Teacher effect in general

Student level data matters:

* (Aaronson et al., 2007) A brief sampling of other work on teacher effects includes Murnane (1975), Goldhaber and Brewer (1997), Angrist and Lavy (2001), Jepsen and Rivkin (2002), Rivers and Sanders (2002), Jacob and Lefgren (2004), Rockoff (2004), Kane and Staiger (2005), Rivkin, Hanushek, and Kain (2005), and Kane, Rockoff, and Staiger (2006). The earliest studies on teacher quality were hampered by data availability and thus often relied on state- or school-level variation. Ag- gregation and measurement error compounded by proxies such as student-teacher ratios and average teacher experience can introduce significant bias. More recent studies, such as Rockoff (2004), Kane and Staiger (2005), Rivkin et al. (2005), and Kane et al. (2006), use administrative data like ours to minimize these concerns.

Human capital characteristics

In general, researchers agree that human capital measures frequently used in teacher evaluation explain little of teacher’s contribution to student academic growth (e.g., Aaronson et al., 2007).

Teacher education background/teacher preparation

Aaronson et al., 2007:

* Measures
  + Graduate degree
  + Major
  + And more
* Findings
  + No relationship with teacher value-added on math in Chicago public high schools

Teacher experience/return to teaching

Aaronson et al., 2007:

* Models and measures
  + Directly using years measure (age-education-6 then take average within teacher)
  + Also check the dummy variable years<=1
* Findings
  + No relationship with teacher value-added on math in Chicago public high schools

Clotfelter et al., 2007:

* Models and measures
  + “Indicator variable model”, “by using within-bin variation to estimate the year effects, the Indicator Variable Model relies on a similar functional form assumption. In this case, it assumes that teacher productivity does not change meaningfully within each of these experience bins” (Papay and Kraft, 2-15)
  + Student fixed-effects
  + 10 years of north Carolina data
  + Specify years of experience as a series of indicator variables (1-2, 3-5, 6-12, 13-20, 21-27, and 27+), with the base/left-out category being no experience
* Findings (p.676)
  + Larger effects for math than for reading
  + On student score gains, all coefficients of teacher experience indicators are significant; size ranging from 0.072-0.118 in math and 0.043-0.096 in reading

Papay and Kraft, 2015:

* Models
  + Censored growth model
  + Indicator variable model
  + Discontinuous career model
  + Two-stage model
* Findings
  + using “estimated contributions to student test score gains as a proxy for productivity”, we find “that teachers in the district improve most rapidly at the beginning of their careers.
  + However, across models, we find that teachers continue to improve, albeit at lesser rates, past their first five years in the classroom.
  + We also find suggestive evidence of continued returns to experience throughout the career, particularly in mathematics” in a large southern United States district.

Harris and Sass, 2011:

* Methods and measures
  + Indicator variable modle
  + Panel data; leveraging student, teacher, and school fixed effects (see paper for the advanced methods getting around computational challenge)
  + Compare teachers with 1-2, 3-4, 5-9, 10-14, 15-24, and 25+ years’ experience separately to new teachers
* Findings (p.805)
  + For elementary and middle school teachers, experience effects are quantitatively substantial, ranging from 0.03-0.06 SD for the first 1-2 years of experience as much as 0.16 SD for 15-24 years of experience
  + High school teachers are the opposite, more experienced teachers are less productive than when they were new teachers (teacher fixed effects)

Hu et al., 2017:

* using generalized additive modeling (GAM), a nonlinear method for “identifying likely thresholds by estimating the relations between an independent variable and a dependent variable without making any assumptions about whether the relation is linear or non-linear
  + likely thresholds are identified by graphically identifying the regions where there appears to by systematic change in the relation between the two variables and both baseline and ceiling thresholds are possible
  + also a graphic representation of the non-linear regression trend between the two variables
  + it doesn’t provide exact cut-off points, rather, it provides visual guidance on the score ranges within which thresholds are likely to exist
* then using piecewise regression (spline regression approach) to validate the possible thresholds
  + meaning to test whether the regression slopes vary across the different regions thus provide evidence of the validity of the GAM-derived thresholds
  + for each outcome variable, the results from the simple linear regression model (assuming one constant slope) and the piece- wise regression model (assuming varying slopes as defined by the thresholds) could be compared statistically. e.g., statistical test, adjusted R2s from two models, and the Akaike information criterion (AIC; Akaike, 1974) are available as evidence for the viability of the thresholds.
  + Lastly, compare linear regression with piecewise regression based on F statistics (statistical significance), adjusted R2 (higher value indicating better fit), and AIC (lower value indicating better fit)

Graphical user interface, text, application, email

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Causal evidence

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Model specifications

Graphical user interface, text, application

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