Do Teacher Expectations Matter?*

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ABSTRACT: Despite widely-held views that teacher expectations matter for student outcomes, it is difficult to credibly identify a causal relationship. The reason is that teacher expectations may simply reflect accurate forecasts about student potential. If so, estimates relating teacher expectations to observed student outcomes suffer from omitted variables bias. We develop an empirical model to assess how teacher expectations affect student outcomes. We estimate the model using a large, nationally representative data set following tenth graders in the U.S. (the ELS-2002). The data set includes teacher expectations collected when students were in the 10th grade (in 2002) and also measures educational attainment of the same students 10 years later. The model we estimate leverages a unique feature of the data set: two teachers evaluate each student, which means we can treat forecast errors that lead teachers to disagree as measurement errors of an underlying factor. We use this insight to disentangle how teacher expectations both reflect objective probabilities of college completion for 10th graders and may also drive educational attainment. We estimate the model separately for black and white 10th grade students. Model estimates suggest a positive impact of 10th grade teacher expectations on the likelihood of college completion. We also show that existing disparities between blacks and white student college completion probabilities are exacerbated by differences in how teachers form biases for different race groups.

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1 Introduction

At least since Becker (1964) cast schooling as an investment in human capital, economists have been concerned with understanding what factors drive variation in education decisions. One goal of this research has been to understand socio-demographic gaps in educational attainment, which are especially concerning if they reflect sub-optimal investments in human capital by under-represented or traditionally disadvantaged groups. Teacher expectations constitute one potentially important, but relatively understudied, source of educational attainment gaps. Despite widely-held views that teacher expectations matter, however, it is difficult to credibly identify their causal effects on student outcomes. The reason is that teacher expectations may simply reflect accurate forecasts about educational attainment. If so, then teacher expectations do not influence outcomes, but instead reflect the information teachers have about true student potential.

In this paper, we study how teacher expectations affect students' educational outcomes. In particular, we aim to assess whether biases in teacher expectations can help to explain socio-demographic gaps in educational attainment. One potential mechanism is information transmission. Given that information acquisition is costly, students rely on teachers as important sources of information about their education. If the information they receive from teachers is biased, students may incorporate these biases and make sub-optimal investment decisions. This effect may be particularly pronounced for traditionally disadvantaged students, who likely have limited access to alternative sources of information about their educational potential and the returns to educational investments. Another potential mechanism linking teacher expectations to student outcomes is that teachers, based on their expectations, could modify how they teach, evaluate, and advise their students, again influencing students' educational investment decisions. Notice, in both of these scenarios, biased expectations can create a feedback loop that functions like a self-fulfilling prophecy that perpetuates educational attainment gaps.[1] Differences if how biases arise or affect outcomes are especially concerning if they differ by group, e.g., blacks versus whites, which could exacerbate existing disparities that already exist in the 10th grade.

Our first contribution is to establish several stylized facts about reported teacher expectations as they relate to student outcomes using data from a large, nationally representative, longitudinal study of U.S. students who were in the 10th grade in the year 2002. The data set is known as the Education Longitudinal Study of 2002 (ELS-2002). First, we show that

[1] A related literature in education studies *stereotype threat*. The idea is that low expectations either cause emotional responses that directly harm performance or cause students to *disidentify* with educational environments (Steele, 1997).

teacher expectations predict student educational attainment 10 years after the expectations data were collected. This predictive power remains even after we control for a host of variables describing achievement along with student and teacher demographics. We also find that teacher expectations are higher for students who perform better on traditional measures of academic achievement and who come from higher income backgrounds. Moreover, though teacher expectations are informative, there are some systematic discrepancies or "forecast errors" in teachers' expectations. For example, we find that teachers tend to be too optimistic on average, but that over-optimism declines with teacher experience. Finally, we leverage a unique feature of the ELS-2002 data to assess disagreements between teachers over students. This is possible because two teachers report expectations for each student in the ELS-2002. Teachers frequently agree in their expectations for a particular student, but there is also a healthy amount of disagreement. Conceptually, if two teachers disagree when evaluating the same student, at least one of them is necessarily wrong. Observed disagreement is therefore useful in identifying cases where teacher expectations may be biased.

Armed with this set of empirical facts, we develop an econometric model that can identify the causal impact of teacher biases. The econometric model is designed to explicitly address the endogeneity of teacher expectations arising from omitted variables that jointly influence teacher expectations and student outcomes. It is not surprising that low teacher expectations are correlated with low academic achievement. It is perhaps more surprising that this relationship persists even after we condition on several measures of academic achievement and household socioeconomic status. However, teachers form expectations about their students based on far more information than is collected in the ELS-2002 data. Therefore, even if we control for various measures capturing performance in school, aptitude and other determinants of educational attainment, such as family income, it remains difficult to argue that we have purged the model entirely of omitted variables correlated with teacher expectations.

To address omitted variables bias, the econometric approach we develop relies on a unique feature of the ELS-2002 data set. Two teachers report how far they expect students to go in school. Intuitively, our identification strategy exploits instances where two teachers report different expectations for the same student. Using lessons from the measurement error literature, such disagreements allow us to treat teacher expectations as consisting of two components. The first is an unbiased expectation of student outcomes given the information sets common to both teachers (including information that is not observed by the econometrician and that induces omitted variables bias). The second component is treated as measurement or forecast error. For example, a teacher might have an especially positive or negative interaction with a student just prior to reporting their forecast. This type of forecast error mimics exogenous shifts in teacher expectations. Therefore, we identify the impact of expectations by studying how forecast errors affect student outcomes. We estimate the model separately for black and white students. This way, we can assess whether there are differences by student race in how teachers form bias or how these biases affect student outcomes.

Model estimates show that the objective probability of college completion is already different for black versus white students once they reach the 10th grade. This likely reflects differences in early-childhood inputs, such as school quality. Next, we show show that teacher expectations matter across groups, in that they have a positive impact on the probability of college completion. However, biases differ in important ways across groups. In particular, teachers biases are relatively worse for black students even after we account for existing disparities in the 10th grade. In other words, the production function of teacher biases differs by student race in a way that puts black students at a disadvantage. Finally, we show that biases affect race groups differently, again in a way that favors white students. Altogether, this means that black students would do better if they faced the same bias as whites. This implies that existing disparities in the likelihood of college completion are exacerbated by teacher expectations. A resulting policy conclusion is that de-biasing efforts or information interventions aimed at the teaching force could be helpful in closing socio-demographic achievement gaps.

The current study contributes to several literatures. One line of inquiry studies gaps in educational outcomes. Socio-demographic gaps in educational attainment are well documented (Bailey and Dynarski, 2011; Bound and Turner, 2011). Closing such gaps has been a longstanding goal of education policy. A primary reason for this focus is that education increases earnings (Blundell, Dearden, and Sianesi, 2005; Card, 1999). Further, education has a direct, causal effect on a number of important social and behavioral outcomes such as civic engagement (Dee, 2004; Milligan, Moretti, and Oreopoulos, 2004), health (Grossman, 2006; Silles, 2009), and crime (Lochner and Moretti, 2004; Machin, Marie, and Vujić, 2011). Much literature has attempted to understand the sources of socio-demographic education gaps. Differences in students' beliefs and expectations about school are one potentially important, but relatively understudied, source of educational attainment gaps (Hoxby and Turner, 2013; Morgan et al., 2013). For example, Fortin, Oreopoulos, and Phipps (2015) find that gender differences in students' expectations about their educational attainment are among the leading sources of gender gaps in secondary students' academic performance. Moreover, these effects may be important. Lavy and Sand (2015) show that grading biases in earlier grades can have long lasting impacts on academic achievement and course taking in high school.

We also contribute to a large literature in both economics and education that shows that teachers are the most important school-provided educational input. It has been established that teachers have strong effects on both academic achievement and long-run socioeconomic outcomes (e.g., Chetty, Friedman, and Rockoff (2013); Harris (2011); Jackson (2012); Hanushek and Rivkin (2010)). However, the mechanisms through which teachers affect long-run outcomes are poorly understood. Providing (mis)information to students via biased expectations may be one mechanism through which documented teacher effects on long-run student outcomes operate.

Our research also connects to literature on biases in beliefs and costly information acquisition. If information acquisition is costly, students may form expectations based on information sources that are readily available, e.g., teachers. This can lead to sub-optimal investments if the information students receive from teachers is biased. In a different context, DellaVigna and Kaplan (2007) argue that biased media sources can influence voting patterns of individuals to whom they are made available, presumably by modifying viewers' expectations about candidate quality. Moreover, data on teacher expectations seem to support the idea that teacher biases could affect students. Several studies report that teachers' expectations strongly predict student outcomes such as educational attainment, though it is currently unknown whether this is a causal relationship, as expectations may accurately measure unobservable (to the analyst) student ability (Gregory and Huang, 2013; Boser, Wilhelm, and Hanna, 2014). One exception is a famous experiment in which researchers manipulated teachers' beliefs of student ability by providing false information regarding students' performance on a nonexistent test and found significantly greater school-year gains among the students who were falsely identified to teachers as having exceptionally high test scores (i.e., growth spurters) (Rosenthal and Jacobson, 1968).[2]

Even if teacher biases causally affect student outcomes, it is also not clear if teacher expectations are systematically biased. There is strong evidence that observable characteristics affect how teachers perceive and evaluate students, which suggests that systematic biases are possible. For example, teachers have significantly lower expectations for the educational attainment of socioeconomically disadvantaged and racial minority students (Boser, Wilhelm, and Hanna, 2014). One explanation is that teachers resort to using rules-of-thumb to form expectations for low-SES and racial and ethnic minority students, who are more likely to attend disadvantaged and unsafe schools. This may be more common if such students' teachers are under greater levels of stress, and thus have less available mental bandwidth, than their counterparts in more advantaged schools and neighborhoods (Mullainathan and Shafir, 2013). Related, Riegle-Crumb and Humphries (2012) provides evidence that math teachers

[2]Indeed, teachers themselves believe that their expectations can affect student outcomes (Markow and Pieters, 2010) and some observers have speculated that the success of Catholic schools in educating socioeconomically disadvantaged students in urban settings is due to Catholic schools' culture of maintaining high expectations for all students (Bempechat, 1998).

systematically under-estimate female students' mathematical aptitude. Finally, there is also robust evidence of gender, racial, and ethnic biases in how teachers grade exams in a variety of educational contexts (Burgess and Greaves, 2013; Cornwell, Mustard, and Van Parys, 2013; Hanna and Linden, 2012; Lavy, 2008).[3]

The aforementioned evidence indicates that teachers have different expectations for different groups of students. However, there is no evidence of a bias as different groups may have different objective likelihoods of reaching a given level of educational attainment. Direct evidence of bias is found in Gershenson, Holt, and Papageorge (2015), who use the ELS-2002 data to show that teacher expectations are in part driven by their race and gender relative to that of their students. For example, in cases where black students have a black and a white teacher, the white teacher is about 30 percent more likely than the black teacher to expect that the student will not finish high school and about 30 percent less likely than the black teacher to expect that the student will complete a 4-year college degree. This result is important to the current study because either black teachers over-estimate black student potential or white teachers under-estimate it (or some combination of the two). In other words, Gershenson, Holt, and Papageorge (2015) provide evidence of systematic biases in teachers' expectations for at least a subset of students. However, the degree to which these sorts of biases in teachers' expectations affect student outcomes remains an open question that we address in the current study.

Should we find that stigmatization affects student outcomes, policies such as information interventions aimed at correcting biases could be helpful. Evidence that this is possible is mounting. For example, Wiswall and Zafar (2015) show that biases in college students' expectations can be corrected by interventions that provide accurate information. These interventions are premised on the idea that expectations are malleable. Information interventions could be designed to provide personalized information and assistance regarding the college application and admissions process to qualified secondary students from disadvantaged backgrounds via mailers (Hoxby and Turner, 2013), text messages (Castleman and Page, 2014), and counseling sessions (Avery, 2010; Stephan and Rosenbaum, 2013).

The remainder of this paper is organized as follows. Section 2 describes the data set used in this project. Section 3 presents key empirical relationships between teacher expectations and student outcomes. Section 4 describes the measurement error model we use to identify causal effects of teacher biases on educational attainment. Section 5 reports results of policy simulations. Section 6 concludes.

[3]Related, in a seminal paper, Dee (2005) leverages multiple teacher reports for a given student to show that race and gender differences between teachers and students can affect teachers' perceptions of students' behaviors.

2 Data

The current study utilizes data from the 2002 Education Longitudinal Study (ELS 2002), which are nationally representative of the cohort of U.S. students who entered 10th grade in 2002. The ELS data are collected, maintained, and made available to researchers by the National Center for Education Statistics.[4] These data are well suited for the current study for several reasons. First, and most importantly, the ELS is the only nationally representative survey of which we are aware that contains multiple subjective reports of teachers' expectations for each student's educational attainment. Second, the ELS data contain rich information on students' socio-demographic backgrounds and their secondary and postsecondary schooling outcomes (including educational attainment through 2012, or within 8 years of an "on time" high school graduation). Third, the ELS sampled students within schools and includes school identifiers that facilitate within-school (school fixed effects) analyses. Finally, a handful of observed teacher characteristics are included, such as teaching experience, demographic background, and credentials.

We use five sets of variables: (I) teachers' subjective expectations for students' ultimate educational attainment, (II) observed (actual) student educational attainment, (III) observed teacher characteristics, (IV) observed student characteristics, and (V) student performance in school, including course grades, course taking in both secondary and post-secondary school, and performance on math and reading standardized tests in 10th grade that were administered by the ELS. Variable sets (I) and (II) form the basis for measurement, as they relate teachers' potentially biased expectations for students' educational attainment to students' realized educational attainment. The variables in (III) and (IV) are potential moderators and mediators of this relationship. Finally, the variables in (V) will be used to assess the bias in teachers' expectations, based on students' academic performance. The last two exercises are formally described in Section 4.

The analytic sample is restricted to the 6,060 students for whom all variables in (I)-(V) are observed. Because there are two teacher expectations per student, the analytic sample contains 12,130 teachers.[5] Table 1 summarizes the students who comprise the analytic sample. Column (1) does so for the full sample and columns (2)-(5) do so separately by student race and sex.

The outcome of interest, educational attainment, is coded as a categorical variable in the ELS. Translating this to years of schooling, we see that the overall average is almost 15 years of schooling, indicating that the average student completed at least some college

[4] See `https://nces.ed.gov/surveys/els2002`.

[5] All sample sizes are rounded to nearest 10 in accordance with NCES regulations for restricted data.

but did not earn a four-year degree. The "years of schooling" measure is a useful summary measure that facilitates the specification and estimation of linear models, yet it precludes more nuanced analyses of the distribution of educational attainment. Thus Table 1 also summarizes the percentage of students who fail to complete high school and who earn a four-year college degree (or more). Indeed, columns (2) and (3) show that while the mean racial difference in years of schooling of less than one year are modest in size, racial differences in credential obtainment are pronounced: blacks are twice as likely to fail to earn a high school diploma as whites while whites are almost twice as likely to earn a four-year college degree as blacks. Similarly, columns (4) and (5) reveal the well documented fact that women are now significantly more likely to complete a four-year college degree than are men.

Teachers' expectations are summarized in the next section of Table 1 and a histogram is presented in Figure 1. Expectations for black students are significantly lower than for white students, and similarly for male students relative to females. These patterns are consistent with the patterns in actual educational attainment described above. Note that there are two sets of expectations per student: one from a math teacher and one from an English teacher. Two aspects of the average expectations merit notice. First, on average, teachers are optimistic about students' educational attainment. For example, overall, about two-thirds of teachers expected their students to complete at least a four-year college degree, while only 45 percent of students did so. A similar amount of over-optimism about the likelihood of completing college exists for each demographic subgroup. Interestingly, however, black students' teachers seem to be overly pessimistic about their likelihood of completing high school, at least for those students on the margin. We provide a more nuanced analysis of such discrepancies between teachers' expectations and students' educational attainment in Section 3.2. Second, while math and reading teachers' expectations are similar on average, English teachers' expectations tend to be slightly higher, particularly among black students. A more nuanced comparison of math and English teachers' expectations, including analyses of the frequency and extent to which teachers have divergent expectations for the same student, is provided in Section 3.3.

The final two panels of Table 1 report students' average academic and socioeconomic characteristics, both overall and separately by race and sex. A comparison of columns (2) and (3) shows that white students have significantly higher test scores, GPAs, and household incomes than black students, as well as better educated mothers, all of which is consistent with longstanding racial disparities in academic performance and socioeconomic status (Fryer Jr, 2010). Another notable difference by student race is in their assigned teacher's race: black students are four to five times as likely as white students to be assigned a black teacher, which is due to non-white teachers being more likely to teach in majority non-white schools (Hanushek, Kain, and Rivkin, 2004; Jackson, 2009). Nonetheless, the majority of students, white and black, have white teachers. This is troubling in the context of the current study, as Gershenson, Holt, and Papageorge (2015) show that student-teacher racial mismatch has significant, arguably causal effects on teachers' educational expectations for students. Columns (4) and (5) of Table 1 show that girls have higher GPAs and perform better on reading assessments than boys, while boys perform better on math assessments. This is consistent with the literature (Jacob, 2002). Unsurprisingly, there are no significant differences in SES by sex.

