Like Teacher, Like Student:

Teachers and the Development of Student Noncognitive Skills

Albert Cheng*

University of Arkansas

EDRE Working Paper No. 2015-02

Last Updated January 2016

Please Do Not Cite Without Author Permission

Abstract
Teacher quality is typically conceptualized as a teacher's ability to raise student cognitive ability, or achievement on standardized tests. High-quality teachers have large and meaningful impacts on their students' cognitive ability as well as their long-run life outcomes such as educational attainment. Noncognitive skills, which include personality dispositions typically not captured by standardized tests, are also important determinants of student outcomes. Yet little is known about whether teachers affect student noncognitive skills or, if so, how and which teachers do. This study addresses the research gap. Using longitudinal data from a nationally-representative set of US students, I employ student fixed effects to control for time-invariant heterogeneity and use a behavioral task of noncognitive skills, namely, item response rates on surveys. I highlight two findings. First, consistent with previous research on noncognitive skills, item response rates are important predictors of educational attainment and employment, independent of cognitive skills. Second, students experience gains in noncognitive skills when they are taught by teachers that exhibit higher levels of that same noncognitive skill. This is the first study to demonstrate a relationship between teacher and student performance on the same behavioral task. These findings have implications for the understanding of teacher quality.

Keywords: Noncognitive Skills; Teacher Quality

Acknowledgements: The author would like to thank Gema Zamarro, Jay Greene, Collin Hitt, and Julie Trivitt for their helpful comments.

Like Teacher, Like Student:

Teachers and the Development of Student Noncognitive Skills

School reform and improvement efforts are often judged by how well they improve student cognitive ability as measured by student achievement on standardized test scores. This emphasis is not entirely misplaced. Student achievement growth on test scores is a meaningful predictor of later-life outcomes such as educational attainment and income (Chetty, Friedman, & Rockoff, 2014; Hanushek, 2011; Murnane et al., 2000). Schools, therefore, play an important role in developing cognitive skills among their students because it pertains to their students' future wellbeing.

However, schools do not only convey content knowledge and develop cognitive skills. They also convey value systems and social norms that may shape their students' personality, behavioral tendencies, and character. These traits are referred to as noncognitive skills, or skills that are not easily captured by test scores in math or reading (Borghans et al., 2008; Duckworth & Yeager, 2015). Economists, psychologists, and other social scientists are paying greater attention to noncognitive skills as emerging research demonstrates that noncognitive skills are positively linked to student outcomes such as health, crime, educational attainment, income, and employment (Almlund et al., 2011, Heckman, Stixrud, & Urzua, 2006). Importantly, the relationship between noncognitive skills and student outcomes holds above and beyond the impact of cognitive skills on these outcomes. Such a result has spurred additional inquiry into how schools and other educational institutions can inculcate these noncognitive skills for their students' wellbeing.

Existing research shows that teachers play a large role in affecting cognitive skills (Rivkin, Hanushek, & Kain 2005; Rockoff, 2004). Given that teachers have impacts on student cognitive skills, it is reasonable to expect that teachers may also have impacts on student noncognitive skills. However, there is less research showing the extent to which teachers affect student noncognitive skills (Jackson, 2012; Jennings & DiPrete, 2010; Koedel, 2008). There are largely two reasons for this gap in the research. First, the little research of teacher impacts on student noncognitive skills is partly due to the predominant focus by researchers and policymakers on cognitive skill development. A second reason for the lack of research on noncognitive skills is the difficulty in measuring noncognitive skills. Unlike standardized tests, self-reported surveys of noncognitive skills are rarely administered on a regular basis. And even if those surveys are regularly administered, they are prone to nontrivial measurement issues such as social desirability bias or reference group bias (Duckworth & Yeager, 2015).

This study is motivated by the lack of research into the role that teachers play in their students' noncognitive skill development. Providing additional empirical evidence of the ability for teachers to influence student noncognitive skills would provide a broader picture of the effects that teachers have on their students. If so, further work to identify observable teacher characteristics associated with effects on student noncognitive skills would advance the understanding of the noncognitive skill development process. For instance, one could ask why a particular type of teacher influences student noncognitive skills more than others and use that insight to develop theories about the development of noncognitive skills. Such insight would also be useful for developing effective educational interventions aimed at improving student noncognitive skills. Evidence that teachers affect student noncognitive skills would also carry implications for conceptualizations of teacher quality, which at the moment is typically limited to a teacher's ability to improve student cognitive ability.

In this study, I use a five-year, longitudinal dataset of students with student fixed effects to track student noncognitive skill development. Moreover, I avoid typical issues when it comes to measuring noncognitive skills by using a behavioral measure, as opposed to a self-reported measure, of noncognitive skills. Specifically, I use item response rates on surveys as a proxy for student noncognitive skills related to conscientiousness. There are theoretical reasons to believe that survey response patterns are not random but are related to certain noncognitive skills. Indeed, some research has demonstrated this proposition (Robinson-Cimpian, 2014). Other work has explicitly validated item response rates as a measure of survey effort as a proxy for noncognitive skills related to effort and persistence (Hitt, Trivitt, & Cheng, forthcoming).

As I show below, item response rates for students in my data, like particular noncognitive skills, are predictive of their educational attainment and employment status measured nearly 20 years later. More importantly, I find that students experience increases in item response rates when they have teachers that are diligent enough to complete and return their own surveys for data collection. This pattern may suggest that teachers with a particular set of noncognitive skills instill similar noncognitive skills into their students. This is the first study to demonstrate a relationship between teacher and student performance on similar behavioral tasks. Interestingly, teachers that influence student noncognitive skills do not appear to influence student cognitive skills as measured by test scores.

The remainder of the article is divided into four sections. In the subsequent section, I review the research on noncognitive skills, paying particular attention to the theory of how they can be inculcated in students. I then detail the methods of this study in the second section and present the results in the third section. I discuss these findings in greater detail and conclude in the fourth section. Overall, I interpret these results as evidence that teachers play a role in inculcating certain noncognitive skills that are important for students' long-run life outcomes. Furthermore, different teachers have varying effects on the development of their student noncognitive as well as cognitive skills.

Literature Review

Teacher Impacts on Student Cognitive Ability

Teacher quality is the most important school factor for improving student cognitive ability (Rivkin et al., 2005; Rockoff, 2004). Some research indicates that high-quality teachers, as measured by their ability to raise student math and reading test scores, improve longer-run outcomes such as their students' educational attainment and employment income (Chetty et al., 2014; but see Rothstein, 2014).

