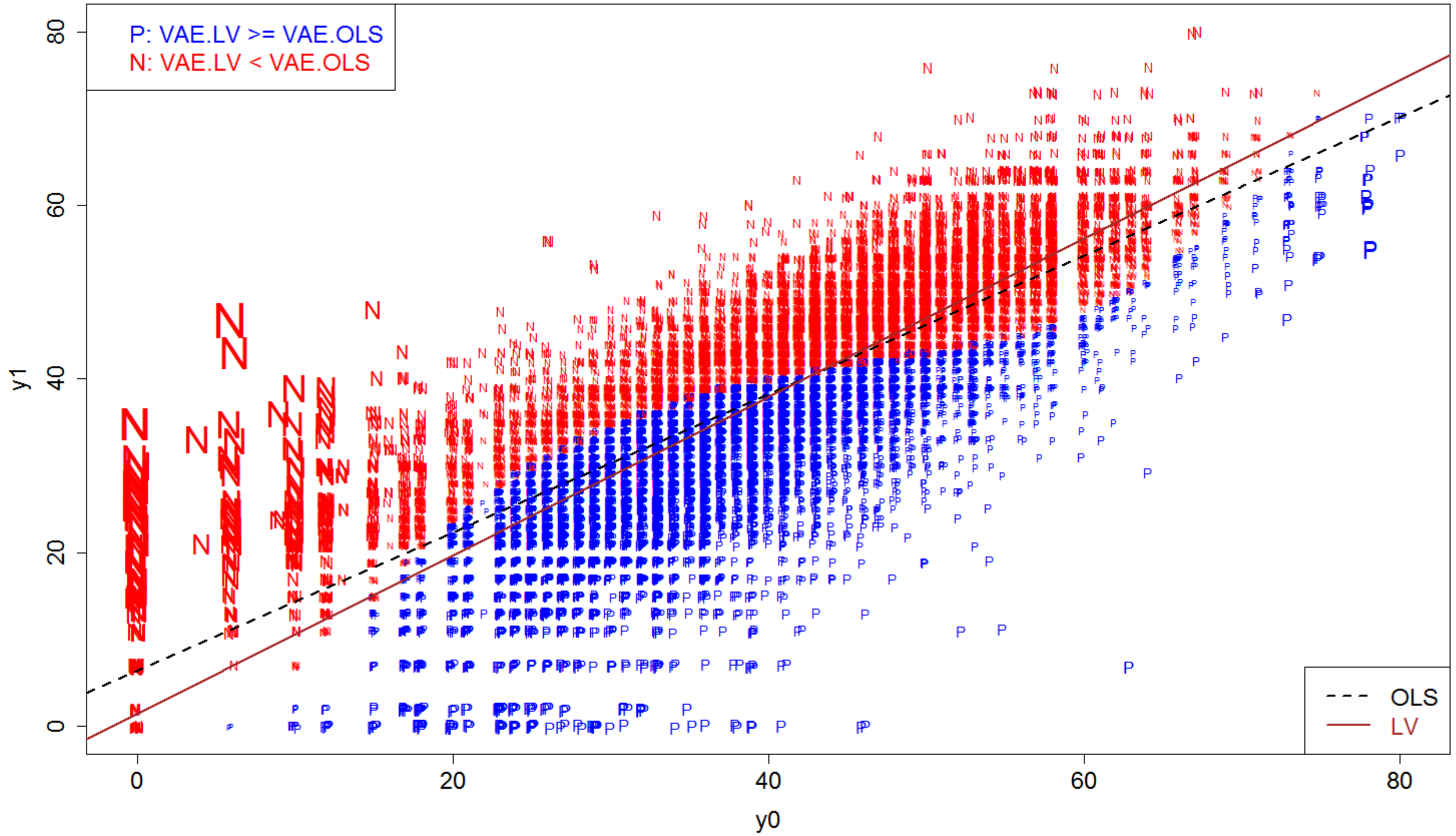
$$Y_{1i} = \beta_0 + \beta_1 Y_{0i}^* + u_i, \; where \; Y_{0i}^* = Y_{0i} + e_i, \; e_i \sim N(0, CSEM^2(Y_{0i}))$$

$$Latent\ variable\ regression: \boldsymbol{\beta} = (X'_{LV} X_{LV})^{-1} X'_{LV} Y_1$$