Table 2 similarly summarizes the teachers represented in the analytic sample. Overall, 11 percent of teachers are nonwhite and nonwhite teachers are evenly represented across subjects and sex. The average teacher has about 15 years of experience though 16 percent of teachers have 3 or fewer years of teaching experience. Math teachers are a bit more experienced than English teachers, on average, as are black teachers relative to white teachers. Almost half of teachers have an undergraduate degree in the subject they teach. A similar percentage hold a graduate degree. The bottom panel of Table 2 confirms that black teachers are significantly more likely to teach black students than are teachers from other racial backgrounds.

3 Empirical Patterns

We now establish several patterns in the relationship between teacher expectations and student outcomes. First, we show that teacher expectations are informative. Specifically, even after conditioning on a rich set of observed student, household, and school characteristics that likely jointly influence both teacher expectations and student outcomes, teacher expectations significantly predict students' ultimate educational attainment. Second, we show that teacher expectations are frequently incorrect. That is, teachers frequently over- or under-estimate the students' educational attainment and that, on average, teacher expectations exceed actual outcomes. Third, we show that this optimism is somewhat attenuated by teachers' experience and other observed characteristics, especially with regard to female (students or teachers). Fourth, consistent with Gershenson, Holt, and Papageorge (2015), we show that teachers frequently disagree in their assessments of the same students, sometimes in systematic ways.[6]

[6] Additional reduced-form empirical results are found in Appendix A.

3.1 Teacher Expectations and Student Outcomes

This section documents the positive, robust, statistically significant association between teacher expectations and student attainment. Formally, let y_i be a measure of student i's actual educational attainment by 2012. In practice, y can be either a count measure of years of completed schooling or a categorical indicator of highest degree obtained, though both measures produce qualitatively similar results. We are interested, then, in how math (T_{1i}) and English (T_{2i}) teacher expectations relate to y. Regressing y on T is a purely descriptive exercise, of course, as a multitude of factors affect both T and y. Accordingly, we estimate a series of linear regressions of the form

$$y_i = \gamma_1 T_{1i} + \gamma_2 T_{2i} + X_i \beta + \epsilon_i \quad (1)$$

where the vector X includes a progressively richer set of statistical controls, up to and including school fixed effects (FE). Standard errors are clustered by school, as teachers and students are nested in schools.

Table 3 reports baseline estimates of equation (1) in which y is measured in years of schooling.[7] Column (1) of Table 3 presents estimates of the unconditional association between teachers' expectations and student attainment. The estimates for math and reading teachers are nearly identical, strongly statistically significant, and indicate that on average, an additional year of *expected* schooling by a teacher is associated with about 0.3 additional years of actual schooling completed by the student. Column (2) shows that the point estimates of about 0.3 in the unconditional model are robust to controlling for teachers' demographic backgrounds and observed credentials such as experience, graduate degree, and undergraduate field of study.

Column (3) of Table 3 augments the parsimonious model to also control for students' socio-demographic background, adding indicators of students' sex, race, household income, and mothers' educational attainment to X. Doing so reduces the estimates of γ by about 5 percentage points (17 percent) to 0.24 for English and 0.26 for Math, though both remain strongly statistically significant. Column (4) further enriches the model to condition on students' 9th grade GPA and performance on standardized math and reading assessments, which proxy for students' non-cognitive and cognitive ability, respectively. Adding these controls to the model reduces the estimates of γ by about 7 percentage points (28 percent) to 0.17 (English) and 0.19 (English), which once again remain strongly statistically significant. Finally, the model estimated in column (5) further expands X to include a full set of school

[7]Online Appendix Tables A1 and A2 provide analogs of Table 3 in which y is a binary indicator for "college degree or more" and "no high school diploma", respectively.

FE, which control for school climate and neighborhood effects. Again, this results in modest decreases in the estimates of γ, which remain positive and strongly statistically significant at about 0.15.

Table 4 reports estimates of the fully specified equation (1) separately by students' demographic background. The estimates in column (1) of Table 4, for the population of white students, are nearly identical to those for the full sample in column (5) of Table 3. This is unsurprising, as the analytic sample is overwhelmingly white. Columns (2) and (3) of Table 4 estimate the model separately for black and Hispanic students, respectively. These estimates are less precise, as the standard errors are more than three times as large as those for the full sample, which is likely due to the significant reduction in sample size. Interestingly, though, math teachers appear to have a larger association with black students' outcomes while reading teachers appear to be more highly predictive of Hispanic students' outcomes. This result merits further analysis. Finally, columns (4) and (5) of Table 4 estimate the full model separately by students' gender, and find no evidence that teachers' expectations differentially affect students' educational attainment.

That conditioning on measures of cognitive ability, course grades, and school FE reduces the estimated magnitude of teachers' educational expectations' effects on students' educational attainment is unsurprising, as teachers' expectations are undoubtedly informed by their observations and perceptions of students' innate ability and determination as well as students' home and neighborhood environments outside of the school setting. Thus, the unconditional (naive) estimates in column (1) of Table 3 were biased upwards by the omission of determinants of y that are positively correlated with teachers' expectations. It is striking, however, that teachers' expectations continue to have a fairly large, positive, statistically significant effect on y even after conditioning on school FE and a wide range of student characteristics. Moreover, as shown in Table 4, these effects persist across demographic groups. While the estimates of γ reported in column 5 of Table 3 and in Table 4 cannot be given a causal interpretation, they are suggestive of a causal relationship. We investigate this relationship further in Section 4, where we present a measurement-error-based strategy for identifying the impact of teachers' expectations on student outcomes.

3.2 Are Teachers Systematically Over-Optimistic?

Having provided evidence that teachers' expectations are strongly associated with student outcomes, we now turn to the degree to which teachers systematically over- or under-estimate students' ultimate educational attainment, as the degree of wrongness has implications for the measurement model. We document the frequency and degree to which math teachers' expectations are misaligned with actual student outcomes in a series of transition matrixes in Table 5.[8] The transition matrixes are organized with student outcomes in columns and teachers' expectations in rows.

The first transition matrix in Table 5 is for all students. Recall that in Table 1, we saw 63 percent of math teachers expected the student to earn at least a four-year degree while only 45 percent of students did so. These overall averages appear in the "Bachelor's or more"-"Total" entries in the bottom right corner of the first transition matrix, which also provide further information about (i) the attainment of students who were expected to earn a four-year degree but did not and (ii) the expectations for students who did earn a four-year degree but were not expected to. The full sample transition matrix shows that almost 25 percent of students were expected to complete a four-year degree but did not. The majority of these students attended some college, but a nontrivial 1.5 percent of the sample did not attend any college. Meanwhile, a little more than 5 percent of students earned a four-year degree, exceeding their teachers' expectations in the process. Again, most of the "error" was due to teachers expecting only some college, but 0.7 percent of math teachers expected students who ultimately graduated from college to accrue no formal schooling after high school. Similar bouts of teacher optimism are observed on the high school graduation margin. For example, of the 1.3 percent of students who failed to complete high school, 85 percent of their teachers expected a high school diploma or more. Similarly, of the 8.7 percent of students who earned only a high school diploma, more than half of their math teachers expected them to attend at least some college. The remaining panels in Table 5 reproduce the same transition matrix separately by student race and gender, which yield qualitatively similar results. Together, the transition matrixes in Table 5 confirm that teachers' expectations are frequently incorrect, and when they are, are systematically too optimistic rather than too pessimistic. Interestingly, this over-optimism is present across all demographic subgroups.

While the basic pattern of over-optimism appears across several broad demographic groups, it could be that certain types of students (teachers) are particularly prone to receiving (providing) incorrect expectations. Accordingly, we estimate a series of descriptive ordered probit models to identify the predictors of incorrect teacher expectations. The dependent variables in these models take one of three values: teacher's expectation was pessimistic, teacher's expectation was accurate, or teacher's expectation was optimistic. Table 6 presents the estimated ordered probit coefficients and average partial effects (APE) on

[8] Appendix Table A3 reports analogous transition matrixes for English teachers' expectations, which yield qualitatively similar results.

each outcome for the full analytic sample.[9] Four predictors stand out. Teachers' race and experience are both significantly related to the mismatch between teachers' expectations and actual student outcomes. Regarding the former, nonwhite teachers are significantly less likely to be pessimistic and almost seven percentage points more likely to be optimistic than their white counterparts. One potential explanation of this finding is that nonwhite teachers are more likely to teach nonwhite students, and Gershenson, Holt, and Papageorge (2015) find robust evidence of an effect of student-teacher racial match on teachers' expectations for black students. Regarding the latter, the APE in Table 6 suggest that more experienced teachers are less likely to be optimistic and more likely to be accurate or pessimistic.[10] This could be because teachers enter the profession too optimistic, and, after learning on the job, reduce their expectations towards some "correct" level. On the student side, teachers are significantly less likely to be optimistic when appraising black students. Again, this result could be driven by the preponderance of white teachers and the main result in Gershenson, Holt, and Papageorge (2015) that white teachers have significantly lower expectations for black students than they do for white students. Finally, 9th grade GPA strongly predicts optimism. This is interesting, as it suggests that teachers place too much stock in students' secondary course grades when assessing their prospects for future educational attainment. Similar patterns are observed in Tables A7-A11, which repeat this exercise for a variety of demographic subsets of the student sample.

3.3 When, Why, and to What Degree do Teachers Disagree?

Finally, we investigate the extent to which teachers disagree in their assessments of students. Some amount of disagreement is likely, if for no other reason than random chance. However, previous research has identified at least one source of systematic disagreement in teachers' expectations: student-teacher racial mismatch (Gershenson, Holt, and Papageorge, 2015). In this section we investigate other sources of systematic disagreement between teachers, as well as the frequency and degree of teacher disagreement.

In Table 7, we begin by reporting transition matrixes similar to those reported in Table 5. These are at the student level, and diagonal elements measure the percentage of students about whom both the math and English teacher agreed. Teachers largely agreed about college-going, as when one teacher expected a four year degree or more, the other teacher agreed in about 85 percent of cases. When teachers disagreed with a colleague who expected a four-year college degree, it was usually in the neighboring "some college" category.

[9] We repeat this exercise separately by race and gender groups. Results are reported in Appendix Tables A4-A6.

[10] In future work we will model experience non-parametrically.

Unsurprisingly, there is more disagreement in the middle of the attainment distribution, as teachers can disagree in either of two directions (i.e., by being more pessimistic or more optimistic than their colleague). Indeed, when one teacher expects the student to complete a high school diploma, the other teacher is actually more likely to disagree with this assessment than to agree with it. These patterns are similar, if not more pronounced, when the transition matrixes are stratified by race or sex.

Finally, we attempt to isolate the student-level correlates of disagreements in teachers' expectations by estimating a series of linear probability models (LPM) in which the dependent variable is an indicator variable equal to one if the teachers disagreed about the student, and zero otherwise. Column 1 of Table 8 estimates this descriptive regression for the full analytic sample. Students of college educated mothers and students who had higher 9th grade GPAs are significantly less likely to have teachers who have contradictory educational expectations for the student. The remaining columns of Table 8 estimate the same LPM separately by race and sex. The result for mothers' schooling is only statistically significant in the white and female samples, and actually changes sign in the black student sample. The GPA result is robust across all demographic groups.

4 Do Teacher Expectations Matter?

Results from the previous section show that teacher expectations predict student outcomes. However, we cannot assign estimated coefficients a causal interpretation. The reason is that teacher expectations may reflect student characteristics that predict educational attainment. If these characteristics are not observed by the econometrician, then they induce an omitted variables bias in OLS estimates of the impact of teacher expectations on student outcomes.

In this section, we develop an econometric model designed to isolate the causal impact of teacher biases on outcomes. The idea is to use multiple teacher expectations to isolate and then control for the unobserved information teachers use when forming expectations. This purges estimates of omitted variables bias arising from information observed by both teachers. The framework draws upon lessons from the measurement error literature to treat each teacher's expectation as a measurement of underlying student potential.

We begin by introducing a simplified version of the model we estimate. The aim is to illustrate the omitted variables bias problem and to develop intuition regarding the use of multiple teacher expectations to solve the problem. This includes identification arguments. Second, we present a linear version of the econometric measurement error model we estimate. Third, we derive estimating equations. Fourth, we discuss estimation using simulated maximum likelihood. Fifth, we describe changes needed to the basic linear model to account for discrete outcomes. We ultimately estimate (and present results from) a model where the outcome variable is college completion. To account for discrete outcomes, we reformulate the linear model as a probit so that teacher expectations can influence the probability of college completion. Finally, we end this section by presenting parameter estimates.

4.1 Conceptual Model and Omitted Variables Bias

Suppose there is a production function for an outcome Y, which is a function of three sets of variables: X, Z and e^Y:

$$Y = T_1\gamma_1 + T_2\gamma_2 + X + Z + e^Y \tag{2}$$

where T_1 and T_2 are teacher expectations that also affect Y through γ_1 and γ_2. In the production function, X consists of variables that are observed by both the econometrician and by the teacher forming expectations. Z consists of variables that both teachers observe when forming expectations, but that the econometrician does not. e^Y contains all remaining factors affecting Y. By construction these three information sets are independent.[11] The production functions for teacher expectations are written as:

$$T_1 = X + Z + b_1 \tag{3}$$
$$T_2 = X + Z + b_2 \tag{4}$$

where b_1 and b_2 are forecast errors. Notice, if we could control for X and Z when estimating γ in the production function, there would be no omitted variables bias. The reason is that e^Y, though it affects Y, does not affect T_1 or T_1 and is also independent of Z and X, which means the estimated relationship between expectations and Y is not biased if we omit e^Y. Still, the fact that we do not observe Z means there is an omitted variables bias.

Next, it is useful to define expected Y given Z and X:

$$E[Y|X, Z] = f(X, Z) \equiv \theta \tag{5}$$

where $E(\cdot)$ is the expectations operator. Here, it is important to understand that θ is not the true unconditional expectation of Y. Rather, it is the objective expectation of Y given

[11] This assumption is not restrictive, but is used to help develop intuition. Suppose that ω_1 is assigned to e^Y, but that it is correlated with information in Z. Then, we would assign the part of ω_1 that is explained by Z to the information set Z and the remainder, denoted $\tilde{\omega}_1$ would be assigned to e^Y.

information contained in X and Z. Next, we can rewrite the production functions for Y and teacher expectations as follows:

$$\begin{aligned} Y &= T_1\gamma_1 + T_2\gamma_2 + \theta + e^Y \\ T_1 &= \theta + b_1 \\ T_2 &= \theta + b_2 \end{aligned} \tag{6}$$

According to a theorem in Kotlarski (1967), the second two equations can be used to identify the distributions of θ, b_1, and b_2 if we assume that all three random variables are independent.[12] Next, we substitute the production functions for T into the production function for Y to obtain the following equation:

$$Y = \theta\delta + b_1\gamma_1 + b_2\gamma_2 + e^Y \tag{7}$$

where $\delta = 1 - \gamma_1 - \gamma_2$. Notice, when we did not incorporate the production function of teacher expectations into the model for Y, the γ were biased due to our inability to control for elements in θ, particularly, information in Z that is observed by both teachers, but not by the econometrician. The current equation allows us to condition on θ. Moreover, equation (7) emphasizes the idea that we estimate the impact of teacher expectations using differences in teacher expectations for the same student, captured by the forecast error b

Intuitively, we are estimating the impact of teacher expectations through differences in b, which are factors that affect one teacher's forecasts, but which are not observed by both teachers. Identifying a causal parameter requires that e^Y be independent of b_1 and b_2. Notice, if information in e^Y is observed by both teachers, then it forms part of the information in Z as is captured by θ. Therefore, the key identifying assumption is that factors that are not observed by both teachers are not systematically related to student outcomes except through the impact of teacher bias on outcomes. To fix ideas, suppose a teacher forms high expectations because a student is motivated and polite (which both teachers can observe) but also because of a positive chance interaction. The chance encounter leads the teacher to have a higher forecast for reasons not related to the set of variables that both teachers observe.

[12] In the econometric model we estimate, we use additional data to relax some of these independence assumptions.