Nonetheless, scholars are generally unable to identify high quality teachers based upon observable characteristics absent measures of student achievement. For instance, years of teaching experience is generally uncorrelated with teacher quality after the first three to five years of teaching (Buddin & Zamarro, 2009; Hanushek & Rivkin, 2006; Clotfelter, Ladd, & Vigdor, 2006; Goldhaber, 2007; Kane, Rockoff, & Staiger 2008). Teacher licensure is likewise not strongly correlated with a teacher's ability to raise student scores on achievement tests (Hanushek & Rivkin, 2006; Podgursky, 2005).

Although there is some evidence that having more content knowledge, as measured by the number of courses taken in that content area, is associated with higher teacher quality, this relationship largely holds for secondary school teachers in math or science (Clotfelter et al., 2006). There is also a lack of evidence that pedagogical knowledge for a specific content area is linked with student achievement (Hill, Rowan, & Ball, 2005). Although some research has demonstrated that achievement is higher for students with teachers that have higher cognitive ability, as measured by their performance on the Praxis or other standardized licensure tests (Goldhaber, 2007; Clotfelter et al., 2006), other work finds no relationship between teacher cognitive ability and student achievement (Buddin & Zamarro 2009). Finally, Duckworth, Quinn, and Selgiman (2009) provide suggestive evidence that some teacher noncognitive abilities (e.g., grit and life satisfaction) are positively correlated with student gains in cognitive ability. However, their analysis is based upon a convenience sample of an atypical group of teachers — first- and second-year Teach for America teachers.

In summary, research suggests that teacher quality matters for student wellbeing, but it is difficult to predict teacher quality solely based on teacher inputs and observable characteristics. This has led to some proposals to relax the selection of teachers based upon inputs (e.g., credentials) and to evaluate teachers based upon their outputs or actual performance (e.g., student achievement) (Podgursky, 2005; Kane et al., 2008; Hanushek, 2011). Notably, these proposals all define teacher quality as the ability to increase student achievement, or cognitive ability, as measured by growth on standardized test in math and reading. This approach raises the important issue of whether teachers are able to raise student noncognitive ability and whether these increases in noncognitive ability yield benefits for students in the long-run net of increases in cognitive ability. If so, there may be reason to consider teacher impacts on student noncognitive ability when conceptualizing teacher quality, especially if teachers who have impacts on student noncognitive ability are not the same teachers who have impacts on student test scores.

Teacher Impacts on Student Noncognitive Ability

Whether teachers have impacts on student noncognitive ability has received little empirical attention. One reason for the lack of this research is the infrequent systematic collection of noncognitive skill measures. Consider student achievement data, or measures of cognitive skills. Given mandates for annual testing and data systems that link student data to data about their teachers, researchers can estimate value-added models and identify causal effects of teachers on student cognitive skills, though there is debate about the validity of these models (Gaurino, Reckase, & Wooldridge, 2014; Koedel & Betts, 2011; Rothstein, 2009). In contrast, measures of noncognitive skills are not sufficiently developed for accountability purposes (Duckworth & Yeager, 2015). Nor are measures of noncognitive skills typically administered to students, much less linked to the students' teachers.

There are, however, exceptions to the dearth of research into teacher impacts on student noncognitive skills. Using data from North Carolina, Jackson (2012) estimates a factor model based on a set of non-test score outcomes (i.e., GPA, classroom attendance, suspensions, on-time grade progression) to proxy for a student's noncognitive skills. He finds that teachers have demonstrable effects on this measure of student noncognitive skills net of their impacts on student test scores (i.e., cognitive skills). In other work, Koedel (2008) provides evidence that variation in teacher quality explains differences in high school dropout rates. This finding can be interpreted as teacher having differential effects student noncognitive skills that lead to different attainment outcomes, assuming that educational attainment is driven by noncognitive skills, as Heckman and Rubenstein (2001) suggest. However, it is not clear how much of the association between teacher quality and dropout rates is driven by teacher impacts on student cognitive skills as cognitive skills are also important determinants of educational attainment. It is also possible that improvements to noncognitive skills lead to improvements in cognitive skills, which in turn, lead to positive student outcomes (Heckman, 2000). Moreover, teachers that have impacts on noncognitive skills may not necessarily be the same ones that have impacts on cognitive skills. Jackson (2012) finds this to be the case in his work, as do Jennings and DiPrete (2010).

Other research indirectly suggests that schools and teachers have impacts on student noncognitive skills. Several educational interventions have not demonstrably improved student test scores yet have improved other student outcomes attributable to gains in noncognitive skills. For example, evaluations of several school choice programs, such charter schools and private-school vouchers, have little to no impact on test scores but do have impacts on educational attainment (Booker et al., 2013; Chingos & Peterson, 2015; Wolf et al., 2013). Likewise, gains in cognitive ability from being randomly assigned to early-childhood interventions, such as the Perry Preschool Project, are known to dissipate when children enter elementary school. Yet students who participated in these early childhood interventions realize improvements in labor-market and health outcomes in adulthood as well as reductions in the incidence of criminal behavior (Heckman, Pinto, & Savelyev, 2013). The effects that these educational interventions have on educational attainment, health, crime, and labor market outcomes together with *the lack* of corresponding gains in cognitive ability suggests that schools and teachers have important impacts on student noncognitive skills.

How Do Teachers Affect Student Noncognitive Ability?

Although schools and their teachers appear to have impacts on student noncognitive ability, the channels through which they have such impacts are unclear. Character education and other similar formal curricula, for example, are aimed at improving noncognitive skills but there is little understanding of how they alter noncognitive skills. In fact, there is little evaluation of whether character education programs even alter noncognitive skills in the first place (Berkowitz & Bier, 2004).

Other work has investigated whether particular instructional approaches are more effective at improving noncognitive skills, but no strong relationship between the two has been found (Jennings & DiPrete, 2010). Presumably, different pedagogical practices could generate different experiences for students and lead to the development of particular noncognitive skills (Ames, 1992; Dweck, 2006; Yeager et al., 2014). Still, research on noncognitive skills is relatively nascent and has merely established the importance of noncognitive skills for student outcomes. Scholars have not empirically demonstrated systematic ways to improve noncognitive skills for students in primary and secondary schools at scale. Nor do they clearly understand the mechanisms behind the development of noncognitive skills.

It is also possible that noncognitive skill development occurs in less technical ways. Psychologists and sociologists have long proposed that learning is social (Bandura, 1977). Some have more specifically argued that individuals learn group norms by observing the behaviors of other group members, called social referents, in specific situations. A social referent helps individuals discern what types of behaviors are acceptable or unacceptable by allowing them to observe what behaviors are rewarded or sanctioned within the group (Sherif & Sherif, 1964). Teachers are particularly well-situated to act as role models, instilling a set of traits derived from a certain value system into their students (Berkowitz & Bier, 2004). Indeed, some scholars believe this mechanism partially explains why Catholic schools have been successful at improving student outcomes. Catholic schools are rich communities with a well-defined value system that is embodied by their teachers and other school workers. The values, in turn, are inculcated into their students and play a role in the formation of particular character traits and personality dispositions (Bryk et al., 1993; Coleman & Hoffer, 1987).