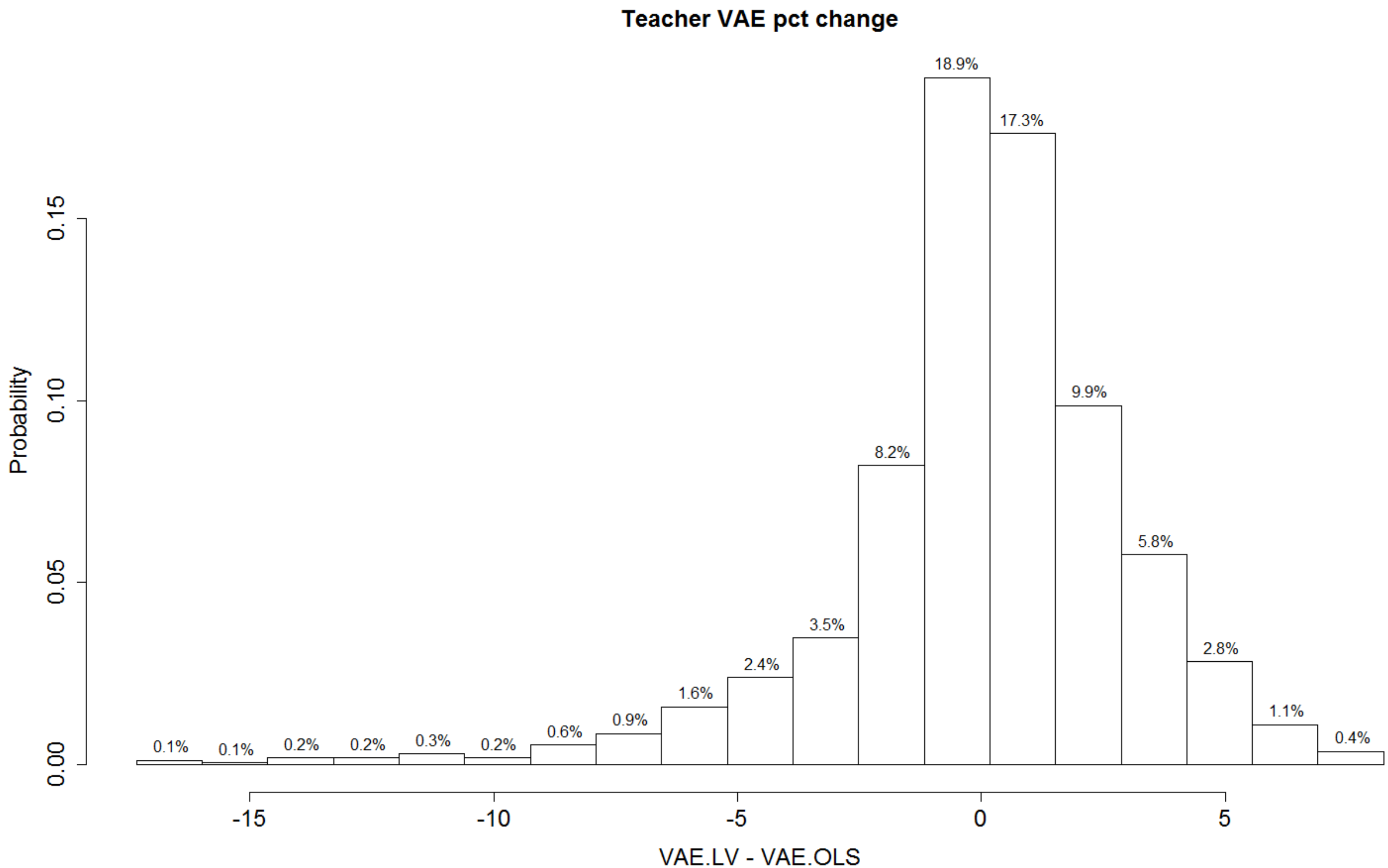
$$Y_{0i}^* = Y_{0i} + e_i, Y_{0i}^* \sim N(Y_{0i}, CSEM^2(Y_{0i}))$$

$$Growth_i = Y_{1i} - \hat{Y}_{1i} = (\beta_0 + \beta_1 Y_{0i} + u_i'') - (\beta_0 + \beta_1 Y_{0i}) = u_i''$$