4.2 An Empirical Model of Teacher Biases and Student Outcomes

In this section, we present the empirical model of teacher expectations and student outcomes we will estimate. The model is similar to the simplified model presented in the previous section. Student educational outcomes y_i (e.g., years of education or college completion) are described by the following equation.

$$Y_i = c + \theta_i + G_i\beta + b_{1i}\gamma_1 + b_{2i}\gamma_2 + \epsilon_i^Y \tag{8}$$

According to this formulation, years of education are a function of a constant c and underlying student ability θ_i, where we assume that

$$\theta_i \sim N(0, \sigma_\theta^2) \tag{9}$$

Educational attainment is also a function of 9th-grade grades, G_i with associated coefficient β, and of teacher biases b_{ij}, where $j \in \{1, 2\}$ indexes the teacher and the γ parameters map biases to outcomes. ϵ_i^Y is an *iid* disturbance. Teacher expectations, denoted T_{1i} and T_{2i} for teachers 1 and 2, respectively, are given by:

$$\begin{aligned} T_{1i} &= c_1 + \phi_1\theta_i + G_i\beta_1 + e_{1i} \\ T_{2i} &= c_2 + \phi_2\theta_i + G_i\beta_2 + e_{2i} \end{aligned} \tag{10}$$

It is useful to derive an expressions for unbiased teacher expectations:

$$\mathrm{E}[Y_i|\theta_i, G_i, b_{1i} = 0, b_{2i} = 0] = \theta_i + G_i\beta \tag{11}$$

Therefore, we can rewrite the teacher expectation equations as follows:

$$\begin{aligned} T_{ij} &= \mathrm{E}[Y_i|\theta_i, G_i, b_{1i} = 0, b_{2i} = 0] + b_{ij} \\ &= c + \theta_i + G_i\beta + (c_j - c) + (\phi_j - 1)\theta_i + G_i(\beta_j - \beta) + e_{ij} \end{aligned} \tag{12}$$

Written as such, teacher expectations are given by expected performance, conditional on observables G_i and unobserved ability θ_i (given by $c + \theta_i + G_i\beta$) along with four sources of bias. To clarify, we define bias as follows:

$$\begin{aligned} b_{1i} &\equiv T_{1i} - c - \theta_i - G_i\beta = (c_1 - c) + (\phi_1 - 1)\theta_i + G_i(\beta_1 - \beta) + e_{1i} \\ b_{2i} &\equiv T_{2i} - c - \theta_i - G_i\beta = (c_2 - c) + (\phi_2 - 1)\theta_i + G_i(\beta_1 - \beta) + e_{2i} \end{aligned} \tag{13}$$

We explicitly allow teacher expectations to be biased and this bias assumes several forms. This amounts to ways that teacher expectations deviate from the true production function of student outcomes given by equation (8). Given reduced form evidence, we allow teachers to be wrong on average, meaning c_j can deviate from c. Teachers may also be wrong about how ability θ_i maps into outcomes, which occurs if $\phi_j \neq 1$. For example, the reduced form finding that teachers seem to over-estimate low and high educational attainment outcomes despite our controlling for a host of observables could mean that $\phi_j > 1$. Third, teachers may be biased in how they map observable grades G_i to outcomes, in which case $\beta_j \neq \beta$. This would be consistent with findings in the previous section suggesting that teachers over-estimate the impact of 9th grade GPA on student educational attainment. Finally, teachers may be wrong for idiosyncratic reasons, which is captured in the disturbances e_{1i} and e_{2i}. We assume that the disturbances are *iid* and normally distributed with variances equation to σ^2_{T1} and σ^2_{T2}, respectively.

Here, it is important to mention that the term $\phi_j - 1$ may capture how teachers have biased beliefs about how a given θ_i affects outcomes. It may also capture that teachers correctly map ability to outcomes, but mis-estimate θ_i. We cannot separately identify these effects. Similarly, the term $(\beta_j$ may represent that teachers are biased in the mapping or in their observation of G_i. Again, we are unable to separately identify these mechanisms. For ease of interpretation, we will assume that teachers observe G_i and θ_i, but incorrectly map these to outcomes when forming expectations. Moreover, in defining bias in this manner as we have in equation (25), we have assumed that (i) teachers assume that their bias is equal to zero and (ii) teachers assume that the other teacher's bias is also equal to zero. The former assumption is defensible as it is effectively tautological: teachers report expectations that they themselves think to be correct. In contrast, the second assumption is potentially problematic. We argue that this assumption can be relaxed. In other words, it should be possible to assess the robustness of our results after redefining bias so that each teacher, when forming expectations, takes account of the other teacher's expected bias, including the impact of this expected bias on student outcomes.

Given the model we have posited, the goal is to estimate the following parameters:

$$\Theta = \langle c, c_1, c_2, \beta, \beta_1, \beta_2 \gamma_1, \gamma_2, \phi_1, \phi_2, \sigma_Y, \sigma_{T1}, \sigma_{T2} \rangle \tag{14}$$

4.3 Deriving Estimation Equations

In this section, we reformulate the model of teacher expectations and student outcomes into a set of estimating equations. Next, we discuss what additional assumptions or data are needed to prove that the system of equations is econometrically identified. First, we substitute equations describing bias into equation (23) to obtain:

$$\begin{aligned} Y_i &= c + \theta_i + G_i\beta + b_{1i}\gamma_1 + b_{2i}\gamma + \epsilon_i^Y \\ Y_i &= c + \theta_i + G_i\beta + [T_{1i} - c - \theta_i]\gamma_1 + [T_{2i} - c - \theta_i]\gamma + \epsilon_i^Y \\ Y_i &= c(1 - \gamma_1 - \gamma_2) + \theta_i(1 - \gamma_1 - \gamma_2) + G_i\beta(1 - \gamma_1 - \gamma_2) + T_{1i}\gamma_1 + T_{2i}\gamma_2 + \epsilon_i^Y \end{aligned} \tag{15}$$

We are therefore left with the following system of equations to estimate:

$$\begin{aligned} Y_i &= \tilde{c} + \tilde{\theta}_i + G_i\tilde{\beta} + T_{1i}\gamma_1 + T_{2i}\gamma_2 + \epsilon_i^Y \\ T_{1i} &= c_1 + \phi_1\theta_i + G_i\beta_1 + e_{1i} \\ T_{2i} &= c_2 + \phi_2\theta_i + G_i\beta_2 + e_{2i} \end{aligned} \tag{16}$$

where the latter two equations are the original production functions for teacher expectations using equation (15). As written, however, the system of estimation equations defined here is not identified absent further restrictions or additional data. The reason is that the two expectation equations, which are used as imperfect measurements of student ability, are also regressors in the outcome equation. One possibility it to place additional restrictions on parameters. In Appendix B, we show that parameter estimates of the impact of bias remain similar to our main results if we are willing to restrict $\gamma_1 = \gamma_2 \equiv \gamma$ and $\phi_1 = \phi_2 \equiv \phi$, we obtain an identified system of equations.

Parameter restrictions are a useful alternative when there are not obvious exclusion restrictions on additional data, i.e., variables that only enter into the expectations or the outcome equations, but not both. Typically, it is difficult to defend such exclusions. Fortunately, two exams (a math and a reading test) were administered to all ELS-2002 subjects. Results from these exams were not revealed to students or teachers. Therefore, we argue that the exams can be used as additional (mis)measurements of student ability, but do not enter into the student outcome equation once we have conditioned on ability. In other words, scores on these exams should only be associated with educational attainment because they reflect student ability.

We also control for 9th grade grades in the outcome equation, allow grades to affect teacher expectations, and also use grades to identify θ_i. This is useful for a couple of reasons. First, we might be concerned that math and reading test scores do not contain the full set of skills that teachers observe, in which case there would be bias in the impact of teacher forecast error on Y.[13] Several papers (see e.g., Cunha et al (2012)) argue that test scores might not contain non-cognitive skills, such as motivation or grit, but that grades

[13] We think we can rule this out in a series of sensitivity analyses.

would. Moreover, we do not want to see grades as independent of θ, which requires that we model its relationship with θ. Finally, we want to illustrate how teacher bias can be due to a mis-reading of a mapping of skills to outcomes, where some skills are observed by the econometrician and some are not.

Formally, we add three equations to the estimation system:

$$\begin{aligned} Y_i &= \tilde{c} + \tilde{\theta}_i + G_i\tilde{\beta} + T_{1i}\gamma_1 + T_{2i}\gamma_2 + \epsilon_i^Y \\ T_{1i} &= c_1 + \phi_1\theta_i + G_i\beta_1 + e_{1i} \\ T_{2i} &= c_2 + \phi_2\theta_i + G_i\beta_2 + e_{2i} \\ S_{Mi} &= c_M + \phi_M\theta_i + e_{Mi} \\ S_{Ri} &= c_R + \phi_R\theta_i + e_{Ri} \\ G_i &= c_G + \phi_G\theta_i + e_{Gi} \end{aligned} \tag{17}$$

where the latter three equations indicate that scores on math (reading) test, given by S_{Mi} (S_{Ri}), and G are function of a constant c_M (c_R), student ability θ_i mapped to the test with coefficient α_M (α_R), and a disturbance e_{Mi} (e_{Ri}). In Appendix B, we show that the system is identified. Moreover, the additional data means that we can identify θ_i and also allow for limited dependent response variables for the teacher expectation and student outcome equations. This is not possible if, rather than use test score data, we rely on parameter restrictions. Therefore, the parameters we estimate are collected into a parameter vector $\tilde{\Theta}$

$$\tilde{\Theta} = \left\langle \tilde{c}, c_1, c_2, \tilde{\beta}, \beta_1, \beta_2\gamma_1, \gamma_2, \phi_1, \phi_2, \sigma_\theta, \sigma_Y, \sigma_{T1}, \sigma_{T2}, [c_M, c_R, \phi_M, \phi_R, \beta_M, \beta_R, \sigma_M, \sigma_R] \right\rangle \tag{18}$$

We recover the parameters in Θ from estimates of parameters $\tilde{\Theta}$ using the following identities:

$$\begin{aligned} \tilde{c} &= c(1-\gamma_1-\gamma_2) \iff c = \tfrac{\tilde{c}}{1-\gamma_1-\gamma_2} \\ \tilde{\beta} &= \beta(1-\gamma_1-\gamma_2) \iff \beta = \tfrac{\tilde{\beta}}{1-\gamma_1-\gamma_2} \end{aligned} \tag{19}$$

Finally, notice, that the first equation in the system is similar to our reduced form equations from the previous section. The difference is that the educational attainment equation explaining Y_i also includes unobserved ability. In other words, one way to re-interpret the estimating equations is as an extension to the reduced-form model from the previous section where, rather than controlling for a large set of observable characteristics, we have instead controlled for latent college potential, which includes all information observed by two teachers. Controlling for student college potential means that we can assess the impact of teacher expectations on outcomes after we have already controlled for how their expectations reflect potential. In the previous section, we controlled for a number of variables that could proxy student potential, but were unable to claim that we had controlled for all of the information that teachers see in assessing student potential. Now, we have controlled for unobserved, identifying ability from student test scores, grades and teacher expectations themselves.

4.4 Estimation

We estimate this model using simulated maximum likelihood. There are three main steps to the estimation procedure. First, at each set of parameter value suggestions, the latent factor, θ_i, is drawn multiple times for each individual in the sample. Second, we compute each individual's average likelihood contribution, where the average is taken over the number of draws. We then sum over average likelihood contributions for each individual and compute the log. Thereafter, parameters are chosen that maximize the likelihood function as with standard likelihood functions.

Formally, for individual $i \in \{1, \ldots, N\}$ and for a given set of candidate parameters $\tilde{\Theta}^{(g)}$, where $\tilde{\Theta}^{(g)}$ is g^{th} set of suggested values for parameters given in equation (18), we simulate θ K times and denote as θ_{ik} the k-th simulation for individual i. Given assumptions on the normality of the latent potential and error terms, we compute the simulated individual likelihood contribution for each simulation and individual:

$$\begin{aligned} L_{ik}(\tilde{\Theta}^{(g)}) &= f_Y(Y_i|\theta_{ik}, T_{1ik}, T_{2ik}, S_{Mik}, S_{Rik}, X_i, ; \tilde{\Theta}^{(g)}) \times \textstyle\prod_{j=1}^{2} f_{T_j}(T_{ikj}|\theta_{ik}, X_i; \tilde{\Theta}^{(g)}) \\ &\times \textstyle\prod_{\tau \in \{M,R\}} f_{S_\tau}(S_{\tau ik}|\theta_{i\tau}, X_i; \tilde{\Theta}^{(g)}) \end{aligned} \tag{20}$$

where f_Y is the conditional distribution of Y given simulated potential θ_{ik}, expectations T_{1ik} and T_{2ik} and observable characteristics X_i. The second component in the likelihood is the product over density functions for T_{1ik} and T_{2ik} (denoted f_{T1} and f_{T2}, respectively) conditional on observable characteristics X_i and potential θ_{ik}. The last component in the likelihood is the product over density functions for S_{Mik} and S_{Rik} conditional on the same sets of observable characteristics and potential as in the second component.

After constructing L_{ik} for each individual i, we take log of each individual's contribution and then sum over to obtain the log-likelihood:

$$l^{(g)} = \sum_{i=1}^{N} log \left(\frac{1}{K} \sum_{k=1}^{K} L_{ik} \right) \tag{21}$$

We evaluate $l^{(g)}$, and using quasi-newton method, search until a maximum is found.

4.5 Discrete Outcomes

In the following section, we present results from a version of the model where the outcome variable is discrete: college completion. To account for limited dependence, we reformulate the model as a set of probits. Before describing how this changes the model, it is important to mention that our results, in particular, the impact of bias, are similar under alternative specifications. For example, one alternative is to focus on college completion, but estimate linear probability models. A second alternative is to convert the outcome and teacher expectations variables into variables measuring years of education. Moreover, in either case, we can restrict parameters so that identification no longer requres test score or GPA data and still estimate similar effects. In other words, our estimates of the impact of teacher expectations on student outcomes, which exploit forecast error to control for teachers' information sets, are robust across a variety of specifications and estimation strategies.

If we reformulate the model of student outcomes and teacher expectations as a probit, the most important change is in how we define bias. We define it as the difference between what a teacher reports and the objective probability of college completion. In particular, using notation from before, college completion is denoted Y_i, which takes the value 1 if student i graduates from a 4-year college and 0 otherwise. The probability that $Y_i = 1$ is given by:

$$Pr(Y_i = 1) = \Phi(c + \theta_i + G_i\beta + b_{1i}\gamma_1 + b_{2i}\gamma_2) \tag{22}$$

where $\Phi(\cdot)$ is the standard normal cdf. Teacher expectations, denoted T_{1i} and T_{2i} for teachers 1 and 2, respectively, are given by:

$$\begin{aligned} Pr(T_{1i} = 1) &= \Phi(c_1 + \phi_1\theta_i + G_i\beta_1) \\ Pr(T_{2i} = 1) &= \Phi(c_2 + \phi_2\theta_i + G_i\beta_2) \end{aligned} \tag{23}$$

Define expectations given information observed by both teachers and given parameters corresponding to the production function given by equation (22):

$$\mathrm{E}[Y_i|\theta_i, G_i, b_{1i} = 0, b_{2i} = 0] = \Phi(c + \theta_i + G_i\beta) \tag{24}$$

Bias is defined as follows:

$$\begin{aligned} b_{1i} &\equiv T_{1i} - \Phi(c + \theta_i + G_i\beta) \\ b_{2i} &\equiv T_{2i} - \Phi(c + \theta_i + G_i\beta) \end{aligned} \tag{25}$$

In other words, bias is defined as the difference between what a teacher reports T_{ij} and what a teacher would report given parameters in the objective production function and assuming observation of θ_i and G_i. Notice, similar to the linear case, teacher expectations can be wrong due to the difference between c_j and c, if $\phi_j \neq 1$ or if $\beta_j \neq \beta$. Moreover, our definition of bias in the probit case means that $b_{ji} \in (-1, 1)$.

4.6 Parameter Estimates

[*Preliminary and subject to change.*]

Results from estimating this model are in Table 9. We estimated the model for the full sample and then separately for whites, blacks, and other-race categories. The first two rows in the table contain estimates of the γ, which are the impact of teacher expectations on student college going. These parameters should be interpreted as probit coefficients and so the corresponding partial effects vary, which we explain more below. That said, the parameters are positive for both teachers and across groups. To illustrate their magnitude, Figure 2 plots the simulated probability of college completion for different levels of bias and different levels of θ. Not surprisingly, the largest impact of bias occurs for individuals in the middle of the distribution. In other words, if a student is already very likely to go to college, a negative bias will not affect him much. If a student is on the margin, however, a high teacher expectation could lead to additional resources that put him over the edge.

The magnitude of the impact of teacher expectations is smaller for black students' reading teachers, which is 0.24 versus 0.56 for white students' reading teachers and 0.51 for black students' math teachers. This finding means that the causal impact of expectations of reading teachers is relatively small for black students. In other words, for black students, an exogenous upward shift in reading teacher expectations does not translate to a higher probability of college completion. One possibility is that black students are under-prepared in math and that this is why they are unable to complete college. If so, then an upward shift in math teacher expectations could lead to the math teacher shifting resources to the student, which could affect college completion. For white students, this might not be the case since they are less likely to face the possibility of not completing college due to being under-trained in math.

The second set of rows in Table 9 presents remaining elements in the equations for college and for teacher expectations. First, we discuss parameters that determine college going, c_y and σ_θ, which are the mean and the standard deviation, respectively, of the distribution of θ. According to estimates, absent the impact of teacher expectations on Y, most students do not complete college. Moreover, black students are less likely on average to go to college (captured by a lower c_y, but the variance is higher. For comparison, we plot the distributions for blacks and whites in Figure 3. To do this, we use the estimated parameters of the distribution of θ to simulate 100,000 individuals. The figure shows clear differences across races. Recall θ is not student ability; it is the expectation of college completion given information available to both teachers when the student is in the 10th grade. The distributions show that, objectively, by the 10th grade, black students are less likely to be expected to go to college (though there is larger variance in θ). This is illustrated in Figure 3, where we plot θ by race. Finally β_y indicates that a higher GPA independently predicts a higher probability of college, though less so for blacks than for whites, which may reflect differences in school quality.

Next, we consider teacher expectations (the third set of rows in Table 9). Here, it is important to see various sources of teacher bias. First, the constants c_1 and c_2, which govern the mean expectation, are much larger than c_y. This accords with the pattern that teachers are optimistic on average. Moreover, the coefficients on θ are not equal to 1. Interestingly, for whites, the coefficient is larger than 1, which means that teacher bias rises for students with higher θ. This would mean that teachers over-estimate the likelihood of college completion for white students, but that they do so more for students who are objectively more likely to go to college. For black students, the pattern is opposite. Teachers are more biased for students with relatively low θ. Finally, β_1 and β_2 seem to indicate the teachers are fairly correct in how they map grades to college completion.