Issues with measuring noncognitive skills

Previously described evidence from school choice and early childhood education research supports the prevalent intuition that schools affect student noncognitive skills. Nonetheless, there have been very few direct empirical tests of whether individual teachers influence student noncognitive skills. This study fills this gap and uses a novel method to measure noncognitive skills to do so.

As mentioned earlier, one reason for the lack of this evidence is the infrequent collection of noncognitive skill measures. But even if psychometric scales were regularly administered to students, researchers have another problem: Scales designed to measure noncognitive skills are prone to social desirability bias, satisficing, and similar problems endemic to survey data. The potential for this type of systematic error is always present in self-reported data.

And even students honestly answer items on a survey, another problem remains. Consider an item that asks a student to specify how hard-working he is. Although that student may be honest in his response, his assessment of what it means to be a hard worker is relative to some external standard. This problem is called reference group bias and may be the reason behind paradoxical research results where students who experience improved outcomes (e.g., test scores, educational attainment, criminal behavior) rate themselves lower on the very noncognitive skills that are supposedly positively correlated with those outcomes (Duckworth & Yeager, 2015; Dobbie & Fryer, 2013; West et al., 2014).

To circumvent the limitations of using self-reported measures of noncognitive skills, I use a performance task to solicit behavioral measure of noncognitive skills. Specifically, completing a survey can be viewed as a performance task. Surveys of sufficient length are tedious tasks and much like homework assignments. Completing them and refraining from skipping items requires a great deal of diligence and persistence. Students need to heed instructions, respect those who are assigning the task, and exert basic effort to respond to the items. In this respect, survey effort is a measure of a particular set of noncognitive skills (Robinson-Cimpian, 2014). In the analysis below, I use item response rates — or the extent to which students do not shirk and skip questions — as measures noncognitive skills to examine whether individual teachers are able to alter their students' noncognitive skills. Using six large-scale longitudinal data sets Hitt et al. (forthcoming) have validated using item response rates on surveys as a measure of persistence and effort. They find, for instance, that individuals who have higher item response rates in adolescence complete more years of schooling, even after controlling for measures of cognitive ability. So there is not only theoretical reason to believe that item response rates capture traits associated with conscientiousness but also empirical evidence to do so as the measure predicts later-life outcomes in the same way as expected from those noncognitive skills. In the next section, I present the use of item response rates and other methods of my analysis in greater detail.

Methods

Data

Data for this analysis come from the Longitudinal Study of American Youth (LSAY). In 1987, a nationally representative sample of public school seventh and tenth graders was selected to participate in the panel. LSAY was intended to provide descriptive data about students from adolescence into adulthood. In particular, LSAY focused on gathering information about students' attitudes towards science and math, their career prospects in those fields, and opinions regarding their math and science classes.

This study focuses on LSAY's seventh-grade cohort, which consists of approximately 3,000 students. These students were biannually surveyed and annually completed standardized tests in math and science through their twelfth-grade year in 1994. Surveys and standardized tests occurred in separate 50-minute sessions during the school day and were administered by research coordinators. Students were subsequently surveyed as adults from 2007-2011, also on an annual basis. LSAY additionally surveyed each student's respective math and science teachers in each year of the study. Teachers received surveys and were provided the means to return completed surveys via the postal service. Because teachers were not surveyed when this student cohort was in twelfth grade, the analysis is based upon data from the seventh through eleventh grades.

Response Rate as a Proxy for Noncognitive Skills

Item response rates on student surveys are used as behavioral measures for student noncognitive skills related to conscientiousness. In each wave of the LSAY, students generally faced between 150 and 360 items on the questionnaires. Such a lengthy survey lends additional credence for interpreting item response rates as behavioral indications of noncognitive skills. Item response rates are simply the proportion of items that students answer out of the total number of questions students were asked to answer. Item response rates are computed for each wave of LSAY. Table 1 displays summary statistics of item response rates for students from seventh through eleventh grade. Most students complete a majority of the surveys they are asked to fill out, though there is still variation in the number of items that they skip. For the analysis, student item response rates are standardized by year.

≪Table 1 Here≫

Initially, I computed teacher item response rates just as I calculated student item response rates. However, unlike students who were required to complete surveys during an assigned time in school, teachers were mailed surveys via the postal service and asked to return completed forms. This data collection method resulted in a large number of teachers who never completed a survey. Moreover, those who did complete a survey completed between 90 and 100 percent of the items, yielding little variation in teacher item response rate and little study power. Consequently, I use a binary variable indicating whether a teacher did or did not return the survey during each respective wave of LSAY.

The assumption is that this binary variable also captures each teacher's level of conscientiousness, which was required to complete and return the survey via postal mail.[1] To summarize, whether a teacher returns the survey is the measure of teacher noncognitive skills, while item response rate is the measure of student noncognitive skills. Table 1 shows summary statistics for teacher return rates.

Empirical Strategy

Validation of Item Response Rates. Before conducting the analysis to determine if teachers affect student noncognitive ability, it would be helpful to empirically validate student item response rate as measures of noncognitive ability instead of only relying on aforementioned theoretical reasons and prior research of other datasets to argue that item response rates capture noncognitive skills. To provide empirical validation of response rate as a proxy for noncognitive skills, I follow Hitt et al. (forthcoming) and run a series of regressions using item response rates to predict long-run life outcomes. It is sufficient to show that item response rate in adolescence mimics other measures of noncognitive skills by being an important and independent determinant of long-run life outcomes (Almlund et al., 2011). In particular, I average each student's survey response rates from seventh through ninth grade[2] and use them as independent variables in regressions to predict educational attainment and future employment. I then estimate

[1] One may worry that a binary indicator for whether a teacher returns a survey is a noisy measure of teacher conscientiousness. It is possible that such an indicator has low year-to-year correlation for individual teachers. Because hardly any teachers were asked to complete a survey in consecutive years — they were only asked to complete a survey if they had a student in the LSAY sample — such correlations cannot be calculated. Nevertheless, a low year-to-year correlation in the dummy variable indicating whether a teacher returns the survey leads to conservative hypothesis tests. Thus, one can be more confident that statistically significant correlations between this variable and other variables are material and not spurious, should such correlations be found.

