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

At large, researchers agree that human capital measures, even those 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

Causal evidence

Teacher experience/return to teaching

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.

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

Description automatically generated

Causal evidence

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Model specifications

Graphical user interface, text, application

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