The fourth set of parameter estimates describe the relationship between θ and additional outcomes. As expected, θ is positively correlated with math and reading test scores and grades. Black students perform worse on all measures in relation to whites. Variance, however, is similar.

5 Results

[*Preliminary and subject to change.*]

Here, we discuss how bias differs by group and conduct two preliminary policy experiments. The policy experiments are meant to show that there are differences in objective expectations at the 10th grade, but that the structure of biases by race exacerbate these differences.

5.1 Teacher Biases and Race

In Figure 4, we show the magnitude of bias for different levels of θ. In particular, we simulate 100,000 individuals given the parameters of the distribution of θ. Next, we use estimated parameters to simulate teacher bias. We plot bias as a function of θ for different race and teacher pairs. To understand the result, consider the upper-left panel of the figure. Start where θ is equal to 0. At this point, some teachers will overestimate (positive bias) and others will under-estimate (negative bias). This is likely to be the case for students who do not have especially high or low θ, which means that the probability that they go to college is neither very high nor very low. In contrast, if we look at high and low θ, the size of bias diminishes. The reason is that a very high θ means that a student is very likely to go to college. Moreover, the bias is zero since teachers will expect that outcome.

In Figure 5, we consider the distribution (pdf) of bias for whites and blacks. Here, it is important to understand that there are two reasons that biases are different. First, the bias parameters themselves are different for blacks versus whites. Second, the bias parameters are a function of θ, which also varies for blacks versus whites. In Figure 5, we plot bias differences arising from both differences across races. For blacks, there is a higher proportion of individuals where the bias is equal to or slightly below zero. This means there is a mass of people for whom the teacher is correct. Most of these are due to black students for whom the objective likelihood of no college completion is near zero, which is correctly forecasted by teachers. In comparison, there are relatively few whites for whom the objective probability of college completion (given teachers' information sets) is near zero. In fact, a larger mass of bias for white students is above zero, which means that for students with positive θ, teachers are more likely to over-estimate. This accords with parameter estimates suggesting that white students with higher θ face positive bias. For blacks, this is not the case.

Figure 6 shows the distribution of bias for black and white students with white students' θ. Recall, the distributions of bias are in part due to differences in θ across race categories. In contrast, in Figure 6, the goal is to assess the distribution of bias for black and white students assuming that both begin with the same θ. This is akin to asking: how does bias look for black versus white students if both groups face the same objective probability of college going at the 10th grade. One way to think about this is to assume that a set of white students after the 10th grade (and given θ) are then faced with the same bias as that typically faced by black students. The plots in Figure 6 are more similar across race categories. However, it is still the case that teachers are more likely to underestimate the probability of college completion for blacks than they do for whites. In other words, for the same 10th grade objective probability (which includes all differences and forecasts) black students face a higher likelihood of negative bias. In the following section, we assess if this negative bias in teacher expectations matters.

5.2 The Impact of Bias on College Going

In Table 10, we report results establishing how college going decisions change if we remove bias altogether. To understand the table, consider the first row, where we consider white students. We then assess what happens if we remove the impact of bias (by setting the γ to zero). 50% of students do not go to college in either case. About 0.7% switch to college due to removal of bias. About 11% switch to no college if we remove bias. This is because bias is generally positive. About 37.5% of white students complete college with or without bias. For blacks, the positive impact of bias is smaller (about 6.1% of students switch out of college absent bias).

5.3 What if Black Students Faced White Students' Bias?

Having established that bias appears to matter, we now see whether it matters differently across race categories. In particular, in Figure 7, we consider how differences in bias translate into outcomes. We plot the cdf of the probability of college going for blacks and whites. Consistent with reduced form estimates and summary statistics, the distribution of college going probabilities is shifted to the right for whites versus blacks. In fact, the distribution for black students is first-order stochastically dominated by the distribution for white students. Next, we ask what would happen to outcomes if black students faced the same objective probability of college completion in the 10th grade as whites, but were subjected to the estimated bias of black students. The resulting simulated distribution is the dotted line. Low θ black students face little change. However, as θ rises, the black student cdf starts to mimic the white student cdf. Again, this is consistent with the idea that high θ students face large positive bias for whites versus blacks. Table 11 shows results by different points on the distribution of θ if blacks face white students' γ. Consistent with earlier results, individuals with very low or very high probability of going to college in the 10th grade see little change. Those in the middle, however, see large changes. Moreover, the relationship is non-monotonic. For example, we see that individuals with a 43% probability of college completion could instead face a 53% probability if they faced white students' impact of expectations.

An alternative exercise is to show what happens if black and white students have the same θ, but face different bias. In particular, we simulate outcomes after simulating θ from the white student distribution and then subjecting individuals to the black student bias for given θ. We find that this larger helps individuals with low θ. For higher θ, where bias is smaller for black students, the positive impact of bias largely disappears. Returning to Table 11, we again see largest effects in the middle of the distribution. Whites at the 40th percentile see a drop from 57% to 48% for college completion probability if they face black returns to high expectations.

6 Conclusion

[*Preliminary and subject to change.*]

The positive correlation between teacher expectations and student outcomes is likely due to accurate forecasts, but may also arise from forecast error, which could lead teachers to communicate biases or shift resources to students. This leads to a sort of self-fulfilling prophecy where teacher expectations drive student outcomes. In this paper, we use lessons from the measurement error literature to control for the information that both teachers use to form expectations. The impact of biases is identified off of forecast error, which is driven by the information that one teacher uses to form expectations and that the other teacher does not observe. The key identifying assumption is that any information that can affect one teacher's forecast, but is not observed by the other teacher, is not important enough to drive outcomes except through the impact of teacher expectations.

We show using our model that teacher expectations matter. Moreover, we show that there are important differences across races. Perhaps most troubling, it appears that black students face a higher rate of negative bias for a given objective probability of college completion. This suggests that black students, who already face a lower objective probability of college going by the time they reach the 10th grade, face an additional penalty due to excessive negative biases in teacher expectations. This compounds inequality in educational outcomes. Our results suggest that policies combatting negative bias among teachers of racial minorities could reduce inequality by improving educational outcomes.

References

Avery, Christopher. 2010. "The Effects of College Counseling on High-Achieving, Low-Income Students." NBER Working Paper.

Bailey, Martha J. and Susan M. Dynarski. 2011. "Inequality in Postsecondary Education."

In *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances*, edited by G. Duncan and R. Murnane. New York, NY: Russell Sage Foundation, pp. 171–132.

Becker, G.S. 1964. *Human Capital: A Theoretical Analysis with Special Reference to Education.* Columbia University Press.

Bempechat, Janine. 1998. *Against the Odds: How "At-Risk" Children Exceed Expectations.* Jossey-Bass Inc.

Blundell, Richard, Lorraine Dearden, and Barbara Sianesi. 2005. "Evaluating the Effect of Education on Earnings: Models, Methods and Results from the National Child Development Survey." *Journal of the Royal Statistical Society: Series A (Statistics in Society)* 168 (3):473–512.

Boser, Ulrich, Megan Wilhelm, and Robert Hanna. 2014. "The Power of the Pygmalion Effect: Teachers Expectations Strongly Predict College Completion." *The Center for American Progress* :1–7.

Bound, John and Sarah Turner. 2011. "Dropouts and Diplomas: The Divergence in Collegiate Outcomes." In *Handbook of the Economics of Education*, vol. 4, edited by E. Hanushek, S. Machin, and L. Woessmann. New York, NY: Russell Sage Foundation, 573–613.

Burgess, Simon and Ellen Greaves. 2013. "Test Scores, Subjective Assessment, and Stereotyping of Ethnic Minorities." *Journal of Labor Economics* 31 (3):535–576.

Card, David. 1999. "The Causal Effect of Education on Earnings." *Handbook of Labor Economics* 3:1801–1863.

Castleman, Benjamin L and Lindsay C Page. 2014. "Freshman Year Financial Aid Nudges: An Experiment to Increase FAFSA Renewal and College Persistence." *Journal of Human Resources* 95 (1):202–220.

Chetty, Raj, John N Friedman, and Jonah E Rockoff. 2013. "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood." *American Economic Review* 104 (9):2633–79.

Cornwell, Christopher, David B Mustard, and Jessica Van Parys. 2013. "Noncognitive Skills and the Gender Disparities in Test Scores and Teacher Assessments: Evidence from Primary School." *Journal of Human Resources* 48 (1):236–264.

Dee, Thomas S. 2004. "Are There Civic Returns to Education?" *Journal of Public Economics* 88 (9):1697–1720.

———. 2005. "A Teacher Like Me: Does Race, Ethnicity, or Gender Matter?" *American Economic Review* 95 (2):158–165.

DellaVigna, S. and E. Kaplan. 2007. "The Fox News Effect: Media Bias and Voting." *Quarterly Journal of Economics* 122 (3):1187–1234.

Fortin, Nicole M., Philip Oreopoulos, and Shelley Phipps. 2015. "Leaving Boys Behind: Gender Disparities in High Academic Achievement." *Journal of Human Resources* 50 (3):549–579.

Fryer Jr, Roland G. 2010. "Racial Inequality in the 21st century: The Declining Significance of Discrimination." NBER Working Paper.

Gershenson, Seth, Stephen B Holt, and Nicholas Papageorge. 2015. "Who Believes in Me? The Effect of Student-Teacher Demographic Match on Teacher Expectations." IZA Discussion Paper No. 9202.

Gregory, Anne and Francis Huang. 2013. "It Takes a Village: The Effects of 10th Grade College-Going Expectations of Students, Parents, and Teachers Four Years Later." *American Journal of Community Psychology* 52 (1-2):41–55.

Grossman, Michael. 2006. "Education and Nonmarket Outcomes." *Handbook of the Economics of Education* 1:577–633.

Hanna, Rema N and Leigh L Linden. 2012. "Discrimination in Grading." *American Economic Journal: Economic Policy* 4 (4):146–168.

Hanushek, Eric A, John F Kain, and Steven G Rivkin. 2004. "Why Public Schools Lose Teachers." *Journal of Human Resources* 39 (2):326–354.

Hanushek, Eric A and Steven G Rivkin. 2010. "Generalizations about Using Value-Added Measures of Teacher Quality." *American Economic Review* 100 (2):267–271.

Harris, Douglas N. 2011. *Value-Added Measures in Education: What Every Educator Needs to Know.* Harvard Education Press.

Hoxby, Caroline and Sarah Turner. 2013. "Expanding College Opportunities for High-Achieving, Low Income Students." Stanford Institute for Economic Policy Research Discussion Paper.

Jackson, C Kirabo. 2009. "Student Demographics, Teacher Sorting, and Teacher Quality: Evidence from the End of School Desegregation." *Journal of Labor Economics* 27 (2):213–256.

———. 2012. "Non-cognitive Ability, Test Scores, and Teacher Quality: Evidence from 9th Grade Teachers in North Carolina." NBER Working Paper.

Jacob, Brian A. 2002. "Where the Boys Aren't: Non-Cognitive Skills, Returns to School and the Gender Gap in Higher Education." *Economics of Education Review* 21 (6):589–598.

Kotlarski, Ignacy. 1967. "On Characterizing the Gamma and the Normal Distribution." *Pacific Journal of Mathematics* 20 (1):69–76.

Lavy, Victor. 2008. "Do Gender Stereotypes Reduce Girls' or Boys' Human Capital Outcomes? Evidence from a Natural Experiment." *Journal of Public Economics* 92 (10):2083–2105.

Lavy, Victor and Edith Sand. 2015. "On The Origins of Gender Human Capital Gaps: Short and Long Term Consequences of Teachers? Stereotypical Biases." NBER Working Paper.

Lochner, Lance and Enrico Moretti. 2004. "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports." *American Economic Review* 94 (1):155–189.

Machin, Stephen, Olivier Marie, and Sunčica Vujić. 2011. "The Crime Reducing Effect of Education." *Economic Journal* 121 (552):463–484.

Markow, Dana and Andrea Pieters. 2010. *The MetLife Survey of the American Teacher: Collaborating for Student Success*. MetLife.

Milligan, Kevin, Enrico Moretti, and Philip Oreopoulos. 2004. "Does Education Improve Citizenship? Evidence from the United States and the United Kingdom." *Journal of Public Economics* 88 (9):1667–1695.

Morgan, Stephen L, Theodore S Leenman, Jennifer J Todd, and Kim A Weeden. 2013. "Occupational Plans, Beliefs about Educational Requirements, and Patterns of College Entry." *Sociology of Education* 86 (3):197–217.

Mullainathan, Sendhil and Eldar Shafir. 2013. *Scarcity: Why Having too Little Means so Much*. Macmillan.

Riegle-Crumb, Catherine and Melissa Humphries. 2012. "Exploring Bias in Math Teachers' Perceptions of Students' Ability by Gender and Race/Ethnicity." *Gender & Society* 26 (2):290–322.

Rosenthal, Robert and Lenore Jacobson. 1968. "Pygmalion in the Classroom." *The Urban Review* 3 (1):16–20.

Silles, Mary A. 2009. "The Causal Effect of Education on Health: Evidence from the United Kingdom." *Economics of Education Review* 28 (1):122–128.

Steele, Claude M. 1997. "A Threat in the Air: How Stereotypes Shape Intellectual Identity and Performance." *American Psychologist* 52 (6):613.

Stephan, Jennifer L and James E Rosenbaum. 2013. "Can High Schools Reduce College Enrollment Gaps with a New Counseling Model?" *Educational Evaluation and Policy Analysis* 35 (2):200–219.

Wiswall, Matthew and Basit Zafar. 2015. "Determinants of College Major Choice: Identification Using an Information Experiment." *Review of Economic Studies* 82 (2):791–824.

Figures and Tables

Table 1: Analytic Sample Mean - Students

Sample (Students) :	All (1)	White (2)	Black (3)	Male (4)	Female (5)
Outcome					
Education Completed, Years	14.67	14.83	14.08	14.51	14.81
	(2.06)	(2.06)	(1.84)	(2.05)	(2.07)
Completed < HS Diploma	0.01	0.01	0.02	0.01	0.01
	(0.11)	(0.09)	(0.16)	(0.12)	(0.11)
Completed More than College	0.45	0.49	0.29	0.43	0.47
	(0.50)	(0.50)	(0.45)	(0.49)	(0.50)
Expectations					
Eng. Teacher Exp., Years	15.65	15.78	14.86	15.48	15.80
	(2.23)	(2.14)	(2.21)	(2.29)	(2.16)
Expect < HS, English	0.01	0.01	0.03	0.02	0.01
	(0.12)	(0.11)	(0.17)	(0.13)	(0.10)
More than College, English	0.64	0.67	0.48	0.60	0.67
	(0.48)	(0.47)	(0.50)	(0.49)	(0.47)
Math Teacher Exp., Years	15.51	15.65	14.66	15.43	15.59
	(2.09)	(1.99)	(2.07)	(2.16)	(2.03)
Expect < HS, Math	0.01	0.01	0.03	0.01	0.01
	(0.10)	(0.08)	(0.18)	(0.10)	(0.11)
More than College, Math	0.63	0.66	0.44	0.61	0.65
	(0.48)	(0.47)	(0.50)	(0.49)	(0.48)
Achievements					
Reading Assessment	52.82	54.67	46.71	52.39	53.21
	(9.83)	(9.26)	(8.99)	(10.20)	(9.47)
Math Assessment	53.01	54.71	45.77	54.00	52.12
	(9.67)	(8.78)	(8.88)	(10.13)	(9.15)
9th grade GPA	2.92	3.02	2.44	2.82	3.01
	(0.78)	(0.73)	(0.76)	(0.78)	(0.77)
Demographics and SES					
Income < 20K	0.11	0.06	0.26	0.09	0.13
	(0.32)	(0.25)	(0.44)	(0.29)	(0.34)
HH income > 100K	0.18	0.21	0.08	0.19	0.17
	(0.38)	(0.41)	(0.27)	(0.39)	(0.37)
Mother has $\leq$ HS diploma	0.34	0.29	0.39	0.32	0.35
	(0.47)	(0.46)	(0.49)	(0.47)	(0.48)
Mother has a Bachelor's or More	0.11	0.12	0.07	0.12	0.10
	(0.31)	(0.33)	(0.26)	(0.33)	(0.30)
Teacher					
Eng. Teacher Non-White	0.10	0.05	0.26	0.10	0.10
	(0.30)	(0.22)	(0.44)	(0.30)	(0.30)
Math Teacher Non-White	0.11	0.06	0.21	0.11	0.11
	(0.32)	(0.23)	(0.41)	(0.32)	(0.32)
Observations	6060	3970	610	2870	3190

Each entry represents the mean over individuals for the group specified in the first row. Reading and Math assessment entries are on a 100-point scale. 9th grade GPA is uses a 4.0 scale. With the exception of entries marked as in years, all other entries are proportions.

