Economics 513, USC, Fall 2016

Lecture 16: Value added

Notes based on: 'Measuring the Impacts of Teachers, I and II', by Chetty, Friedman, and Rockoff, American Economic review, 2014 (CFR)

Value added and teacher evaluation

Quality of teachers is difficult to assess. Some issues

- Outcome measure could be student test scores (method will apply to other outcome measures). Teaching to the test. Impact on long-term student outcomes?
- Class test scores depend on teacher and student inputs (student sorting). How do we make sure that this does not bias measure of teacher quality?
- Also school quality is important. How do we make sure that this does not bias measure of teacher quality?

Model for test scores with i student, j teacher, and t year

$$A_{it} = \beta x_{it} + \mu_{jt} + \theta_c + \varepsilon_{it}$$

The teacher effect μ_{jt} changes over time, θ_c and ε_{it} are random errors. The observed student variables include past test scores, but also school dummies (has issues that we will discuss later). The parameter of interest is the teacher effect μ_{jt}.

All classrooms have n students and each teacher teaches one class per year.

If there are no observed student characteristics, then

$$\hat{\mu}_{jt} = \overline{A}_{jt} = \mu_{jt} + \theta_c + \overline{\varepsilon}_{jt}$$

If a teacher is assigned a 'good class', i.e. with large $\overline{\varepsilon}_{jt}$ then her estimated effectiveness is over estimated.

We can think of this as measurement error in the measurement of teacher effectiveness.

Regression model with measurement error

$$y = \beta x^* + \varepsilon \qquad x = x^* + \eta$$

Here x^* is the unobserved true value of the independent variable. The observed value is x and η is the measurement error.

Substitution gives

$$y = \beta(x - \eta) + \varepsilon = \beta x + \varepsilon - \beta\eta$$

Now we have

$$E(x(\varepsilon - \beta\eta)) = E[(x^* + \eta)(\varepsilon - \beta\eta)] = -\beta\sigma_\eta^2$$

where we assume that x^*, η are uncorrelated (classical measurement error) and also η, ε and x^*, ε.

Note that if $\beta > 0$ the correlation is negative, so that OLS has a downward (towards 0) bias.

If we have an instrument z that is uncorrelated with ε, η, but is correlated with x^*, then z can be used as an instrumental variable for x and β can be estimated by 2SLS.

In CFR the instrumental variables are $\overline{A}_{j,t-1}, \ldots, \overline{A}_{j1}$.

CFR essentially estimate the test score model by 2SLS where in the first stage they estimate a linear regression of $\overline{A}_{jt}$ on $\overline{A}_{j,t-1}, \ldots, \overline{A}_{j1}$.

The predicted values $\hat{\mu}_{jt}$ are included in the regression

$$A_{it} = \beta x_{it} + \lambda\hat{\mu}_{jt} + \theta_c + \varepsilon_{it}$$

The parameter of interest is λ. The predicted value $\hat{\mu}_{jt}$ is called the value added of the teacher j. If $\lambda = 1$ the value added is an unbiased estimate of teacher quality.

If we include school dummies in x_{it} we need teachers who switch schools. Without such switchers we cannot separate school and teacher effects.
Data

CFR use a unique data set. Administrative data on students and teachers 1988-1989 until 2008-2009. About 2.5 million children in grades 3-8. Test scores, teacher assignments, ethnicity, gender, age, special ed. Tax data from US federal tax returns 1996-2011 that have parents' income and other family back ground variables.

Data were linked on name, date of birth, state of birth, gender. About 88% of students were linked to a tax record.
Estimation

First stage in Fig 1 and Table 2

Estimate of λ in Table 3.

Remaining bias in estimate

$$B = \frac{cov(\varepsilon_{it}, \hat{\mu}_{it})}{var(\hat{\mu}_{it})}$$

Of course ε_{it} is not observed, but potential components, as parents' income that are not in the VA model are observable (see columns (2) and (4)). In column (4) sorting on student score lagged twice is considered.

Further issues

In companion paper CFR consider impact of VA on outcomes up to 20 years later and they find a significant effect on college enrollment and completion and other outcome measures.