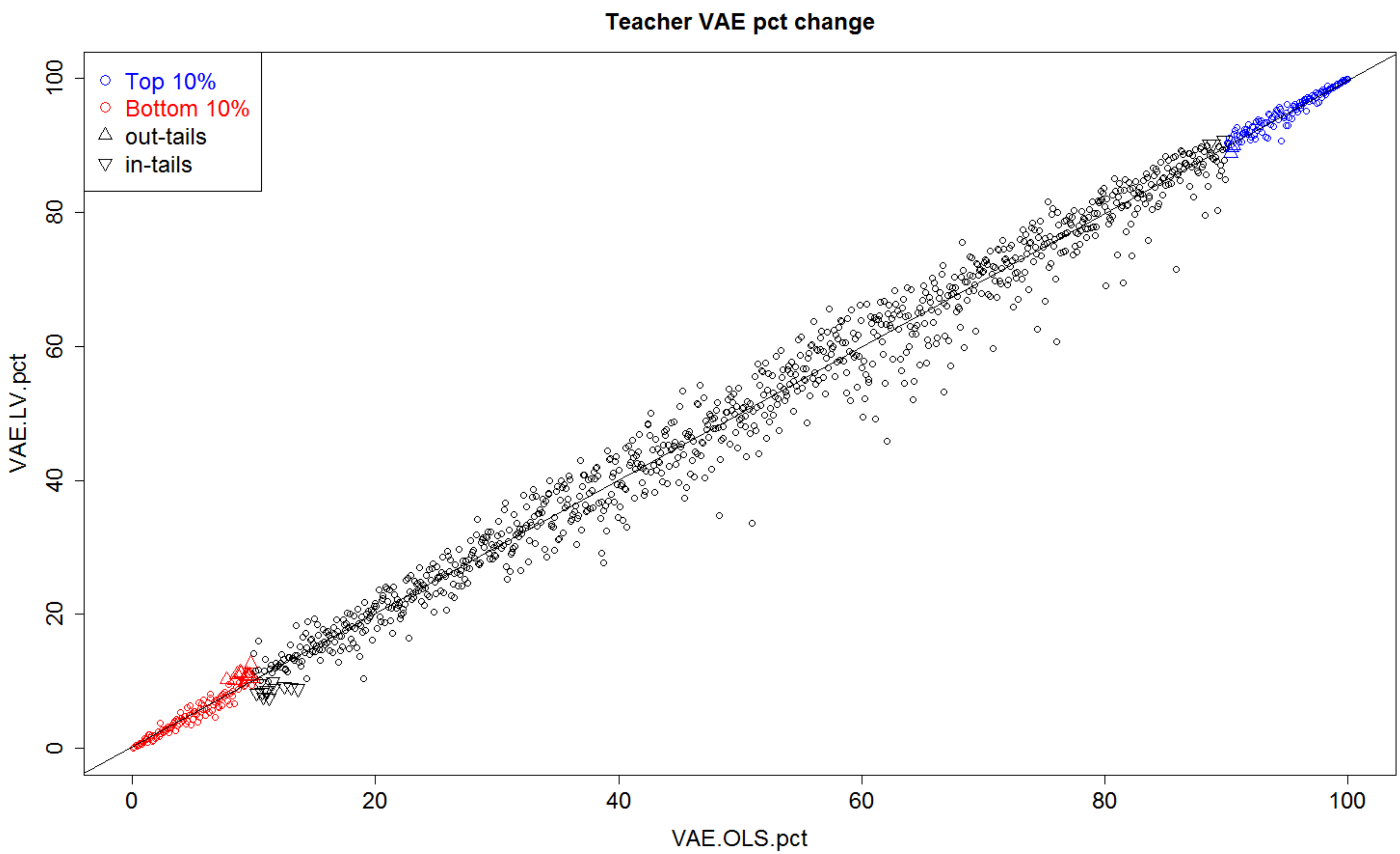
Student growth with latent variable approach