Table 2: Analytic Sample Mean - Teachers

Sample (Teachers) :	All	Math Teachers	English Teachers	White Teachers	Black Teachers	Male Teachers	Female Teachers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Teacher Characteristics							
Non-White	0.11	0.11	0.10	0.00	1.00	0.10	0.11
	(0.31)	(0.32)	(0.30)	(0.00)	(0.00)	(0.30)	(0.31)
Math Teacher	0.50	1.00	0.00	0.50	0.47	0.62	0.43
	(0.50)	(0.00)	(0.00)	(0.50)	(0.50)	(0.49)	(0.50)
Male	0.35	0.44	0.27	0.36	0.26	1.00	0.00
	(0.48)	(0.50)	(0.44)	(0.48)	(0.44)	(0.00)	(0.00)
Experience	14.89	15.35	14.44	15.17	15.01	15.56	14.53
	(10.76)	(10.74)	(10.77)	(10.80)	(11.28)	(11.61)	(10.25)
Low Experience	0.16	0.14	0.19	0.15	0.21	0.16	0.16
	(0.37)	(0.34)	(0.39)	(0.36)	(0.41)	(0.37)	(0.37)
Without regular certificate	0.17	0.15	0.18	0.16	0.21	0.21	0.14
	(0.37)	(0.36)	(0.39)	(0.37)	(0.41)	(0.41)	(0.35)
Major in subject taught	0.48	0.47	0.49	0.49	0.48	0.42	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)
Has graduate degree	0.47	0.48	0.47	0.49	0.45	0.51	0.46
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Student Demographics							
American Indian	0.00	0.00	0.00	0.00	0.00	0.01	0.00
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.06)
Asian	0.08	0.08	0.08	0.07	0.05	0.09	0.07
	(0.27)	(0.27)	(0.27)	(0.26)	(0.22)	(0.28)	(0.26)
Black	0.10	0.10	0.10	0.09	0.47	0.09	0.11
	(0.30)	(0.30)	(0.30)	(0.28)	(0.50)	(0.29)	(0.31)
Hispanic	0.12	0.12	0.12	0.10	0.12	0.13	0.11
	(0.32)	(0.32)	(0.32)	(0.30)	(0.33)	(0.34)	(0.32)
Multiple Race	0.04	0.04	0.04	0.04	0.04	0.05	0.04
	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)	(0.21)	(0.20)
Male	0.47	0.47	0.47	0.47	0.44	0.51	0.45
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Observations	12130	6060	6060	10830	470	4300	7820

Each entry represents the mean over individuals for the group specified in the first row. Experience is in years. All other entries are proportions. All sample sizes are rounded to the nearest 10 in accordance with NCES regulations for restricted data.

Table 3: Preliminary Analysis - Effect of Expectation on Education

	(1)	(2)	(3)	(4)	(5)
Years Expected, English	0.291***	0.283***	0.239***	0.172***	0.157***
	(0.014)	(0.014)	(0.013)	(0.014)	(0.016)
Years Expected, Math	0.304***	0.302***	0.261***	0.187***	0.153***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)
Teacher Controls	No	Yes	Yes	Yes	Yes
Student SES	No	No	Yes	Yes	Yes
9th Grade GPA	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
Adj. R^2	0.312	0.317	0.347	0.369	0.288
N	6060	6060	6060	6060	6060

OLS regression explaining years of schooling (imputed from highest education level reported) as a function of english and math teachers' expectations conditional on set of student and teacher characteristics. English and Math teacher expectations separately have statistically significant predictive power for student outcomes. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level.

Table 4: Preliminary Analysis - Effect of Expectation on Education - Subgroups

	(1) White	(2) Black	(3) Hispanic	(4) Male	(5) Female
Years Expected, English	0.166***	0.079	0.308***	0.159***	0.165***
	(0.020)	(0.051)	(0.048)	(0.022)	(0.022)
Years Expected, Math	0.157***	0.145***	0.038	0.137***	0.162***
	(0.022)	(0.053)	(0.054)	(0.025)	(0.026)
Teacher Controls	Yes	Yes	Yes	Yes	Yes
Student SES	Yes	Yes	Yes	Yes	Yes
9th Grade GPA	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.285	0.200	0.346	0.275	0.292
N	3970	610	720	2870	3190

OLS regression explaining years of schooling (imputed from highest education level reported) as a function of english and math teachers' expectations conditional on set of student and teacher characteristics, achievement and school fixed effects. English and math teacher expectations separately have statistically significant predictive power for student outcomes. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level.

Table 5: Summary Statistics - Math Teacher Expectation and Student Outcome

	Student Outcome				
Teacher Expectation	Less than HS	HS Diploma	Some College	Bachelor's or More	Total
	All Students				
Less than HS	0.20	0.36	0.51	0.02	1.09
HS Diploma	0.63	3.58	7.55	0.69	12.45
Some College	0.38	3.25	15.17	4.68	23.49
Bachelor's or More	0.12	1.52	21.72	39.62	62.97
Total	1.32	8.71	44.96	45.01	100.00
	White Students Only				
Less than HS	0.05	0.23	0.35	0.03	0.65
HS Diploma	0.50	3.20	5.91	0.55	10.17
Some College	0.33	3.37	14.40	4.73	22.83
Bachelor's or More	0.03	1.56	20.79	43.97	66.35
Total	0.91	8.36	41.45	49.28	100.00
	Black Students Only				
Less than HS	0.82	0.99	1.48	0.00	3.29
HS Diploma	0.66	3.62	14.99	1.32	20.59
Some College	0.82	2.47	22.41	5.93	31.63
Bachelor's or More	0.16	1.32	21.42	21.58	44.48
Total	2.47	8.40	60.30	28.83	100.00
	Hispanic Students Only				
Less than HS	0.69	0.55	0.83	0.00	2.07
HS Diploma	1.52	5.52	12.15	0.83	20.03
Some College	0.69	3.31	17.27	3.31	24.59
Bachelor's or More	0.41	2.07	25.97	24.86	53.31
Total	3.31	11.46	56.22	29.01	100.00
	Male Students Only				
Less than HS	0.21	0.31	0.45	0.00	0.98
HS Diploma	0.63	4.56	8.82	0.84	14.84
Some College	0.35	3.87	14.74	4.49	23.45
Bachelor's or More	0.17	1.71	21.53	37.32	60.73
Total	1.36	10.45	45.54	42.65	100.00
	Female Students Only				
Less than HS	0.19	0.41	0.56	0.03	1.19
HS Diploma	0.63	2.69	6.42	0.56	10.30
Some College	0.41	2.69	15.57	4.85	23.52
Bachelor's or More	0.06	1.35	21.89	41.68	64.99
Total	1.28	7.14	44.44	47.13	100.00

Math teacher expectation-student educational outcome matrices. Each entry represent percentage of observations that fall in the particular category.

Table 6: Descriptive Regression - Math Teacher Optimism - All Students

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher is Non-white	0.229**	-0.044**	-0.023**	0.067**
	(0.091)	(0.018)	(0.009)	(0.027)
Teacher is Male	-0.022	0.004	0.002	-0.006
	(0.048)	(0.009)	(0.005)	(0.014)
Teacher Experience	-0.007***	0.001***	0.001***	-0.002***
	(0.002)	(0.000)	(0.000)	(0.001)
Teacher major in Math	-0.041	0.008	0.004	-0.012
	(0.046)	(0.009)	(0.005)	(0.013)
Teacher has graduate degree	-0.083	0.016	0.008	-0.024
	(0.053)	(0.010)	(0.005)	(0.015)
Teacher has no regular certificate	0.056	-0.011	-0.006	0.016
	(0.079)	(0.015)	(0.008)	(0.023)
Student is American Indian	0.265	-0.051	-0.026	0.078
	(0.326)	(0.063)	(0.032)	(0.095)
Student is Asian	-0.170*	0.033*	0.017*	-0.050*
	(0.089)	(0.017)	(0.009)	(0.026)
Student is Black	-0.226***	0.044***	0.023***	-0.066***
	(0.073)	(0.014)	(0.007)	(0.021)
Student is Hispanic	-0.044	0.009	0.004	-0.013
	(0.078)	(0.015)	(0.008)	(0.023)
Student is Multiple Race	0.036	-0.007	-0.004	0.011
	(0.087)	(0.017)	(0.009)	(0.026)
Mother has ≥4-year degree	0.034	-0.007	-0.003	0.010
	(0.053)	(0.010)	(0.005)	(0.016)
HH income 20K - 35K	0.160**	-0.031**	-0.016**	0.047**
	(0.078)	(0.015)	(0.008)	(0.023)
HH income 35K - 75K	0.128*	-0.025*	-0.013*	0.038*
	(0.074)	(0.014)	(0.007)	(0.022)
HH income 75K - 100K	0.110	-0.021	-0.011	0.032
	(0.082)	(0.016)	(0.008)	(0.024)
HH income > 100K	0.086	-0.017	-0.009	0.025
	(0.083)	(0.016)	(0.008)	(0.024)
9th grade GPA	0.293***	-0.057***	-0.029***	0.086***
	(0.029)	(0.006)	(0.003)	(0.008)
Pseudo-R^2	0.105			
N	6060			

Ordered probit regressions explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching the actual outcome, and column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table 7: Summary Statistics - Teacher Expectations

Math Teacher Expectation	English Teacher Expectation: Less than HS	HS Diploma	Some College	Bachelor's or More	Total
	All Students				
Less than HS	0.26	0.61	0.16	0.05	1.09
HS Diploma	0.84	5.41	4.63	1.57	12.45
Some College	0.26	4.06	9.90	9.27	23.49
Bachelor's or More	0.07	1.55	8.36	52.99	62.97
Total	1.43	11.63	23.06	63.88	100.00
	White Students				
Less than HS	0.15	0.43	0.08	0.00	0.65
HS Diploma	0.65	4.23	4.08	1.21	10.17
Some College	0.28	3.90	9.56	9.09	22.83
Bachelor's or More	0.05	1.28	8.31	56.71	66.35
Total	1.13	9.84	22.02	67.00	100.00
	Black Students				
Less than HS	1.15	1.32	0.66	0.16	3.29
HS Diploma	1.15	9.56	7.41	2.47	20.59
Some College	0.49	6.59	12.52	12.03	31.63
Bachelor's or More	0.16	2.47	8.07	33.77	44.48
Total	2.97	19.93	28.67	48.43	100.00
	Hispanic Students				
Less than HS	0.41	1.38	0.28	0.00	2.07
HS Diploma	2.07	8.98	5.94	3.04	20.03
Some College	0.14	4.01	11.74	8.70	24.59
Bachelor's or More	0.14	1.93	11.05	40.19	53.31
Total	2.76	16.30	29.01	51.93	100.00
	Male Students				
Less than HS	0.42	0.49	0.07	0.00	0.98
HS Diploma	0.94	6.86	5.54	1.50	14.84
Some College	0.45	4.53	9.86	8.61	23.45
Bachelor's or More	0.03	1.71	8.75	50.24	60.73
Total	1.85	13.59	24.22	60.35	100.00
	Female Students				
Less than HS	0.13	0.72	0.25	0.09	1.19
HS Diploma	0.75	4.10	3.82	1.63	10.30
Some College	0.09	3.63	9.93	9.87	23.52
Bachelor's or More	0.09	1.41	8.02	55.47	64.99
Total	1.06	9.87	22.02	67.05	100.00

Each entry represents the percentage of observations that fall in the particular math teacher expectation-english teacher expectation category.

Table 8: Descriptive Regression - Teacher Disagreements

Student Subsample:	(1) All	(2) White	(3) Black	(4) Hispanic	(5) Male	(6) Female
Student is American Indian	-0.026				-0.057	-0.155
	(0.126)				(0.169)	(0.181)
Student is Asian	-0.037				0.022	-0.080**
	(0.029)				(0.046)	(0.039)
Student is Black	0.030				0.027	0.019
	(0.028)				(0.042)	(0.036)
Student is Hispanic	-0.005				-0.027	-0.012
	(0.026)				(0.038)	(0.037)
Student is Multiple Race	-0.031				-0.065	-0.042
	(0.031)				(0.049)	(0.045)
Student is Male	-0.004	-0.005	-0.031	0.004		
	(0.012)	(0.015)	(0.052)	(0.048)		
Father has HS Diploma	0.046***	0.062***	0.047	0.041	0.046*	0.041*
	(0.017)	(0.021)	(0.054)	(0.059)	(0.028)	(0.023)
Father has Some College	0.003	-0.004	0.034	0.072	0.004	-0.002
	(0.015)	(0.018)	(0.066)	(0.049)	(0.026)	(0.021)
Father has a Bachelor's or More	0.003	0.013	0.023	0.113	-0.005	0.024
	(0.018)	(0.021)	(0.096)	(0.080)	(0.028)	(0.024)
Mother has HS Diploma	0.010	0.014	0.047	-0.019	0.033	-0.005
	(0.017)	(0.021)	(0.072)	(0.057)	(0.027)	(0.025)
Mother has Some College	0.015	0.012	0.086	0.074	-0.016	0.042*
	(0.015)	(0.019)	(0.069)	(0.063)	(0.024)	(0.022)
Mother has a Bachelor's or More	-0.034**	-0.044**	0.099	-0.087	-0.013	-0.064***
	(0.017)	(0.021)	(0.109)	(0.095)	(0.028)	(0.025)
Not have both father and Mother	0.005	0.018	0.062	-0.086**	0.029	-0.018
	(0.014)	(0.016)	(0.056)	(0.043)	(0.021)	(0.019)
HH income 20K - 35K	-0.011	-0.009	0.049	0.023	-0.029	-0.007
	(0.027)	(0.041)	(0.082)	(0.059)	(0.042)	(0.037)
HH income 35K - 75K	0.033	0.040	-0.027	0.061	0.030	0.026
	(0.024)	(0.037)	(0.077)	(0.066)	(0.037)	(0.032)
HH income 75K - 100K	0.023	0.042	-0.135	0.065	-0.002	0.042
	(0.029)	(0.040)	(0.099)	(0.088)	(0.044)	(0.037)
HH income > 100K	0.025	0.036	-0.189	0.112	-0.004	0.042
	(0.029)	(0.039)	(0.132)	(0.111)	(0.045)	(0.038)
Home language not English	-0.007	0.037	-0.064	-0.035	-0.052	0.013
	(0.027)	(0.050)	(0.095)	(0.060)	(0.039)	(0.039)
Parents English not fluent	0.035	0.040	-0.092	0.062	0.007	0.046
	(0.028)	(0.070)	(0.171)	(0.060)	(0.041)	(0.041)
Parents ever held job in US	0.027	0.024	-0.097	0.034	-0.123**	0.108**
	(0.038)	(0.079)	(0.141)	(0.071)	(0.057)	(0.051)
9th grade GPA	-0.200***	-0.220***	-0.093**	-0.125***	-0.185***	-0.230***
	(0.010)	(0.012)	(0.044)	(0.030)	(0.014)	(0.014)
Constant	0.835***	0.876***	0.683***	0.604***	0.950***	0.852***
	(0.052)	(0.087)	(0.171)	(0.128)	(0.075)	(0.073)
R^2	0.114	0.133	0.058	0.066	0.103	0.144
Adj. R^2	0.110	0.130	0.032	0.045	0.096	0.138
N	6060	3970	610	720	2870	3190

OLS estimates of LPM where the dependent variable is equal to 1 if teacher expectations differ and 0 otherwise. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table 9: Structural Estimates

Variable	All	White	Black	Other
		Effect of Bias		
γ_1	0.5275	0.5213	0.5118	0.5310
	(0.0492)	(0.0610)	(0.1572)	(0.1049)
γ_2	0.4838	0.5562	0.2368	0.3851
	(0.0496)	(0.0621)	(0.1543)	(0.1039)
		Y Equation		
c_y	-0.5354	-0.4587	-0.8284	-0.6797
	(0.0411)	(0.0518)	(0.1353)	(0.0957)
σ_θ	0.5775	0.5026	0.7908	0.5798
	(0.0424)	(0.0539)	(0.1360)	(0.0665)
β_y	0.4426	0.4985	0.2703	0.4518
	(0.0370)	(0.0479)	(0.1065)	(0.0718)
		$T1, T2$ Equation		
c_1	0.5134	0.5724	0.2594	0.5051
	(0.0235)	(0.0305)	(0.0826)	(0.0530)
c_2	0.4884	0.5654	0.0692	0.5027
	(0.0240)	(0.0312)	(0.0841)	(0.0553)
ϕ_1	1.1624	1.4673	0.7296	1.1954
	(0.1036)	(0.1824)	(0.1675)	(0.0962)
ϕ_2	1.3272	1.6901	0.8560	1.2727
	(0.1122)	(0.2006)	(0.1964)	(0.1037)
β_1	0.5533	0.5577	0.4715	0.6010
	(0.0259)	(0.0349)	(0.0716)	(0.0508)
β_2	0.5159	0.5105	0.3941	0.5841
	(0.0264)	(0.0348)	(0.0762)	(0.0511)
		SM, SR, GPA Equation		
c_m	-0.0023	0.1739	-0.7530	-0.1658
	(0.0130)	(0.0148)	(0.0376)	(0.0265)
c_r	-0.0022	0.1875	-0.6253	-0.2539
	(0.0131)	(0.0154)	(0.0380)	(0.0269)
c_g	-0.0017	0.1224	-0.6272	-0.0769
	(0.0145)	(0.0173)	(0.0409)	(0.0260)
ϕ_m	1.5291	1.5506	1.0208	1.6904
	(0.1122)	(0.1661)	(0.1802)	(0.0871)
ϕ_r	1.4458	1.5446	0.9623	1.4482
	(0.1058)	(0.1653)	(0.1681)	(0.0811)
ϕ_g	1.0916	1.1631	0.6628	1.0972
	(0.0814)	(0.1268)	(0.1244)	(0.0627)
σ_m	0.4743	0.4721	0.4559	0.4852
	(0.0097)	(0.0106)	(0.0338)	(0.0158)
σ_r	0.5542	0.5387	0.5216	0.5893
	(0.0078)	(0.0096)	(0.0239)	(0.0132)
σ_g	0.7778	0.7411	0.8319	0.8402
	(0.0080)	(0.0092)	(0.0288)	(0.0173)

Standard errors are computed by constructing the Hessian of the likelihood function using the outer product measure. To compute the outer product measure, we calculate two-sided numerical derivatives of the likelihood function for each estimated parameter. In each direction, the derivative is calculated by perturbing each parameter and then computing the likelihood.

