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Abstract

Despite widespread interest and value in introducing and better-preparing students to enter the science, technology, engineering, and mathematics (STEM) fields, a gender gap persists as women are underrepresented among STEM jobs and degree completion. Although some work has evaluated whether interventions and certain pedagogical practices improve growth mindset, little is known about the mediating role of parents and whether those effects are more pronounced for females. In this study, we explore the extent to which the mindsets of a student's parents regarding math ability influence the student's mindset in math ability and longer-term STEM-related outcomes. We pay particular attention to differences between male and female students. We also explore if student outcomes can be attributable to a role modeling effect through parental occupation type (i.e., whether the parent has a job in the STEM field or not) or if there is a remaining direct inheritance from parent growth mindset after controlling for parental occupation. We test these hypotheses in the Education Longitudinal Study of 2002 (ELS), a nationally-representative data set where data for high school students are linked to data from their parents and followed throughout secondary and postsecondary school. Estimating regression models while controlling for a rich set of covariates, we first show that students who exhibit greater levels of growth mindset, self-efficacy, and effort, particularly when it comes to their math coursework, demonstrate higher math achievement, complete more advanced math courses, are more likely to earn a college degree in a STEM field, and are more interested in and likely to actually enter the STEM fields. We then show that parent growth mindset is positively associated with these student non-cognitive skills and outcomes, though the effect seems to fade away over time. On the other hand, although parental occupation type does not consistently explain short- and medium-term STEM outcomes, it does explain longer-term outcomes in early adulthood like graduating with a STEM degree and working in the STEM field. Thus, parent growth mindset and any role modelling effect channeled through parental occupation appear to independently influence student outcomes.

Keywords: STEM gender gaps; growth mindset, role modelling effects

JEL codes: I20, J16, J62

1. Introduction

Despite widespread interest and value in introducing and better-preparing students to enter the science, technology, engineering, and mathematics (STEM) fields, a gender gap persists as women are underrepresented among STEM jobs and degree completion (Beede et al., 2011). Researchers have documented that girls enter kindergarten with similar levels of math ability as their male counterparts but then lose interest in math and science throughout elementary school. They go on to take advanced course work in math and science at lower rates than their male counterparts in secondary school. These trends eventually result in an underrepresentation of women among jobs and degree completion in some STEM fields, particularly in the hard sciences fields such as engineering and computer science (Beede et al., 2011; National Science Board, 2016; Robinson & Lubienski, 2011).

Considerable attention has been paid to address the gap, typically for economic reasons. The scientific community has often pointed out that proficiency in math and science are necessary for a growing number of jobs and that advancements in the STEM field are required for the economic viability of nations in an age of globalization. Others have added that national security, health, and other concerns related to quality of life depend on drawing women into the STEM fields (Members of the 2005 “Rising above the Gathering Storm” Committee, 2010).

Notwithstanding the efficacy of these policy proposals, addressing the gender gap requires understanding of the possible reasons behind it and addressing factors that contribute to it. Scholars have posited that factors such as gender stereotyping, a lack of role models, socialization practices, or a lack of positive peer influences may explain these trends (Dasgupta & Stout, 2014; Jacobs & Bleeker, 2004; Robinson-Cimpian et al., 2014). Researchers have also investigated the ways in which non-cognitive skills such as growth mindset, self-concept, and self-efficacy influence interest in and motivation to enter the STEM fields (Dweck 2008, 2007;

Nix et al., 2015; Simpkins, Davis-Kean, & Eccles, 2006). However, little is known about the origin and development of non-cognitive skills, especially the role of parents in fostering these skills in students.

In our analysis, we focus on the role of student's non-cognitive skills, and specifically examine the role that parental mindsets have on the development of these skills and their impact on STEM outcomes. In particular, we study to what extent parent's growth mindset influences their children's mindset, self-efficacy, and effort as well as subsequent student STEM related outcomes. Our hypothesis is that parents with a growth mindset inculcate their children with those non-cognitive skills that promote more favorable STEM outcomes. In addition, we explore if this effect can be attributable to parent role-modelling as proxied by parent occupation type (i.e., whether the parent has a job in the STEM field or not). There are several ways through which parental occupation type could produce role modeling effects. Maternal occupation could help break gender role stereotypes for her children while both maternal and paternal employment could influence parental investments on STEM activities, even after controlling for direct effects of household income (Dasgupta and Stout, 2014). We also examine whether there is a remaining direct inheritance from parent growth mindset after controlling for parental occupation.