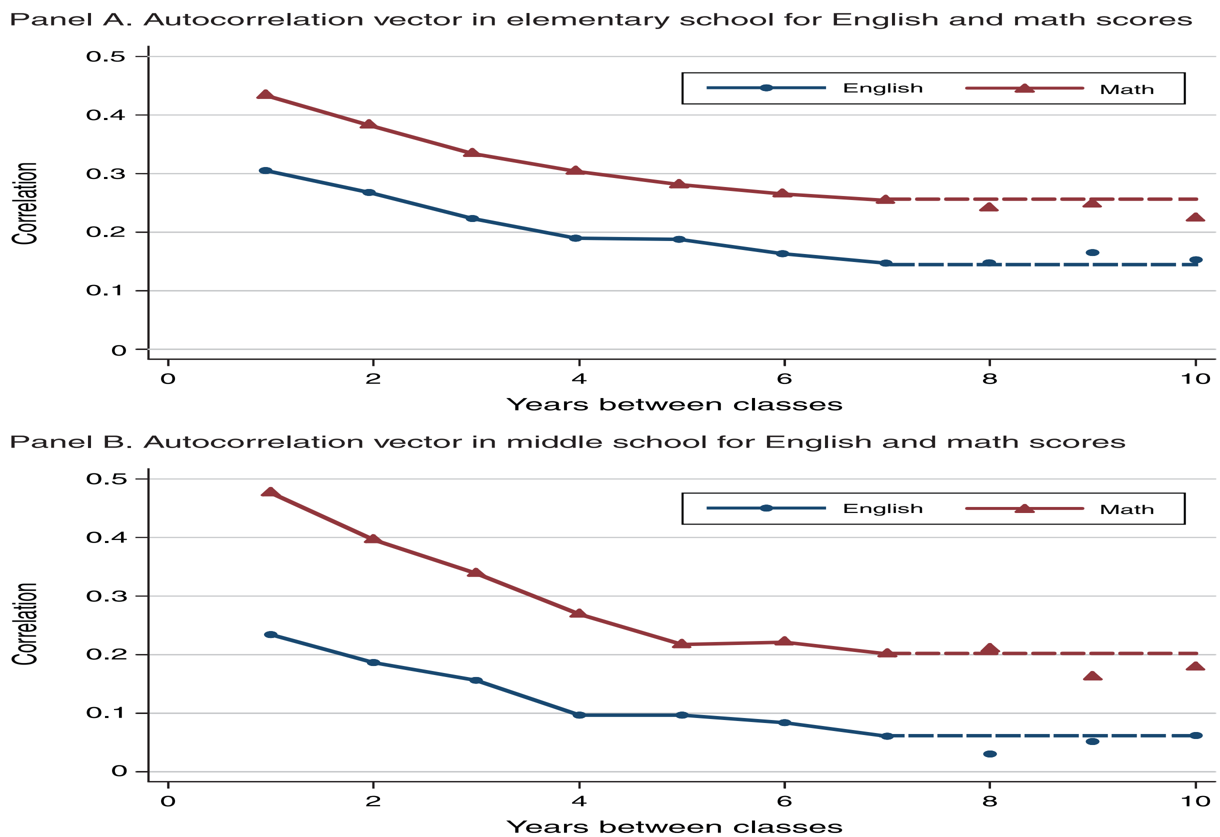

FIGURE 1. DRIFT IN TEACHER VALUE-ADDED ACROSS YEARS

Notes: These figures show the correlation between mean test-score residuals across classes taught by the same teacher in different years. Panels A and B plot autocorrelation vectors for elementary and middle school. To calculate these vectors, we first residualize test scores using within-teacher variation with respect to our baseline control vector (see notes to Table 3). We then calculate a (precision-weighted) mean test score residual across classrooms for each teacher-year. Finally, we calculate the autocorrelation coefficients as the correlation across years for a given teacher, weighting by the sum of students taught in the two years. See online Appendix A for more details on the estimation procedure for these and other parameters of the value-added model.

Table 2—Teacher Value-Added Model Parameter Estimates

	Elementary school		Middle school	
	English	Math	English	Math
Sample	(1)	(2)	(3)	(4)
Panel A. Autocovariance and autocorrelation vectors				
Lag 1	0.013 (0.0003) [0.305]	0.022 (0.0003) [0.434]	0.005 (0.0002) [0.234]	0.013 (0.0002) [0.476]
Lag 2	0.011 (0.0003) [0.267]	0.019 (0.0003) [0.382]	0.004 (0.0002) [0.186]	0.011 (0.0003) [0.396]
Lag 3	0.009 (0.0003) [0.223]	0.017 (0.0004) [0.334]	0.003 (0.0003) [0.156]	0.009 (0.0003) [0.339]
Lag 4	0.008 (0.0004) [0.190]	0.015 (0.0004) [0.303]	0.002 (0.0003) [0.097]	0.007 (0.0004) [0.269]
Lag 5	0.008 (0.0004) [0.187]	0.014 (0.0005) [0.281]	0.002 (0.0004) [0.096]	0.006 (0.0005) [0.217]
Lag 6	0.007 (0.0004) [0.163]	0.013 (0.0006) [0.265]	0.002 (0.0004) [0.084]	0.006 (0.0006) [0.221]
Lag 7	0.006 (0.0005) [0.147]	0.013 (0.0006) [0.254]	0.001 (0.0005) [0.060]	0.005 (0.0006) [0.201]
Lag 8	0.006 (0.0006) [0.147]	0.012 (0.0007) [0.241]	0.001 (0.0005) [0.030]	0.005 (0.0007) [0.210]
Lag 9	0.007 (0.0007) [0.165]	0.013 (0.0008) [0.248]	0.001 (0.0006) [0.051]	0.004 (0.0008) [0.162]
Lag 10	0.007 (0.0008) [0.153]	0.012 (0.0010) [0.224]	0.001 (0.0007) [0.062]	0.005 (0.0012) [0.179]