Table 10: Fraction of Switchers

	Always No-College	Switch to College	Switch to No College	Always College
White, $\gamma_1 = \gamma_2 = 0$	0.506	0.007	0.110	0.376
Black, $\gamma_1 = \gamma_2 = 0$	0.702	0.006	0.061	0.230
White, $\gamma_1 = 0$	0.503	0.010	0.060	0.427
Black, $\gamma_1 = 0$	0.699	0.009	0.050	0.241
White, $\gamma_2 = 0$	0.503	0.010	0.062	0.424
Black, $\gamma_2 = 0$	0.704	0.005	0.020	0.271

Table 11: Counterfactual Analysis : College Graduation Probability

	Blacks		Whites	
Counterfactual	College Graduation	% Change in Graduation	College Graduation	% Change in Graduation
	10th Percentile			
baseline	0.0138	0.0000	0.0668	0.0000
γ_1, γ_2	0.0136	-1.1833	0.0702	5.1025
	20th Percentile			
baseline	0.0351	0.0000	0.1112	0.0000
γ_1, γ_2	0.0342	-2.6783	0.1204	8.2734
	40th Percentile			
baseline	0.0942	0.0000	0.5725	0.0000
γ_1, γ_2	0.0883	-6.2190	0.4777	-16.5522
	50th Percentile			
baseline	0.1320	0.0000	0.6208	0.0000
γ_1, γ_2	0.1211	-8.2316	0.5368	-13.5357
	60th Percentile			
baseline	0.4285	0.0000	0.6650	0.0000
γ_1, γ_2	0.5300	23.6905	0.5933	-10.7798
	80th Percentile			
baseline	0.5888	0.0000	0.7563	0.0000
γ_1, γ_2	0.6615	12.3552	0.7140	-5.5948
	90th Percentile			
baseline	0.6960	0.0000	0.8181	0.0000
γ_1, γ_2	0.7427	6.7097	0.7940	-2.9546

The probability of graduating college for black and white students in the given percentile of θ under counterfactuals where teacher bias has the same effect as the other race. Also recorded are percent changes in college graduation probabilities relative to the baseline where students face race-specific bias and human capital production parameters.

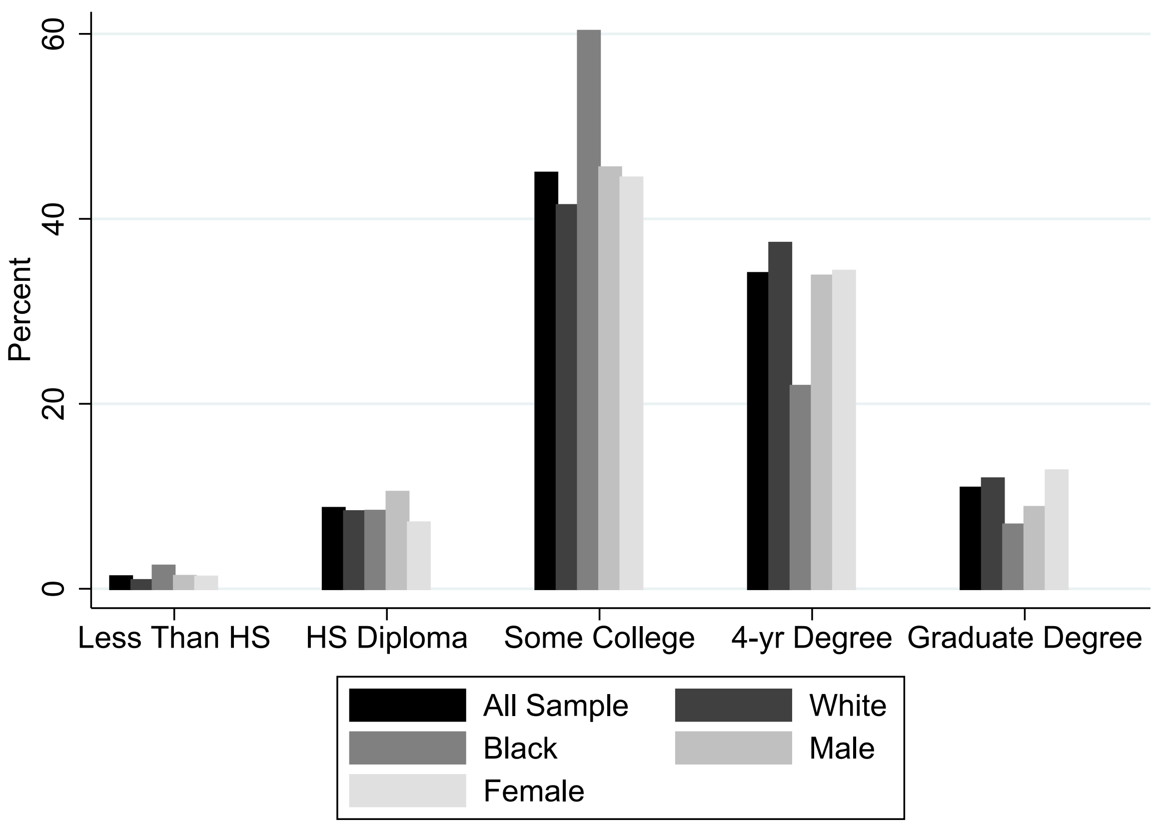

Figure 1: Educational Attainment, by Subgroup

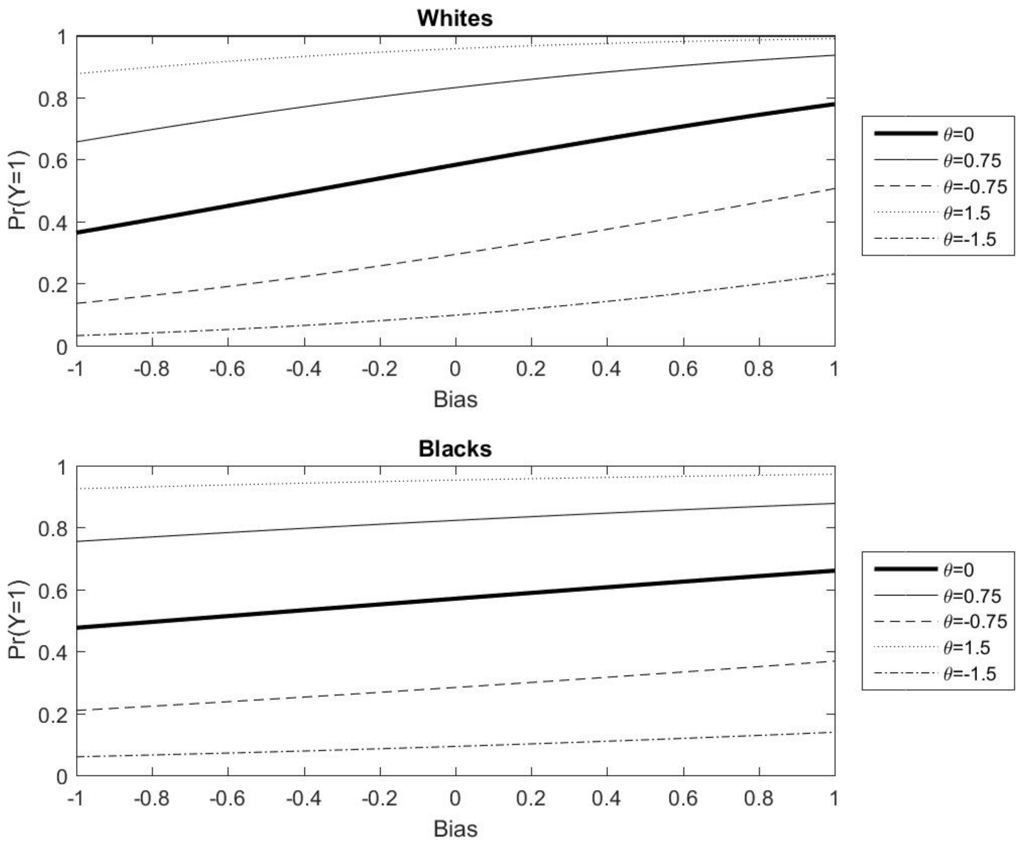

Figure 2: $Pr(Y = 1|GPA, b_2)$

GPA is fixed at population mean for whites (=0.1224), $s.d.(\theta) = 0.5026$, $c_y = -0.4587$ and b_1 is fixed at 0.2722. θ here refers to $c_y + \theta$

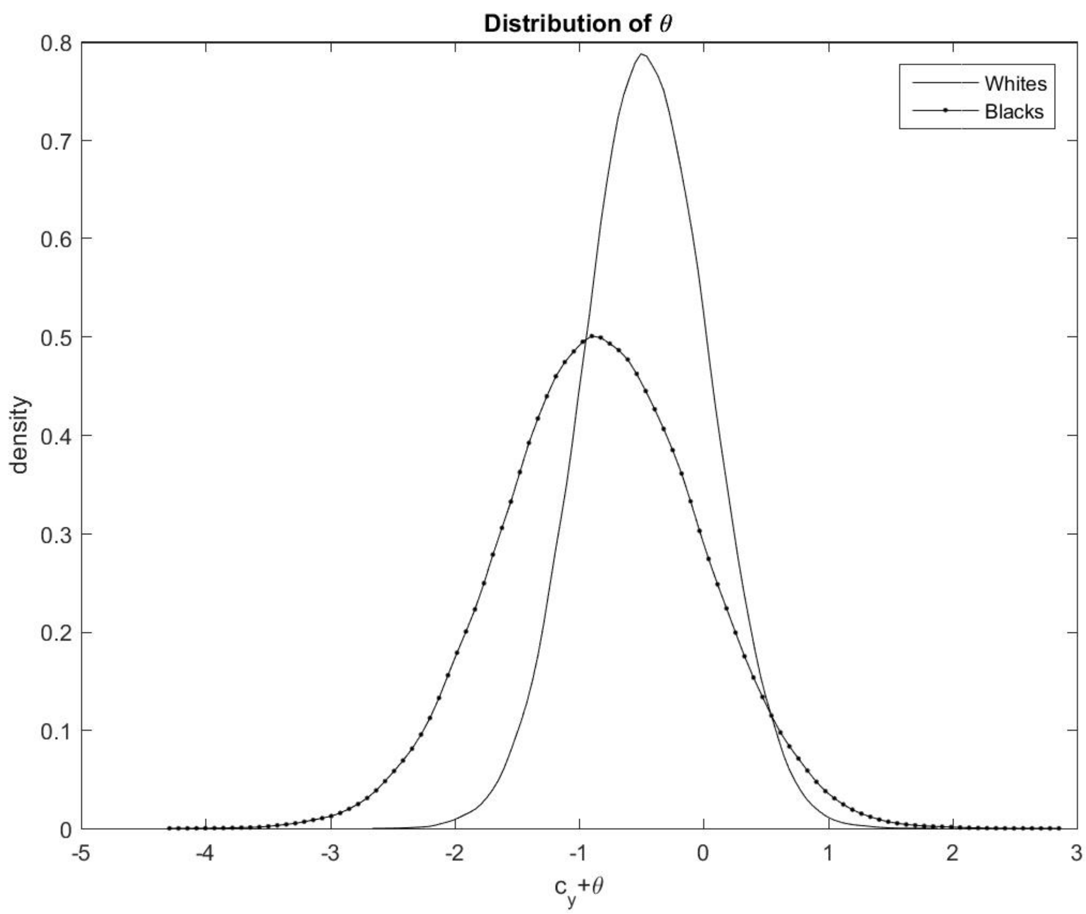

Figure 3: Distribution of θ

Different means reflect difference in c_y : $c_{y,blacks} = -0.8284$, $c_{y,whites} = -0.4587$.