[2] Item response rates and test scores from multiple years are incorporated to improve the precision of these estimates. Point estimates are robust to using fewer years of data. I also do not incorporate information from grades 10 and 11, the point where many students drop out of school, to avoid compositional effects.

$$Y_i = \beta_0 + \beta_1 S_i + \boldsymbol{\beta_2 X_i} + \mu_i, \quad (1)$$

where Y_i is a long-run outcome for student i (e.g., educational attainment, employment status) and S_i is student i's average response rate from seventh through ninth grade. X_i is a vector of student background characteristics, such as student gender, race, mother's education and the urbanicity and US region of the student's school. I also average each student's math and science test scores from the seventh to ninth grade to control for cognitive ability. Outcome variables are measured about 24 years later when the respondents are in their early thirties.

Unfortunately, providing empirical validation of the measure of whether or not teachers turn in the survey captures similar noncognitive skills is not possible in the data. The claim that this behavioral observation captures teacher noncognitive skills related to conscientiousness relies on theoretical assumptions. Discussion of this limitation as it pertains to the results is presented later in the article.

Main analysis. To investigate whether particular types of teachers affect student noncognitive ability, I estimate models that examine changes in a student's noncognitive skills as they are taught by teachers with varying levels of noncognitive skills over his or her secondary schooling experience. I take advantage of the longitudinal nature of the LSAY by including student fixed effects to control for time-invariant heterogeneity across students. I estimate models of the form:

$$Y_{it} = \beta_0 + \beta_1 N_{it} + \boldsymbol{\beta_2 X_{it}} + \boldsymbol{\gamma_{it}} + \nu_i + \epsilon_{it}. \quad (2)$$

In equation (2), Y_{it} is student i's response rate in the spring semester of time period t. Values for Y_{it} are expressed as standard deviations and standardized by year. N_{it} is an indicator equal to one if student i's teacher did not return a survey in time period t and equal to zero otherwise. X_{it} is a vector of time-varying student characteristics such student cognitive ability as measured by standardized math and science tests.[3] Meanwhile, $\boldsymbol{\gamma_{it}}$ is a vector of year dummies that capture secular time trends, ν_i is a student-fixed effect, and ϵ_{it} is the time-varying error term. This model is run twice: once where N_{it} represents the student's math teacher and once where N_{it} represents the student's science teacher. The coefficient of interest, β_1, captures the influence that teachers who either return or fail to return their survey have on student noncognitive skills based on year-to-year variation in student item response rates or test scores.

I also run an additional model to assess marginal changes in student item response rate in years where the student has a math teacher and a science teacher who both do not return the survey. In particular, I estimate:

$$Y_{it} = \beta_0 + \beta_1 N^a_{it} + \beta_2 N^b_{it} + \beta_3 X_{it} + \gamma_{it} + \nu_i + \epsilon_{it}, \qquad (3)$$

where N^a_{it} is an indicator equal to one if either student i's math or science teacher but not both failed to return the survey in time period t. N^b_{it} is an indicator equal to one if both student i's math and science teachers did not return the survey in time period t. The other variables are as they are in equation (2).

One difficulty in conducting research of teacher impacts on student outcomes is accounting for the nonrandom assignment of students to teachers. Without accounting for such patterns, one cannot be confident that causal impacts have been identified (Rothstein, 2009). The inclusion of student fixed effects in this study helps to address this concern by controlling for time-invariant student characteristics that may be correlated

[3] Standardized test scores in reading and language arts are not available in the data. One may question, therefore, the validity of the measure of cognitive ability. However, it should be pointed out that the concern is likely overstated, given that scores on standardized math and science tests are highly correlated with scores on reading tests.

with the assignment of students to teachers. But insofar as such assignment is correlated with time-*invariant* factors, these results do not have a causal interpretation. This caveat must be considered when interpreting the results.

The use of longitudinal data together with the inclusion of student fixed-effects also effectively controls for any observable and unobservable time-invariant student characteristics (e.g., gender, race, socioeconomic status, family background or upbringing) that could affect outcomes of interest. Put differently, item response rates for each student are compared to item response rates for the same student in different years of the data and after accounting for annual trends in response rate over time. Thus, the coefficient estimates of the indicator for whether a teacher completed the survey or not captures annual increases or decreases in student item response rate (i.e., conscientiousness) as the student sorts through teachers who either return or fail to return the teacher-level survey over time (i.e., teachers with varying levels of conscientiousness).

I also run analogous models where the dependent variable is student test scores instead of student item response rate. These models examine whether teachers with the noncognitive skills captured by whether or not they respond to surveys have a differential impact on student cognitive ability relative to teachers who exhibit those noncognitive skills to a lesser extent.

Additional models. Note that the aforementioned models do not control for student item response rates from prior years due to a methodological issue that arises when estimating student fixed-effects models that control for lagged measures of response rate. A key identifying assumption for obtaining valid estimates with student fixed-effects is strict exogeneity, which requires that all model covariates are uncorrelated with the time-varying error term in all periods. But including lagged measures of the dependent variable — here, student response rate — mechanically introduces such correlation. To address this issue and to control for prior-year item response rates, one can first difference equation (2) and instrument for the lagged change in student response rate with twice-lagged student response rate. This instrumental variables technique was originally proposed by Anderson and Hsiao (1981). Alternatively, one could use a general method of moments estimation techniques proposed by Arellano and Bond (1991), which essentially uses additional lags of student response rate to instrument for lagged student response rate. I use both of these techniques to estimate models that include prior-year measures of student response rates, which capture how students' year-to-year growth in conscientiousness changes as they encounter teachers with varying levels of a similar noncognitive skill throughout secondary school.

Results

Validation of Student Item Response Rate

As mentioned earlier, it is worthwhile to provide evidence that item response rate is a legitimate measure of noncognitive skills in LSAY. Table 2 shows the results of regressions where student item response rates and test scores are used to predict two long-run life outcomes, specifically educational attainment and employment. Item response rates are generally associated with these long-run life outcomes much in the same way as noncognitive skills above and beyond the contribution of cognitive ability. As shown in columns 1 and 2, increasing item response rate or test scores by one standard deviation is associated with completing about one additional year of education. Moreover, column 3 indicates that increasing item response rates by one standard deviation is associated with completing almost an additional half of a year of education net of the impact of test scores.[4]

Item response rates in adolescence is also positively correlated with labor-market outcomes — specifically, future employment. As shown in column 4 of Table 2, an increase of one standard deviation in item response rate is associated with approximately a six-percent increase in the likelihood of being employed. Meanwhile, an increase of one standard deviation in cognitive ability as measured by standardized test scores is associated with a four-percent increase in the likelihood of being employed (see column 5). Finally, item response rate remains correlated with employment above and beyond the impact of cognitive ability (see column 6).