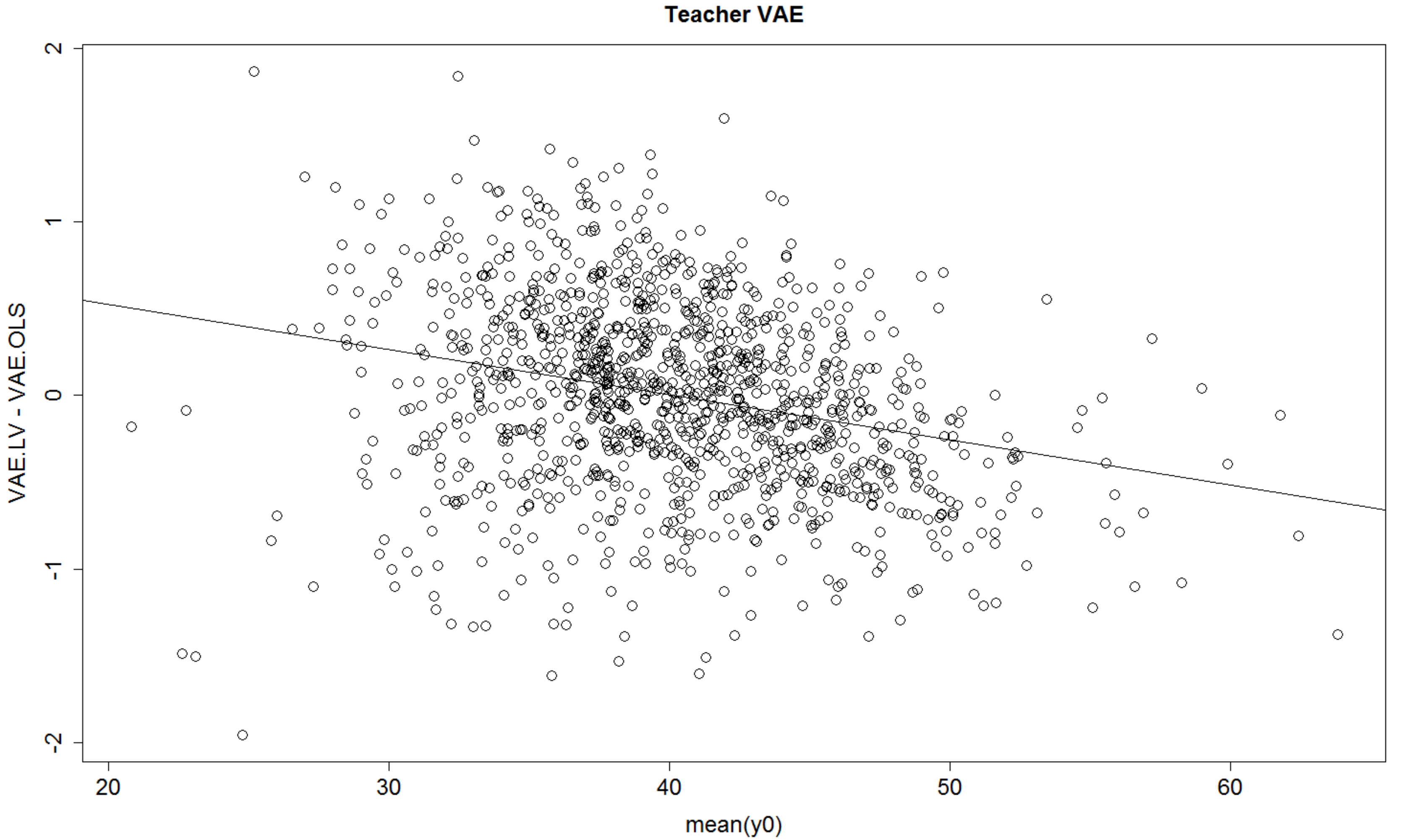
Teacher VAE percentile change with latent variable approach



Teacher VAE percentile change with latent variable approach



Teacher VAE change vs. Y0 mean : latent variable approach



Summary & Policy Implications

- Two different methods sharply show consequences of measurement error correction in terms of changes in student's growth and teacher VAE.
- EiV correction makes students and teachers value-added larger for lower prior year score and smaller for higher prior year score.
- This study shows how two different methods work using the simplest example. The consequences of measurement error correction in complex models (e.g., lots of covariates) would be more complicated depending upon different value-added model specifications.

Summary & Policy Implications (con't)

- Student assignment to a teacher is neither random nor under the teacher's control. Do we let the prior scores determine teacher's value-added as EiV correction method shows?
- These consequences might send "value-added into tailspin" as Guarino et.al. pointed out.
- In addition to methodological issues, implementation of measurement error correction in high-stakes teacher evaluation needs more research and discussions from a policy perspective.

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