(*Continued*)

Table 2—Teacher Value-Added Model Parameter Estimates (*Continued*)

Sample	Elementary school English (1)	Elementary school Math (2)	Middle school English (3)	Middle school Math (4)
Panel B. Within-year variance components				
Total SD	0.537	0.517	0.534	0.499
Individual-level SD	0.506	0.473	0.513	0.466
Class + teacher level SD	0.117	0.166	0.146	0.178
Class-level SD			0.108	0.116
Teacher SD			0.098	0.134
Estimates of teacher SD:				
Lower bound based on lag 1	0.113	0.149	0.068	0.115
Quadratic estimate	0.124	0.163	0.079	0.134

Notes: Panel A reports the estimated autocovariance, the standard error of that covariance estimate clustered at the teacher level (in parentheses), and the autocorrelation (in brackets) of average test score residuals between classrooms taught by the same teacher. We measure these statistics at time lags ranging from one (i.e., two classrooms taught one year apart) to ten years (i.e., two classrooms taught ten years apart), weighting by the sum of the relevant pair of class sizes. Each covariance is estimated separately for English and math and for elementary and middle school classrooms. Panel B reports the raw standard deviation of test score residuals and decomposes this variation into components driven by idiosyncratic student-level variation, classroom shocks, and teacher-level variation. The variances in rows 2 and 3 of panel B sum to that in row 1; the variances in rows 4 and 5 sum to that in row 3. In middle school, we estimate the standard deviation of teacher effects as the square root of the covariance of mean score residuals across a random pair of classrooms within the same year. In elementary schools, we cannot separately identify class-level and teacher-level standard deviations because we observe only one classroom per year. We use the square root of the autocovariance across classrooms at a one year lag to estimate a lower bound on the within-year standard deviation for elementary schools. We also report an estimate of the standard deviation by regressing the log of first seven autocovariances in panel A on the time lag and time lag squared and extrapolating to zero to estimate the within-year covariance.

TABLE 3—ESTIMATES OF FORECAST BIAS USING PARENT CHARACTERISTICS AND LAGGED SCORES

	Score in year t (1)	Pred. score using parent chars. (2)	Score in year t (3)	Pred. score using year $t-2$ score (4)
Teacher VA	0.998	0.002	0.996	0.022
	(0.0057)	(0.0003)	(0.0057)	(0.0019)
Parent chars. controls			X	
Observations	6,942,979	6,942,979	6,942,979	5,096,518

Notes: Each column reports coefficients from an OLS regression, with standard errors clustered by school-cohort in parentheses. The regressions are run on the sample used to estimate the baseline VA model, restricted to observations with a non-missing leave-out teacher VA estimate. There is one observation for each student-subject-school year in all regressions. Teacher VA is scaled in units of student test score standard deviations and is estimated using data from classes taught by the same teacher in other years, following the procedure in Sections IB and III. Teacher VA is estimated using the baseline control vector, which includes: a cubic in lagged own- and cross-subject scores, interacted with the student's grade level; student-level characteristics including ethnicity, gender, age, lagged suspensions and absences, and indicators for grade repetition, special education, and limited English; class size and class-type indicators; cubics in class and school-grade means of lagged own- and cross-subject scores, interacted with grade level; class and school-year means of all the student-level characteristics; and grade and year dummies. When prior test scores in the other subject are missing, we set the other subject prior score to zero and include an indicator for missing data in the other subject interacted with the controls for prior own-subject test scores. In columns 1 and 3, the dependent variable is the student's test score in a given year and subject. In column 2, the dependent variable is the predicted value generated from a regression of test score on mother's age at child's birth, indicators for parent's 401(k) contributions and home ownership, and an indicator for the parent's marital status interacted with a quartic in parent household income, after residualizing all variables with respect to the baseline control vector. In column 4, the dependent variable is the predicted value generated in the same way from twice-lagged test scores. See Section IVB for details of the estimating equation for predicted scores.