≪Table 2 Here≫

Main Analysis

Variation in Independent Variable of Interest. I now return to answering the primary objective of this study, which is to examine whether teachers influence the noncognitive development of their students. Because equations (2) and (3) are estimated using student fixed effects, it is useful to examine the sources of variation in the independent variable of interest, namely, the dummy variable indicating whether a teacher returns the survey or not. Specifically, how much of this variation occurs across

[4] One could also use multinomial logistic regression to estimate the relationship between item response rates and educational attainment specified as a categorical variable indicating the highest level of education completed (e.g., high school dropout, high school diploma, bachelor's degree, etc.). Doing so does not change the results. These estimates are available from the author upon request.

students, and how much occurs within students over time? I present this information in Tables 3 through 5.

The variance decomposition in the dummy variable indicating whether the teacher returns his or her survey is shown in Table 3. More variation in this variable occurs within students than between students over time, which is desirable for the student fixed-effects analysis. About 61 percent of overall variation in whether a math teacher returns the survey occurs between students, with the remaining 39 percent due to variation within students. Likewise, about 66 and 34 percent of overall variation in whether a science teacher returns the survey occurs between and within students, respectively.

≪Table 3 Here≫

Other ways to portray variation in teacher response rate are shown in Table 4. The first column of Table 4 shows the proportion of student-year observations that fell into each category. For example, about 59 percent of student-year observations had math teachers that returned the teacher-level survey, while the math teachers for the other 41 percent of student-year observations did not. Analogous figures for science teachers are similar. The second column shows the proportion of students who at least once throughout the panel had teachers that returned the survey or did not return the survey. About 95 percent of students in the data had a math or science teacher who returned the survey. Meanwhile, about 80 and 87 percent of students had math or science teachers who did not return the survey, respectively. Finally, column 3 shows the proportion of students who only had a teacher in a single category. About 62 percent of students who ever had math teachers who returned the teacher-level survey always had math teachers who returned the survey. In contrast, about half of the students who ever had math teachers who did not return the survey always had such teachers. Similarly, approximately 57 percent of students always had a science teacher that returned the teacher-level survey, while about 54 percent of students always had a science teacher that did not return the teacher-level survey.

≪Table 4 Here≫

Table 5 displays year-to-year transition probabilities across categories of teacher item response rates. Teacher item response rate categories for prior year are listed down the rows, while teacher item response rate categories for subsequent year are listed across the columns. The diagonal shows the proportion of students who remained the same category in teacher item response rate from one year to the next. As shown in the first entry in Table 5a, about 68 students who, for a particular year, had a math teacher that returned the teacher-level survey also had, for the subsequent year, a math teacher that returned the survey. About 75 percent of students who, for a particular year, had a math teacher that failed to return the survey also, for the subsequent year, had a math teacher that failed to return the survey. Figures in the off-diagonal indicate the proportion of students who had different types of teachers in consecutive years. For example, about 30 percent of students who, in a particular year, had math teachers that returned the survey then had, in the subsequent year, math teachers that did not return the survey. About one quarter of students switched teacher types in the opposite direction. Corresponding figures for science teachers are shown in Table 5b.

Figures in Table 3 through 5 depict the variation in the dummy variable indicating whether or not a teacher returns the teacher-level survey. Although Table 3 shows more variation over time (within-student variation) than across students (between-student variation), the last column of Table 4 demonstrates that well over half of the students who encounter one type of teacher (i.e., those that return the survey or those that do not) always have the same type of teacher for all time periods in the data. Further, a relatively low percentage of students switch between the two types of teachers in consecutive years, as depicted in Tables 5a and 5b. These patterns suggest that student-fixed effect methods, which rely on within-student variation, may not be a highly efficient estimation technique. That being said, results based on student-fixed effects estimation represent conservative tests of a relationship between student item response rate and whether the student's teacher returns the teacher-level survey or not.

The models invoking Anderson-Hsiao and Arellano-Bond estimation techniques would be even more conservative because the use of instrumental variables and additionally controlling for lagged measures of the dependent variable, which results in the loss of several periods in the panel, would further lower variation in the dummy variable indicating whether or not a teacher returns his or her survey. Thus, should a relationship between the two variables exist, one can be even more confident that a relationship between the two variables is material and not the result of statistical chance.

≪Table 5≫

Main Analysis Results. Table 6 displays the results of the main analysis. Indeed, there exists a relationship between a student's item response rate on the student-level survey and whether his or her teacher returns the teacher-level survey. Column 1 demonstrates that students experience a drop in their item response rates by about 0.08 standard deviations in years where they have a math teacher who fails to complete the teacher survey. Likewise, column 2 shows that students experience a drop in their item response rates by about 0.09 standard deviations in years where they have a science teacher who fails to complete the teacher survey. Students with math and science teachers who both do not respond to surveys experience a drop of 0.13 standard deviations in their item response rates. In contrast, having teachers who fail to complete the teacher survey does not appear to be related to student test scores (Table 6, Columns 4 through 6).

≪Table 6 Here≫

Results based on the Anderson-Hsiao and Arellano-Bond estimators are shown in Table 7 and Table 8, respectively. The correlations between a student's item response rate and whether his or her math teacher returns the teacher-level survey that were found using the student-fixed effects models are not robust to the Anderson-Hsiao and Arellano-Bond specifications. In contrast, the correlation between student's item response rate and whether his or her science teacher returns the teacher-level survey remains statistically significant in the Anderson-Hsiao and Arellano-Bond specifications. In years when students have a science teacher that fails to return the teacher-level survey, their item response rate decreases by 0.07 standard deviations.

≪Table 7 Here≫

≪Table 8 Here≫

The prevalence of statistically insignificant results, mostly due to the attenuation of the coefficient estimates, are not surprising given the additional loss of variation in the independent variable of interest when using the Anderson-Hsiao and Arellano-Bond techniques. Empirical evidence of this claim is displayed in Tables 9 through 11, which are analogous to Tables 3 through 5 but are restricted to displaying summary statistics for periods in the panel that are used in computing Anderson-Hsiao estimators. As shown in the tables, within-student variation in the dummy variable indicating whether a teacher returns a survey is much lower. For example, whereas there was more variation over time (within-student variation) than across students (between-student variation) in the dummy variable in the student-fixed effects models, there is actually less variation over time within students than across students in the Anderson-Hsiao models (see Table 9). Notably, overall variation is much lower for math teachers than for science teachers, explaining why results based on science teachers but are robust to the Anderson-Hsiao and Arellano-Bond specifications, while results based upon math teachers are not.