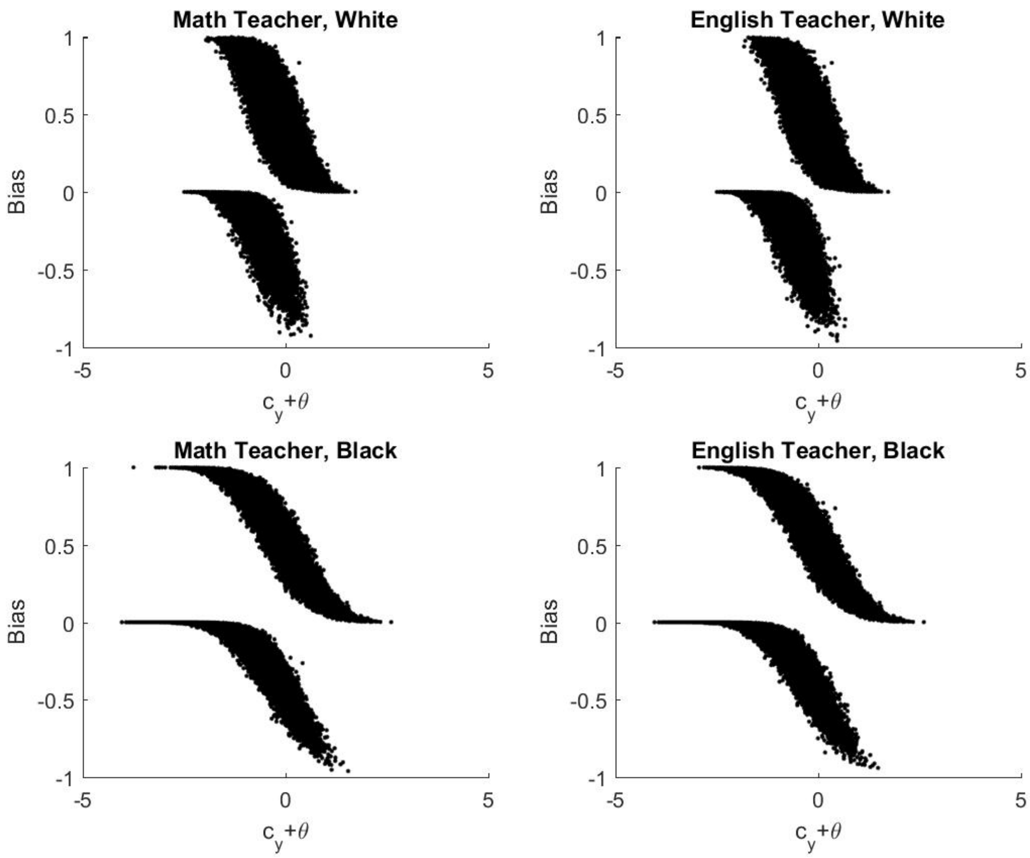

Figure 4: Distribution of b_1, b_2 by Teacher

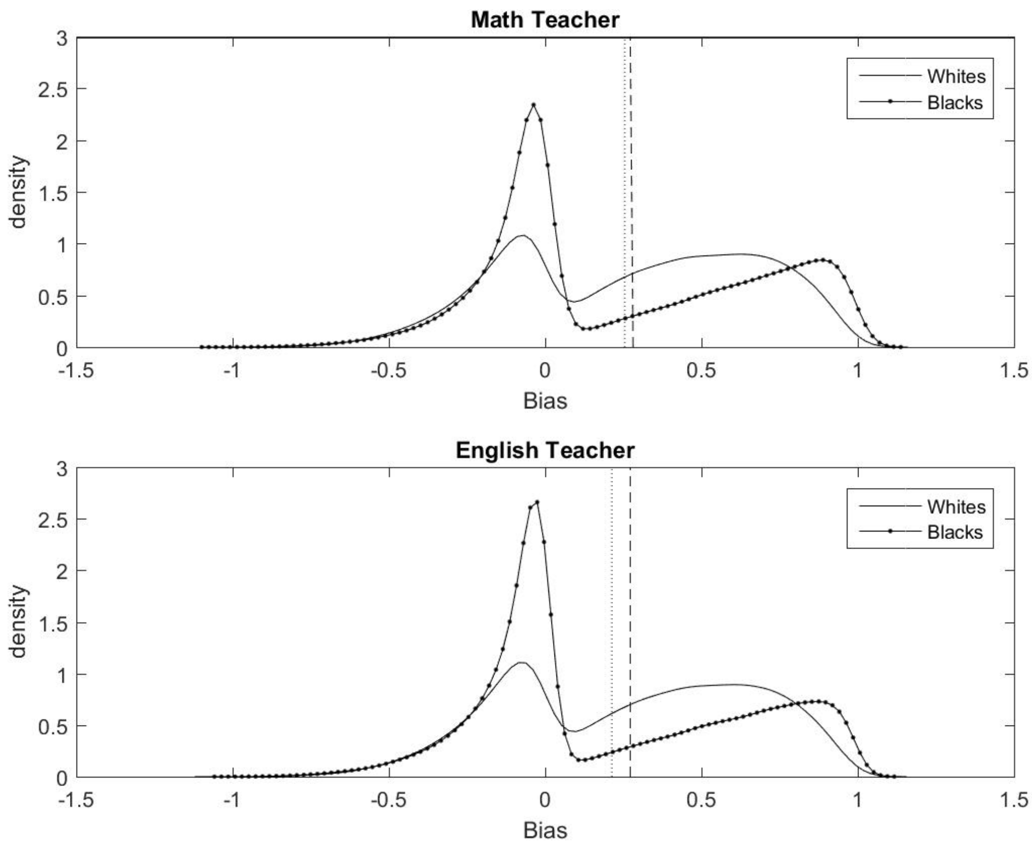

Figure 5: PDF of b_1, b_2 for Whites and Blacks

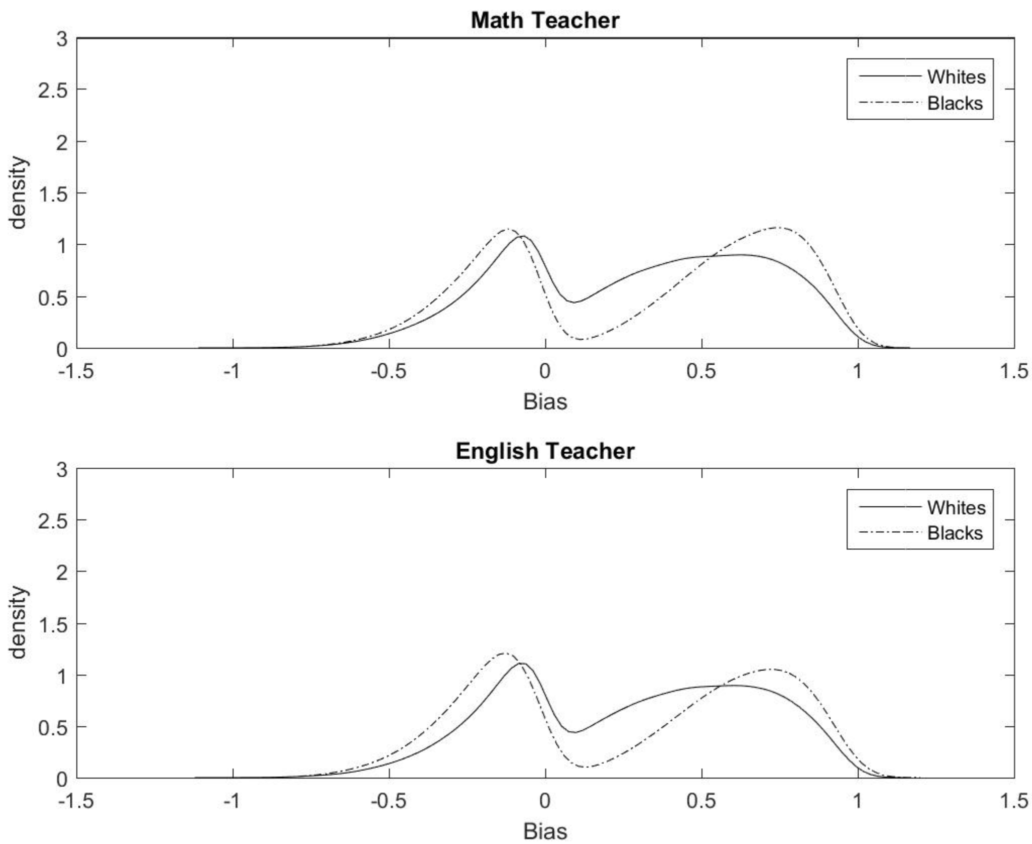

Figure 6: PDF of b_1, b_2 by Teacher

Assuming whites and blacks have the same draws of $c_y + \theta$

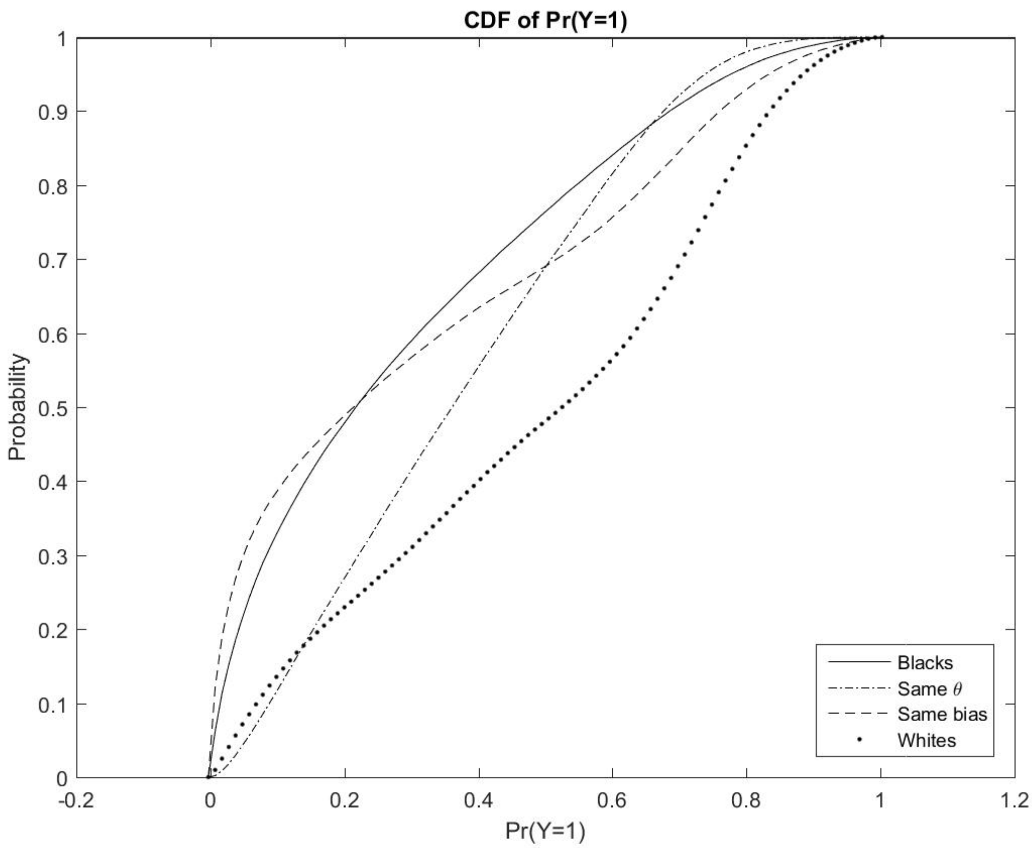

Figure 7: CDF of $Pr(Y = 1)$

Appendix A Additional Results

Table A1: Preliminary Analysis - Effect of Expectation on Education - College

	(1)	(2)	(3)	(4)	(5)
Expect $\geq$ College, English	0.310***	0.303***	0.253***	0.178***	0.155***
	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)
Expect $\geq$ College, Math	0.314***	0.308***	0.260***	0.185***	0.148***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)
Teacher Controls	No	Yes	Yes	Yes	Yes
Student SES	No	No	Yes	Yes	Yes
9th Grade GPA	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
Adj. R^2	0.282	0.292	0.330	0.357	0.269
N	6060	6060	6060	6060	6060

OLS regressions of a LPM of a student attaining at least a 4-year college degree as a function of english and math teachers' expectations conditional on set of student and teacher characteristics. English and math teacher expectations separately have statistically significant predictive power for student outcome. *Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Parentheses contain standard errors that are robust to clustering at the school level.

Table A2: Preliminary Analysis - Effect of Expectation on Education - No HS diploma

	(1)	(2)	(3)	(4)	(5)
Expect $<$ HS diploma, English	0.161***	0.160***	0.150***	0.140***	0.141***
	(0.041)	(0.040)	(0.040)	(0.040)	(0.041)
Expect $<$ HS diploma, Math	0.133***	0.134***	0.125***	0.114***	0.119***
	(0.043)	(0.043)	(0.042)	(0.042)	(0.043)
Teacher Controls	No	Yes	Yes	Yes	Yes
Student SES	No	No	Yes	Yes	Yes
9th Grade GPA	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
Adj. R^2	0.051	0.052	0.062	0.070	0.066
N	6060	6060	6060	6060	6060

OLS regression of a LPM of a student fail to get a highschool diploma or equivalent as a function of english and math teacher's expectations conditional on set of student and teacher characteristics. English and math teacher expectations separately have statistically significant significant predictive power student outcome. *Note: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Parentheses contain standard errors that are robust to clustering at the school level.

Table A3: Summary Statistics - English Teacher Expectation and Student Outcome

	Student Outcome				
Teacher Expectation	Less than HS	HS Diploma	Some College	Bachelor's or More	Total
			All Students		
Less than HS	0.28	0.53	0.61	0.02	1.43
HS Diploma	0.61	3.46	6.86	0.69	11.63
Some College	0.33	3.33	15.01	4.39	23.06
Bachelor's or More	0.10	1.39	22.48	39.91	63.88
Total	1.32	8.71	44.96	45.01	100.00
			White Students		
Less than HS	0.23	0.38	0.50	0.03	1.13
HS Diploma	0.45	3.20	5.66	0.53	9.84
Some College	0.20	3.37	13.67	4.78	22.02
Bachelor's or More	0.03	1.41	21.62	43.95	67.00
Total	0.91	8.36	41.45	49.28	100.00
			Black Students		
Less than HS	0.33	0.99	1.65	0.00	2.97
HS Diploma	0.99	4.78	12.19	1.98	19.93
Some College	0.66	1.48	23.06	3.46	28.67
Bachelor's or More	0.49	1.15	23.39	23.39	48.43
Total	2.47	8.40	60.30	28.83	100.00
			Hispanic Students		
Less than HS	0.83	1.10	0.83	0.00	2.76
HS Diploma	1.52	4.28	9.81	0.69	16.30
Some College	0.83	4.42	20.17	3.59	29.01
Bachelor's or More	0.14	1.66	25.41	24.72	51.93
Total	3.31	11.46	56.22	29.01	100.00
			Male Students		
Less than HS	0.31	0.70	0.80	0.03	1.85
HS Diploma	0.73	4.32	7.60	0.94	13.59
Some College	0.17	4.01	15.12	4.91	24.22
Bachelor's or More	0.14	1.43	22.02	36.76	60.35
Total	1.36	10.45	45.54	42.65	100.00
			Female Students		
Less than HS	0.25	0.38	0.44	0.00	1.06
HS Diploma	0.50	2.69	6.20	0.47	9.87
Some College	0.47	2.72	14.91	3.91	22.02
Bachelor's or More	0.06	1.35	22.89	42.75	67.05
Total	1.28	7.14	44.44	47.13	100.00

Math teacher expectation-student educational outcome transition. Each entry represent percentage of observations that fall in the particular category.

Table A4: Descriptive Regression - English Teacher Optimism

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher Non-White	-0.069	0.013	0.008	-0.020
	(0.098)	(0.018)	(0.011)	(0.029)
Teacher is Male	-0.066	0.012	0.007	-0.020
	(0.059)	(0.011)	(0.006)	(0.018)
Teacher Experience	-0.009***	0.002***	0.001***	-0.003***
	(0.003)	(0.001)	(0.000)	(0.001)
Teacher major in English	-0.018	0.003	0.002	-0.005
	(0.052)	(0.010)	(0.006)	(0.015)
Teacher has graduate degree	-0.012	0.002	0.001	-0.003
	(0.057)	(0.011)	(0.006)	(0.017)
Teacher has no regular certificate	0.064	-0.012	-0.007	0.019
	(0.080)	(0.015)	(0.009)	(0.024)
Student is American Indian	0.364	-0.068	-0.040	0.108
	(0.350)	(0.065)	(0.038)	(0.104)
Student is Asian	-0.095	0.018	0.010	-0.028
	(0.083)	(0.016)	(0.009)	(0.025)
Student is Black	-0.106	0.020	0.012	-0.031
	(0.072)	(0.013)	(0.008)	(0.021)
Student is Hispanic	0.047	-0.009	-0.005	0.014
	(0.077)	(0.014)	(0.008)	(0.023)
Student is Multiple Race	0.090	-0.017	-0.010	0.027
	(0.090)	(0.017)	(0.010)	(0.027)
Mother has a Bachelor's or More	-0.016	0.003	0.002	-0.005
	(0.053)	(0.010)	(0.006)	(0.016)
HH income 20K - 35K	0.172**	-0.032**	-0.019**	0.051**
	(0.080)	(0.015)	(0.009)	(0.024)
HH income 35K - 75K	0.230***	-0.043***	-0.025***	0.068***
	(0.073)	(0.014)	(0.008)	(0.022)
HH income 75K - 100K	0.189**	-0.035**	-0.021**	0.056**
	(0.085)	(0.016)	(0.009)	(0.025)
HH income > 100K	0.133	-0.025	-0.015	0.039
	(0.083)	(0.015)	(0.009)	(0.024)
9th grade GPA	0.288***	-0.054***	-0.031***	0.085***
	(0.028)	(0.005)	(0.003)	(0.008)
Pseudo-R^2	0.105			
N	6060			

Ordered probit regression explaining over/under optimism by english teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectation matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes English Teacher only.

Table A5: Descriptive Regression - Math Teacher Optimism - Experience Level Dummies

	Coefficients (1)	APE - Under (2)	APE - Correct (3)	APE - Over (4)
Teacher Non-White	0.234**	-0.045**	-0.023**	0.069**
	(0.092)	(0.018)	(0.009)	(0.027)
Teacher is Male	-0.031	0.006	0.003	-0.009
	(0.048)	(0.009)	(0.005)	(0.014)
Teacher 2 yrs of Experience	0.007	-0.001	-0.001	0.002
	(0.165)	(0.032)	(0.016)	(0.048)
Teacher 3 yrs of Experience	-0.052	0.010	0.005	-0.015
	(0.149)	(0.029)	(0.015)	(0.044)
Teacher 4 yrs of Experience	-0.168	0.032	0.017	-0.049
	(0.154)	(0.030)	(0.015)	(0.045)
Teacher Experience 5-9 years	-0.073	0.014	0.007	-0.021
	(0.127)	(0.025)	(0.013)	(0.037)
Teacher Experience 10-14 years	-0.131	0.025	0.013	-0.039
	(0.130)	(0.025)	(0.013)	(0.038)
Teacher More than 15 yrs Experience	-0.231*	0.045*	0.023*	-0.068*
	(0.127)	(0.025)	(0.013)	(0.037)
Teacher major in Math	-0.037	0.007	0.004	-0.011
	(0.046)	(0.009)	(0.005)	(0.013)
Teacher has graduate degree	-0.080	0.015	0.008	-0.023
	(0.052)	(0.010)	(0.005)	(0.015)
Teacher has no regular certificate	0.033	-0.006	-0.003	0.010
	(0.085)	(0.016)	(0.008)	(0.025)
Pseudo-R^2	0.105			
N	6060			

Pseudo-$R^2 = 0.105$, $N = 6060$. Ordered probit regression explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables, with experience group categories. Student sociodemographic coefficients and SES appear in table A6. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes English teacher only.

Table A6: Descriptive Regression - Math Teacher Optimism - Experience Level Dummies

	Coefficients (1)	APE - Under (2)	APE - Correct (3)	APE - Over (4)
Student is American Indian	0.275	-0.053	-0.027	0.081
	(0.327)	(0.063)	(0.033)	(0.096)
Student is Asian	-0.172*	0.033*	0.017*	-0.050*
	(0.089)	(0.017)	(0.009)	(0.026)
Student is Black	-0.223***	0.043***	0.022***	-0.065***
	(0.073)	(0.014)	(0.007)	(0.021)
Student is Hispanic	-0.042	0.008	0.004	-0.012
	(0.079)	(0.015)	(0.008)	(0.023)
Student is Multiple Race	0.036	-0.007	-0.004	0.011
	(0.087)	(0.017)	(0.009)	(0.026)
Student is Male	0.034	-0.007	-0.003	0.010
	(0.035)	(0.007)	(0.004)	(0.010)
Father has HS Diploma	0.197***	-0.038***	-0.020***	0.058***
	(0.049)	(0.009)	(0.005)	(0.014)
Father has Some College	0.145***	-0.028***	-0.014***	0.043***
	(0.047)	(0.009)	(0.005)	(0.014)
Father has a Bachelor's or More	0.009	-0.002	-0.001	0.003
	(0.047)	(0.009)	(0.005)	(0.014)
HH income 20K - 35K	0.159**	-0.031**	-0.016**	0.047**
	(0.078)	(0.015)	(0.008)	(0.023)
HH income 35K - 75K	0.126*	-0.024*	-0.013*	0.037*
	(0.074)	(0.014)	(0.007)	(0.022)
HH income 75K - 100K	0.109	-0.021	-0.011	0.032
	(0.082)	(0.016)	(0.008)	(0.024)
HH income > 100K	0.081	-0.016	-0.008	0.024
	(0.084)	(0.016)	(0.008)	(0.024)
9th grade GPA	0.291***	-0.056***	-0.029***	0.085***
	(0.028)	(0.006)	(0.003)	(0.008)
Pseudo-R^2	0.105			
N	6060			

Continuation from table A5. Ordered probit regression explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables, with experience group categories . Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes English teacher only.