<<Table 9≫

<<Table 10≫

<<Table 11≫

Returning to the remaining columns in Table 7 and Table 8, in years when a student’s math and science teachers both fail to return the teacher-level survey, his or her item response rate decreases by about 0.09 standard deviations based on the Arellano-Bond estimator, though the result is only significant at $\alpha = 0.1$. There is no such relationship based upon the Anderson-Hsiao estimator. Finally, note that the relationship between test scores and whether a teacher returns a survey remains null. In general, results based upon these two estimation techniques lend additional confidence in the results of the student-fixed effects models.

Discussion and Conclusion

The purpose of this analysis was twofold: (a) to determine if teacher have impacts on student noncognitive skills and (b) if so, to attempt to shed light onto what kinds of teachers have such impacts. I adopt the approach suggested by Hitt et al. (forthcoming) and use measures of survey effort as a behavioral measure of noncognitive skills related to conscientiousness. Consistent with other research, my results indicate that students who possess higher levels of these noncognitive skills, as measured by item response rates, ultimately have higher levels of educational attainment and are more likely to be employed (Almlund et al., 2011; Heckman et al., 2006). It is worth reiterating that these results hold net of student cognitive skills as measured by standardized tests.

More central to the original purposes of the analysis, the results suggest that students realize gains in these noncognitive skills when they are taught by teachers who also possess a greater degree of similar noncognitive skills. Presumably, teachers require some level of noncognitive skills associated with conscientiousness in order to complete surveys and return them to the data collection agency via postal mail. Students exhibit lower item response rates in years where they have teachers who fail to return surveys and higher item higher response rates in years where they have teachers who do. At the same time, the teachers who return surveys and are having impacts on student noncognitive skills, as captured by item response rates, are not the same teachers that have impacts on student test scores. Such a result is consistent with the emerging research on how teachers contribute to cognitive and noncognitive student outcomes (Jackson, 2012; Jennings & DiPrete, 2012). In short, certain teachers are benefiting their students in ways that are (a) nontrivial for longer-run life outcomes and (b) not fully captured by test scores.

However, this analysis is unable to ascertain how, exactly, noncognitive skills are transmitted from students to teacher. Results are consistent with the theory that such skills are transmitted through role modeling. Teachers with certain proclivities that reflect a lack of conscientiousness may actively or passively transmit those proclivities to their students (Bandura, 1977; Berkowitz & Bier, 2004; Sherif & Sherif, 1964). Alternatively, teachers with particular noncognitive skills may utilize pedagogical approaches conducive to fostering those noncognitive skills. For instance, teachers with growth mindset may teach students in a way that also fosters growth mindset (Dweck, 2006). Such a theory is also consistent with the results. Ultimately, much more inquiry is needed to better understand what phenomena and mechanisms underlie these results.

Additional study limitations are worth considering. First, results hinge on the assumption that teacher response rate captures traits related to conscientiousness. Unlike student item response rates, validating this proposition is not possible in the data. There is a possibility that survey effort could capture different noncognitive skills among adults than adolescents or children.[5] However, there are still theoretical reasons to assume that characteristics associated with completing and returning a survey are related to conscientiousness. And even if such an assumption is not accepted, the fact that the noisy measure of whether a teacher returns a survey or not is correlated with student item response rates and not with student test scores, at the very least, warrants explanation.

It would also be useful to determine what other observable teacher characteristics, if any, predict a teacher's ability to raise student noncognitive skills. Unfortunately, LSAY data are too limited to investigate whether, for example, teacher credentials or experience is correlated with teacher noncognitive skills and their impacts on student noncognitive skills. As a result, restraint should be exercised before drawing policy implications. For instance, teachers with a particular noncognitive skill set appear to have

[5] I am engaged in ongoing work to examine the validity of measures of survey effort as a proxy for particular noncognitive among adults and teachers.

impacts on student noncognitive skills, which in turn, affect student educational attainment net of what is predicted by cognitive skills. One might suggest that schools ought to recruit such teachers. Yet without knowledge of what observable characteristics are correlated with having those noncognitive skills, it is not clear how such teachers can be readily identified. It is possible that observable characteristics, such as teacher credentials or years of experience, are not strongly correlated with a teacher's ability to improve student noncognitive skills, just as they are not strongly correlated with a teacher's ability to improve student cognitive skills (Goldhaber, 2008).

Likewise, one might suggest that appraisals of teacher quality should incorporate teacher impacts on student noncognitive skills. This proposal is not unreasonable given results from this study and other evidence that teachers have impacts on student outcomes not captured by test scores. Still, it is unclear how to effectively measure this dimension of teacher quality in practice, even though it may be desirable to do so. As discussed earlier, self-reported scales have serious sources of bias and survey item response rates, like other behavioral measures, can be misinterpreted and may lack external validity. Both types of measures can easily be corrupted in high-stakes settings as well (Duckworth & Yeager, 2015).

Nonetheless, broadening the understanding of teacher quality to include teacher noncognitive skills and teacher impacts on student noncognitive skills is worthy of more discussion. Likewise, schools play a pivotal role in the development of many children. They do more than deliver content knowledge and improve cognitive skills. Schools and other educational interventions communicate values and influence noncognitive skills. Overlooking this facet of education may result in an incomplete picture of how educational institutions and interventions affect students. Noncognitive-skill research is a field ripe for research and rife with unanswered questions. For instance, to what extent are noncognitive skills malleable? How can they be developed or how are they transmitted (Borghans et al., 2008; Heckman, 2000)? Complete appraisals of educational policies and institutions hinge on answers to many of these questions. This study draws some attention into this otherwise vastly understudied yet important topic.

References

Almlund, M., Duckworth, A. L., Heckman, J., & Kautz, T. D. (2011). Personality Psychology and Economics. In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), *Handbook of the Economics of Education* (pp. 1–181). Amsterdam: Elsevier.

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology*, 84(3), 261-271.

Anderson T.W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, *76*(375), 598-609.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*(2), 277–297.

Bandura, A. (1977). *Social learning theory*. Englewood Cliffs, NJ: Prentice Hall.

Berkowitz, M. W., & Bier, M. C. (2004). Research-Based Character Education. *The Annals of the American Academy of Political an Social Science*, *591*(1), 72–85.

Booker, K., Sass, T., Gill, B., & Zimmer, R. (2014). *Charter high schools' effect on long-term attainment and earnings*. Retrieved from the Mathematical Policy Research website: http://www.mathematica-mpr.com/publications/pdfs/education/charter_long-term_wp.pdf

Borghans, L., Meigers, H., & Bas, ter W. (2008). The role of noncognitive skills in explaining cognitive test scores. *Economic Inquiry*, *46*(1), 2–12.

Bryk, A. S., Lee, V. E., & Holland, P. B. (1993). *Catholic Schools and the Common Good*. Cambridge, MA: Harvard University Press.

Buddin, R., & Zamarro, G. (2009). Teacher qualifications ands achievement in urban elementary schools. *Journal of Urban Economics*, *66*(2), 103–115.

Chetty, R., Friedman, J. N., & Rockoff, J. E. (2014). Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review*, *104*(9), 2633–2679.

Chingos, M. M., & Peterson, P. E. (2015). Experimentally Estimated Impacts of School Vouchers on College Enrollment and Degree Attainment. *Journal of Public Economics*, *122*, 1–12.

Clotfelter, C. T., Ladd, H. F., & Vigdor, J. L. (2006). Teacher-student matching and the assessment of teacher effectiveness. *Journal of Human Resources*, *41*(4), 778–820.

Coleman, J. S., & Hoffer, T. (1987). *Public and Private High Schools*. New York, NY: Basic Books.

Dobbie, W., & Fryer, R. G. (2013). Getting beneath the veil of effective schools: Evidence from New York City. *American Economic Journal: Applied Economics*, *5*(4), 28–60.

Duckworth, A. L., Quinn, P. D., & Seligman, M. E. P. (2009). Positive predictors of teacher effectiveness. *The Journal of Positive Psychology*, *4*(6), 540–547.

Duckworth, A. L., & Yeager, D. S. (2015). Measurement matters: Assessing personal qualities other than cognitive ability for educational purposes. *Educational Researcher*, *44*(4), 237–251.

Dweck, C. (2006). *The psychology of success*. New York, NY: Random House Inc.

Goldhaber, D. D. (2007). Everyone’s doing it but what does teacher testing tell us about teacher effectiveness. *Journal of Human Resources*, *42*(4), 765–794.

Goldhaber, D. D. (2008). Teachers matter, but effective teacher quality policies are elusive. In H. F. Ladd & E. B. Fiske (Eds.), *Handbook of Research in Education Finance and Policy* (pp. 146–165). New York, NY: Routledge.

Guarino, C. M., Reckase, M. D., & Wooldridge, J. M. (2015). Can value-added measures of teacher performance be trusted? *Education Finance and Policy*, *10*(1), 117–156.

Hanushek, E. A. (2011). The economic value of higher teacher quality. *Economics of Education Review*, 30(3), 466–479.

Hanushek, E. A., & Rivkin, S. G. (2006). Teacher quality. In E. A. Hanushek & F. Welch (Eds.), *Handbook of the Economics of Education* (Vol. 2, pp. 1052–1078). Amsterdam: Elsevier.

Heckman, J. (2000). Policies to foster human capital. *Research in Economics*, 54(1), 3–56.

Heckman, J., Pinto, R., & Savelyev, P. (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review*, *103*(6), 2052–2086.

Heckman, J., & Rubenstein, Y. (2001). The importance of noncognitive skills: Lessons from the GED testing program. *American Economic Review*, *91*(2), 145–149.

Heckman, J., Stixrud, J., & Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics*, *24*(3), 411–482.

Hill, H. C., Rowan, B., & Ball, D. L. (2005). Effects of teachers' mathematical knowledge for teaching on student achievement. *American Educational Research Journal*, 42(2), 372–406.

Hitt, C., Trivitt, J., & Cheng, A. (forthcoming). When you say nothing at all: The predictive power of student effort on surveys, *Economics of Education Review*.

Jackson, K. (2012). Non-cognitive ability, test scores, and teacher quality: Evidence from 9th grade teachers in North Carolina (NBER Working Paper No. 18624). Cambridge, MA: National Bureau of Economic Research.

Jennings, J. L., & DiPrete, T. A. (2010). Teacher effects on social and behavioral skills in early elementary school. *Sociology of Education*, *83*(2), 135–159.

Kane, T., Rockoff, J. E., & Staiger, D. (2008). What does certification tell us about teacher effectiveness. *Economics of Education Review, 27*(6), 615–631.

Koedel, C. (2008). Teacher quality and dropout outcomes in a large, urban school district. *Journal of Urban Economics, 64*(3), 560-572.

Koedel, C., and Betts, J. R. (2011). Does student sorting invalidate value-added models of teacher effectiveness? An extended analysis of the Rothstein critique. *Education Finance and Policy, 6*(1), 18–42.

Miller, J.D. (2014). *Longitudinal Study of American Youth: User's manual*. Inter-university Consortium for Political and Social Research, University of Michigan: Ann Arbor, MI.

Murnane, R. J., Willet, J. B., Duhaldeborde, Y., & Tyler, J. H. (2000). How important are the cognitive skills of teenagers in predicting subsequent earnings*? Journal of Policy Analysis and Management*, *19*(4), 547–568.

Podgursky, M. J. (2005). Teacher licensing in U.S. public schools: The case for simplicity and flexibility. *Peabody Journal of Education, 80*(3), 15–43.

Robinson-Cimpian, J.P. (2014). Inaccurate estimation of disparities due to mischievous responders: Several suggestions to assess conclusions. *Educational Researcher, 43*(4), 171-185.

Rockoff, J. E. (2004). The impact of individual teachers on student achievement: Evidence from panel data. *American Economic Review, 94*(2), 247–252.

Rothstein, J. (2009). Student sorting and bias in value-added estimation: Selection on observables and unobservables. *Education Finance and Policy, 4*(4), 537–571.

Rothstein, J. (2014). Revisiting the impacts of teachers [Unpublished manuscript]. University of California, Berkeley: Berkeley, CA.

Sherif, M., & Sherif, C. (1964). *Reference groups: Exploration into conformity and deviation in adolescents*. Chicago, IL: Henry Regnery Company

Wolf, P. J., Kisida, B., Gutmann, B., Puma, M., Eissa, N., & Rizzo, L. (2013). School vouchers and student outcomes: Experimental evidence from Washington, DC. *Journal of Policy Analysis and Management*, *32*(2), 246–270.

Yeager, D.S., Henderson, M.D., Paunesku, D., Walton, G.M., D'mello, S., Spitzer, B.J., & Duckworth, A.L. (2014). Boring but important: A self-transcendent purpose for learning fosters academic self-regulation. *Journal of Personality and Social Psychology, 107*(4), 559-580.