Table A7: Descriptive Regression - Math Teacher Optimism - White Students

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher is Non-White	0.137	-0.023	-0.015	0.038
	(0.132)	(0.022)	(0.015)	(0.037)
Teacher is Male	-0.017	0.003	0.002	-0.005
	(0.062)	(0.010)	(0.007)	(0.017)
Teacher Experience	-0.007***	0.001***	0.001***	-0.002***
	(0.003)	(0.000)	(0.000)	(0.001)
Teacher major in Math	-0.056	0.010	0.006	-0.016
	(0.062)	(0.010)	(0.007)	(0.017)
Teacher has graduate degree	-0.054	0.009	0.006	-0.015
	(0.069)	(0.012)	(0.008)	(0.019)
Teacher has no regular certificate	0.161	-0.027	-0.018	0.045
	(0.102)	(0.017)	(0.011)	(0.029)
Mother has a Bachelor's or More	-0.045	0.008	0.005	-0.013
	(0.066)	(0.011)	(0.007)	(0.019)
HH income 20K - 35K	0.296**	-0.050**	-0.033**	0.083**
	(0.131)	(0.022)	(0.015)	(0.037)
HH income 35K - 75K	0.280**	-0.047**	-0.031**	0.079**
	(0.122)	(0.021)	(0.014)	(0.034)
HH income 75K - 100K	0.199	-0.034	-0.022	0.056
	(0.124)	(0.021)	(0.014)	(0.035)
HH income > 100K	0.209	-0.035	-0.023	0.059
	(0.130)	(0.022)	(0.015)	(0.036)
9th grade GPA	0.271***	-0.046***	-0.030***	0.076***
	(0.037)	(0.006)	(0.004)	(0.010)
Pseudo-R^2	0.127			
N	3970			

Ordered probit regressions explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching the actual outcome, and column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table A8: Descriptive Regression - Math Teacher Optimism - Black Students

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher is Non-White	0.580*	-0.110*	-0.005	0.115*
	(0.304)	(0.057)	(0.003)	(0.060)
Teacher is Male	-0.094	0.018	0.001	-0.019
	(0.222)	(0.042)	(0.002)	(0.044)
Teacher Experience	-0.001	0.000	0.000	-0.000
	(0.013)	(0.002)	(0.000)	(0.003)
Teacher major in Math	0.147	-0.028	-0.001	0.029
	(0.210)	(0.040)	(0.002)	(0.042)
Teacher has graduate degree	-0.255	0.048	0.002	-0.051
	(0.212)	(0.040)	(0.002)	(0.042)
Teacher has no regular certificate	-0.041	0.008	0.000	-0.008
	(0.435)	(0.082)	(0.004)	(0.086)
Mother has a Bachelor's or More	0.248	-0.047	-0.002	0.049
	(0.328)	(0.062)	(0.003)	(0.065)
HH income 20K - 35K	0.155	-0.029	-0.001	0.031
	(0.243)	(0.046)	(0.002)	(0.048)
HH income 35K - 75K	-0.023	0.004	0.000	-0.004
	(0.247)	(0.047)	(0.002)	(0.049)
HH income 75K - 100K	-0.024	0.005	0.000	-0.005
	(0.386)	(0.073)	(0.004)	(0.077)
HH income > 100K	0.165	-0.031	-0.002	0.033
	(0.418)	(0.079)	(0.004)	(0.083)
9th grade GPA	0.553***	-0.105***	-0.005***	0.110***
	(0.132)	(0.023)	(0.002)	(0.024)
Pseudo-R^2	0.355			
N	610			

Ordered probit regressions explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectation matching actual outcome, and column (4) gives APE for teacher's expectation being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table A9: Descriptive Regression - Math Teacher Optimism - Hispanic Students

	(1)	(2)	(3)	(4)
Teacher Non-White	0.342	-0.050	-0.026	0.076
	(0.275)	(0.041)	(0.020)	(0.061)
Teacher is Male	0.042	-0.006	-0.003	0.009
	(0.212)	(0.031)	(0.016)	(0.047)
Teacher Experience	0.002	-0.000	-0.000	0.000
	(0.010)	(0.001)	(0.001)	(0.002)
Teacher major in Math	-0.246	0.036	0.019	-0.055
	(0.201)	(0.030)	(0.015)	(0.045)
Teacher has graduate degree	-0.301	0.044	0.023	-0.067
	(0.233)	(0.034)	(0.018)	(0.052)
Teacher has no regular certificate	-0.160	0.023	0.012	-0.036
	(0.329)	(0.048)	(0.025)	(0.073)
Mother has a Bachelor's or More	0.087	-0.013	-0.007	0.019
	(0.260)	(0.038)	(0.020)	(0.058)
HH income 20K - 35K	-0.170	0.025	0.013	-0.038
	(0.199)	(0.029)	(0.015)	(0.045)
HH income 35K - 75K	-0.187	0.027	0.014	-0.042
	(0.247)	(0.036)	(0.019)	(0.055)
HH income 75K - 100K	0.163	-0.024	-0.012	0.036
	(0.379)	(0.056)	(0.029)	(0.085)
HH income > 100K	-0.009	0.001	0.001	-0.002
	(0.437)	(0.064)	(0.033)	(0.098)
9th grade GPA	0.403***	-0.059***	-0.031***	0.090***
	(0.095)	(0.014)	(0.007)	(0.021)
Pseudo-R^2	0.364			
N	720			

Ordered probit regressions explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table A10: Correlates of over/under optimism, Math Teacher (Ordered Probit Coefficients), Male Students Only

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher is Non-White	0.153	-0.028	-0.013	0.042
	(0.151)	(0.028)	(0.013)	(0.041)
Teacher is Male	0.113	-0.021	-0.010	0.031
	(0.073)	(0.014)	(0.006)	(0.020)
Teacher Experience	-0.009**	0.002**	0.001**	-0.002**
	(0.004)	(0.001)	(0.000)	(0.001)
Teacher major in Math	-0.005	0.001	0.000	-0.001
	(0.073)	(0.014)	(0.006)	(0.020)
Teacher has graduate degree	-0.002	0.000	0.000	-0.001
	(0.085)	(0.016)	(0.007)	(0.023)
Teacher has no regular certificate	0.150	-0.028	-0.013	0.041
	(0.115)	(0.021)	(0.010)	(0.031)
Student is American Indian	0.427	-0.079	-0.037	0.116
	(0.610)	(0.113)	(0.052)	(0.166)
Student is Asian	-0.270**	0.050**	0.023**	-0.073**
	(0.133)	(0.025)	(0.011)	(0.036)
Student is Black	-0.193	0.036	0.017	-0.053
	(0.128)	(0.024)	(0.011)	(0.035)
Student is Hispanic	-0.175	0.033	0.015	-0.048
	(0.126)	(0.023)	(0.011)	(0.034)
Student is Multiple Race	-0.156	0.029	0.013	-0.042
	(0.135)	(0.025)	(0.012)	(0.037)
Mother has a Bachelor's or More	-0.042	0.008	0.004	-0.011
	(0.090)	(0.017)	(0.008)	(0.024)
HH income 20K - 35K	0.272*	-0.051*	-0.023*	0.074*
	(0.143)	(0.026)	(0.012)	(0.039)
HH income 35K - 75K	0.228*	-0.042*	-0.020*	0.062*
	(0.135)	(0.025)	(0.012)	(0.037)
HH income 75K - 100K	0.257*	-0.048*	-0.022*	0.070*
	(0.145)	(0.027)	(0.013)	(0.040)
HH income > 100K	0.197	-0.037	-0.017	0.054
	(0.148)	(0.027)	(0.013)	(0.040)
9th grade GPA	0.279***	-0.052***	-0.024***	0.076***
	(0.044)	(0.008)	(0.004)	(0.012)
Pseudo-R^2	0.171			
N	2870			

Ordered probit regressions explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Table A11: Descriptive Regression - Math Teacher Optimism - Female Students

	Coefficients	APE - Under Prediction	APE - Correct Prediction	APE - Over Prediction
	(1)	(2)	(3)	(4)
Teacher is Non-White	0.260*	-0.044*	-0.025*	0.069*
	(0.143)	(0.024)	(0.014)	(0.038)
Teacher is Male	-0.147**	0.025**	0.014**	-0.039**
	(0.072)	(0.012)	(0.007)	(0.019)
Teacher Experience	-0.007**	0.001**	0.001**	-0.002**
	(0.004)	(0.001)	(0.000)	(0.001)
Teacher major in Math	-0.084	0.014	0.008	-0.022
	(0.072)	(0.012)	(0.007)	(0.019)
Teacher has graduate degree	-0.118	0.020	0.011	-0.031
	(0.079)	(0.013)	(0.008)	(0.021)
Teacher has no regular certificate	0.087	-0.015	-0.008	0.023
	(0.121)	(0.020)	(0.012)	(0.032)
Student is American Indian	0.228	-0.039	-0.022	0.060
	(0.348)	(0.059)	(0.033)	(0.092)
Student is Asian	-0.114	0.019	0.011	-0.030
	(0.150)	(0.025)	(0.014)	(0.040)
Student is Black	-0.265**	0.045**	0.025**	-0.070**
	(0.111)	(0.019)	(0.011)	(0.029)
Student is Hispanic	0.048	-0.008	-0.005	0.013
	(0.115)	(0.019)	(0.011)	(0.030)
Student is Multiple Race	0.249*	-0.042*	-0.024*	0.066*
	(0.139)	(0.024)	(0.013)	(0.037)
Mother has a Bachelor's or More	0.104	-0.018	-0.010	0.028
	(0.083)	(0.014)	(0.008)	(0.022)
HH income 20K - 35K	0.130	-0.022	-0.012	0.034
	(0.116)	(0.020)	(0.011)	(0.031)
HH income 35K - 75K	0.114	-0.019	-0.011	0.030
	(0.106)	(0.018)	(0.010)	(0.028)
HH income 75K - 100K	0.059	-0.010	-0.006	0.016
	(0.117)	(0.020)	(0.011)	(0.031)
HH income > 100K	0.068	-0.012	-0.006	0.018
	(0.118)	(0.020)	(0.011)	(0.031)
9th grade GPA	0.327***	-0.055***	-0.031***	0.086***
	(0.044)	(0.008)	(0.004)	(0.011)
Pseudo-R^2	0.175			
N	3190			

Ordered probit regression explaining over/under optimism by math teachers as a function of teacher characteristics, and student sociodemographic variables. Column (2) gives average partial effects (APE) for the probability that teacher expectations are lower than actual educational attainment, Column (3) gives APE for teacher expectations matching actual outcome, and Column (4) gives APE for teacher expectations being overly optimistic. *Note: * p<0.10, ** p<0.05, *** p<0.01. Parentheses contain standard errors that are robust to clustering at the school level. Teacher denotes math teacher only.

Appendix B Additional Results on Identification

In the main text, we claimed that we could identify the impact of bias without using additional data if were are willing to make parameter restrictions. One of the reasons we instead opt for using additional data is that it will allow us to relax continuity of outcomes. Moreover, we can avoid parameter restrictions. Still, we think it is worth showing here that even if we limit ourselves to teacher expectations and student outcomes, we can still achieve identification of the magnitude bias, its various sources and its impact on outcomes.

In what follows, we omit the subscript i. Y is a continuous outcome. T_j are teacher expectations for teacher $j \in \{1, 2\}$ about the outcome Y. We have suppressed student indices. b_j are biases about the student for teacher j and will be explained below. We allow teachers to have mean expectations that deviate from each other and also from the true mean, denoted c. Teacher means are denoted c_j. This captures how, on average, teachers can be wrong. We also teachers to make a student specific error, which is denoted e_j. We also allow teachers be wrong about how θ maps to outcomes.

$$\begin{aligned} Y &= c_y + \theta + [b_1 + b_2]\gamma + e_y \\ T_1 &= c_1 + \phi\theta + e_1 \\ T_2 &= c_2 + \phi\theta + e_2 \end{aligned} \tag{26}$$

Notice, we have made parameter restrictions. In particular, $\phi_1 = \phi_2 \equiv \phi$ and $\gamma_1 = \gamma_2 \equiv \gamma$. We also assume that the disturbances e and θ are all normally distributed and independent of one another with mean zero:

$$\begin{aligned} \theta &\sim N(0, \sigma_\theta^2) \\ e_y &\sim N(0, \sigma_y^2) \\ e_1 &\sim N(0, \sigma_1^2) \\ e_2 &\sim N(0, \sigma_2^2) \end{aligned} \tag{27}$$

Rewrite the production of expectations to be:

$$\begin{aligned} T_1 &= c_y + \theta + (c_1 - c_y) + (\phi - 1)\theta + e_1 \\ T_2 &= c_y + \theta + (c_2 - c_y) + (\phi - 1)\theta + e_2 \end{aligned} \tag{28}$$

Notice teacher expectations are the correct expectations plus a systematic component $c_1 - c_y$, a component that depends on ability θ and an idiosyncratic component. Bias is defined as follows:

$$\begin{aligned} T_1 - c_y - \theta &\equiv b_1 = (c_1 - c_y) + (\phi - 1)\theta + e_1 \\ T_2 - c_y - \theta &\equiv b_2 = (c_2 - c_y) + (\phi - 1)\theta + e_2 \end{aligned} \tag{29}$$

Given the above, we re-write the outcome equation as follows:

$$\begin{aligned} Y &= c_y + (c_1 + c_2 - 2c_y)\gamma \\ &+ \theta(1 + 2\gamma(\phi - 1)) \\ &+ e_1\gamma + e_2\gamma \\ &+ e_y \end{aligned} \tag{30}$$

Rewrite this as

$$\begin{aligned} Y &= \bar{c}_y + \theta\psi + e_1\gamma + e_2\gamma + e_y \\ T_1 &= c_1 + \phi\theta + e_1 \\ T_2 &= c_2 + \phi\theta + e_2 \\ \bar{c}_y &= c_y + (c_1 + c_2 - 2c_y)\gamma \\ \psi &= 1 + 2\gamma(\phi - 1) \end{aligned} \tag{31}$$

Once again, demean, so that $Y - \bar{c}_y = \tilde{Y}$, $T_1 - c_1 = \tilde{T}_1$ and $T_2 - c_2 = \tilde{T}_2$. Next, independence implies the following:

$$\begin{aligned} \text{Cov}(\tilde{T}_1, \tilde{T}_2) &= \phi^2 \text{Var}(\theta) \\ \text{Cov}(\tilde{Y}, \tilde{T}_1) &= \psi\phi\text{Var}(\theta) + \gamma\text{Var}(e_1) \\ \text{Cov}(\tilde{Y}, \tilde{T}_2) &= \psi\phi\text{Var}(\theta) + \gamma\text{Var}(e_2) \\ \text{Var}(\tilde{T}_1) &= \phi^2\text{Var}(\theta) + \text{Var}(e_1) \\ \text{Var}(\tilde{T}_2) &= \phi^2\text{Var}(\theta) + \text{Var}(e_2) \end{aligned} \tag{32}$$

Notice

$$\begin{aligned} \text{Var}(e_1) &= \text{Var}(\tilde{T}_1) - \text{Cov}(\tilde{T}_1, \tilde{T}_2) \\ \text{Var}(e_2) &= \text{Var}(\tilde{T}_2) - \text{Cov}(\tilde{T}_2, \tilde{T}_2) \\ \text{Cov}(\tilde{Y}, \tilde{T}_1) - \text{Cov}(\tilde{Y}, \tilde{T}_2) &= \gamma[\text{Var}(e_1) - \text{Var}(e_2)] \end{aligned} \tag{33}$$

Therefore

$$\gamma = \frac{\text{Cov}(\tilde{Y}, \tilde{T}_1) - \text{Cov}(\tilde{Y}, \tilde{T}_2)}{\text{Var}(\tilde{T}_1) - \text{Var}(\tilde{T}_2)} \tag{34}$$

Since we have γ, we can identify ϕ and ψ as follows:

$$\begin{aligned} \phi[\text{Cov}(\tilde{Y}, \tilde{T}_1) - \gamma\text{Var}(e_1)] &= \psi\text{Cov}(\tilde{T}_1, \tilde{T}_2) = \psi\phi^2\text{Var}(\theta) \\ \implies \frac{\phi}{\psi} &= \frac{\text{Cov}(\tilde{T}_1, \tilde{T}_2)}{[\text{Cov}(\tilde{Y}, \tilde{T}_1) - \gamma\text{Var}(e_1)]} \\ &= \frac{\text{Cov}(\tilde{T}_1, \tilde{T}_2)}{[\text{Cov}(\tilde{Y}, \tilde{T}_1) - \gamma(\text{Var}(\tilde{T}_1) - \text{Cov}(\tilde{T}_1, \tilde{T}_2))]} \\ &\equiv \Lambda \end{aligned} \tag{35}$$

We also have that

$$\psi = 1 + 2\gamma(\phi - 1) \tag{36}$$

Together, we get that:

$$\psi = \frac{1-2\gamma}{1-2\gamma\Lambda} \tag{37}$$

When we get results, it will sometimes be interesting to decompose the different effects of bias. To make this clear, re-write the outcome equation as follows:

$$\begin{aligned}
Y &= c_y + \theta && : \text{Explains } Y \\
&+ (c_1 + c_2 - 2c_y)\gamma && : \text{Systematic Bias} \\
&+ \theta 2(\phi - 1)\gamma && : \text{Bias as a Function of } \theta \\
&+ (e_1 + e_2)\gamma && : \text{Idiosyncratic Bias} \\
&+ e_y && : \text{Disturbance} \\
T_1 &= c_1 + \phi\theta + e_1 \\
T_2 &= c_2 + \phi\theta + e_2
\end{aligned} \tag{38}$$

Estimating this model purely on expectations and outcomes data yields $\hat{\gamma} = 0.2620$. This estimate is reassuring as it is fairly similar to parameters we estimate in the main analysis. In other words, the additional data do not appear to drive our main results. However, as we mentioned, this model places additional parameter restrictions on the model. Moreover, identification requires continuity, which is something we would like to relax. Therefore, we choose to rely on additional data (test scores) rather than on parameter restrictions to identify the model.