Table 1: Student Item Response Rates and Teacher Response Rates

	Grade 7	Grade 8	Grade 9	Grade 10	Grade 11
Student Item Response Rates (%)					
Mean	97.6	98.3	98.0	86.5	96.8
Standard Deviation	5.5	4.2	4.2	28.9	6.2
Minimum	5.5	3.5	18.8	1.1	9.6
Average Number of Questions Faced	178	265	282	149	288
Math Teacher Return Rates (%)					
Students with Teacher who Returns the Survey	94.4	81.8	89.4	74.6	73.8
Students with Teachers who do not Return the Survey	15.6	18.2	10.6	25.4	26.2
Science Teacher Return Rates (%)					
Students with Teacher who Returns the Survey	82.1	76.6	83.2	69.0	69.2
Students with Teachers who do not Return the Survey	17.9	23.4	16.8	31.0	30.8

Note: Maximum student item response rates for each semester are 100 percent. Teachers were only surveyed in spring semesters. Summary statistics for teacher response rate reflect a percentage of student observations.

Table 2. Student Response Rate, Test Scores, Years of Education, and Employment

	Dependent Variable					
	Years of Education			Employment		
	(1)	(2)	(3)	(4)	(5)	(6)
Item response Rate	0.99** (0.16)		0.49** (0.14)	0.059** (0.016)		0.045* (0.019)
Test Scores		0.98** (0.09)	0.90** (0.10)		0.038** (0.015)	0.029† (0.015)
R^2	0.24	0.32	0.33	n/a	n/a	n/a

Notes: N = 1,556. Linear regression coefficients are reported for educational attainment outcomes. Marginal effects after logit estimation are reported for employment outcomes. Explanatory variables are expressed in standard deviations and are averaged using the respondent's seventh through ninth grade data. Educational attainment and employment outcomes measured 24 years after initial wave of LSAY data collection. Control variables include student's race, gender, and mother's educational attainment as well as the urbanicity and US region of the student's school. †p<0.1, * p<0.05, ** p<0.01.

Table 3. Variation in Teacher Return Rates

	Standard Deviation	Percent of Overall Variance (%)
Math Teachers		
Overall	0.49	n/a
Within Students	0.31	61.1
Between Students	0.39	38.9
Science Teachers		
Overall	0.50	n/a
Within Students	0.29	66.2
Between Students	0.41	33.8

Table 4. Variation in whether Teacher Returns Survey

Category	Proportion of student-year observations that fell into the given category	Proportion of students who fell into the given category at least once throughout the panel	Proportion of students who never switch out of the given category
Math Teachers			
Teacher Returns Survey	58.7	94.9	61.9
Teacher Does not Return Survey	41.3	79.5	51.9
Science Teachers			
Teacher Returns Survey	53.4	94.6	56.5
Teacher Does not Return Survey	46.6	86.8	53.7

Note: All numbers are percentages.

Table 5a: Transition Probabilities for whether Math Teacher Returns Survey

		Status in Year t	
		Math Teacher Returns Survey	Math Teacher Does not Return Survey
Status in Year t-1	Math Teacher Returns Survey	68.7	31.3
	Math Teacher Does not Return Survey	24.9	75.1

Note: All numbers are percentages.

Table 5b: Transition Probabilities for whether Science Teacher Returns Survey

		Status in Year t	
		Science Teacher Returns Survey	Science Teacher Does not Return Survey
Status in Year t-1	Science Teacher Returns Survey	61.1	38.9
	Science Teacher Does not Return Survey	35.0	75.0

Note: All numbers are percentages.

Table 6. Associations between Teacher Response, Student Item Response Rate, and Student Test Scores

	Dependent Variable					
	Student Item Response Rate			Student Test Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
Math Teacher Does Not Respond to Survey	-0.08** (0.03)			0.01 (0.01)		
Science Teacher Does not Respond to Survey		-0.09** (0.03)			-0.00 (0.01)	
Both Teachers do not Respond			-0.13** (0.04)			-0.00 (0.01)
Student Observations	3,040	3,040	3,040	2,918	2,918	2,918

Notes: †p<0.1, *p<0.05, **p<0.01.

Table 7. Anderson-Hsiao Estimates

	Dependent Variable					
	Student Item Response Rate			Student Test Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
Math Teacher Does Not Respond to Survey	-0.01 (0.03)			-0.01 (0.01)		
Science Teacher Does not Respond to Survey		-0.08** (0.03)			-0.00 (0.01)	
Both Teachers do not Respond			-0.07 (0.05)			-0.01 (0.01)
Student Observations	2,215	2,215	2,215	2,826	2,826	2,826

Notes: †p<0.1, *p<0.05, **p<0.01.

Table 8. Arellano-Bond Estimates

	Dependent Variable					
	Student Item Response Rate			Student Test Scores		
	(1)	(2)	(3)	(4)	(5)	(6)
Math Teacher Does Not Respond to Survey	-0.01 (0.03)			-0.01 (0.01)		
Science Teacher Does not Respond to Survey		-0.09** (0.03)			-0.00 (0.01)	
Both Teachers do not Respond			-0.09† (0.05)			-0.01 (0.01)
Student Observations	2,215	2,215	2,215	2,826	2,826	2,826

Notes: *p<0.05, **p<0.01.

Table 9. Variation in Teacher Return Rates for Anderson-Hsiao Models

	Standard Deviation	Percent of Overall Variance (%)
Math Teachers		
Overall	50.0	n/a
Within Students	39.3	38.1
Between Students	30.8	62.0
Science Teachers		
Overall	50.0	n/a
Within Students	36.7	44.3
Between Students	32.7	55.7

Table 10. Variation in whether Teacher Returns Survey for Anderson-Hsiao Models

Category	Proportion of student-year observations that fell into the given category	Proportion of students who fell into the given category at least once throughout the panel	Proportion of students who never switch out of the given category
Math Teachers			
Teacher Returns Survey	48.0	68.3	70.4
Teacher Does not Return Survey	52.0	74.5	69.7
Science Teachers			
Teacher Returns Survey	40.7	64.4	63.2
Teacher Does not Return Survey	59.3	83.7	70.9

Note: All numbers are percentages.

Table 11a: Transition Probabilities for whether Math Teacher Returns Survey for Anderson-Hsiao Models

		Status in Year t	
		Math Teacher Returns Survey	Math Teacher Does not Return Survey
Status in Year t-1	Math Teacher Returns Survey	65.7	34.8
	Math Teacher Does not Return Survey	14.7	85.2

Note: All numbers are percentages.

Table 11b: Transition Probabilities for whether Science Teacher Returns Survey for Anderson-Hsiao Models

		Status in Year t	
		Science Teacher Returns Survey	Science Teacher Does not Return Survey
Status in Year t-1	Science Teacher Returns Survey	55.9	31.3
	Science Teacher Does not Return Survey	17.7	75.1

Note: All numbers are percentages.