Using a longitudinal data set that consists of a nationally-representative sample of about 15,000 high school students, we first show that students who exhibit greater levels of growth mindset, self-efficacy, and effort, particularly when it comes to their math coursework, demonstrate higher math achievement, complete more advanced math courses, are more likely to earn a college degree in a STEM field, and are more interested in and likely to actually enter a STEM profession. We then show that parent growth mindset is positively associated with these student non-cognitive skills and outcomes, though the effect seems to fade away over time. On the other hand, although parental occupation type does not consistently explain short- and medium-term STEM outcomes, it does explain longer-term outcomes in early adulthood. Students whose mothers or fathers work in the STEM field are more likely to complete a degree and to have a job in a STEM field. Moreover, parent growth mindset and any role modelling effect, channeled through parental occupation, appear to independently influence student outcomes.

Importantly, we find that parent growth mindset benefits girls' non-cognitive skills and STEM outcomes more strongly than those for boys. However, we also find that parental mindset does not appear to push girls into hard-science occupations such as engineering or computer science. Rather, girls with parents that exhibit more growth mindset seem to enter soft-science professions, such as those in the social sciences, health, and architecture, at higher rates. In contrast, girls with parents who work in a STEM field are eventually more likely in adulthood to complete a degree in a STEM field or to work in a hard-science occupation. Our findings generally highlight the ways in which parent mindsets and role modelling can potentially foster student non-cognitive skills that can support success and retention on some but not all STEM fields, especially for girls.

2. Literature Review

There is a plethora of literature on the effects of student math mindsets and self-perceptions on various STEM outcomes, including course-taking, student achievement, degree completion, and career decisions. Specifically, we focus on the literature surrounding the differences in these mindsets and perceptions by gender, as females comprise over 50 percent of the US population, but only 24 percent of the STEM workforce (Beede et al., 2011). However, it should be stressed that this is a phenomenon not unique to the U.S. Seventeen of the 144 countries in the Global Gender Gap Report of 2016, report having a gender gap on college graduation with a STEM degree greater than 10 percent, and eight countries report having a STEM gender gap of over 20 percent (Leopold et al., 2016).

2.1 Student Mindsets and the STEM Gender Gap

There is ample evidence in education psychology to suggest that this underrepresentation of females in STEM courses and occupations could in part be due to lower self-perceptions of math ability among girls as they move through their traditional education. Self-efficacy is defined as the degree to which students believe they are capable of organizing their thoughts and executing specific goals or tasks prescribed to them (Zimmerman, 2000). Self-concept differs from self-efficacy in that it does not include task-specific measures and includes concepts such as self-worth (Pajares et al., 1994). Math anxiety is used to describe the extent to which performance in math is hindered by uneasy feelings such as fear and angst while doing math (Ashcraft, 2002).

Researchers have concluded that math self-efficacy, self-concept, and anxiety are all intertwined and highly predictive of academic achievement in math and science coursework. In this respect, math self-efficacy has been found to be more predictive of academic achievement than math self-concept, with males exhibiting higher levels of self-efficacy than their female counterparts, even after controlling for past experience. In fact, these non-cognitive skills appear to influence performance on math assessments at least as strongly as measures of IQ (Pajares & Miller, 1994 & Pajares & Kranzler, 1995). Nix et al. (2015), similarly, showed that among high school students, perceived ability to overcome challenging content in math class also predicted the likelihood of entering particular STEM fields, particularly those in physics, engineering, math, and computer science. Importantly, the authors also found suggestive evidence that girls who reported higher levels of perceived ability were more likely to major in those fields during college (Nix et al., 2015). In general, research suggests that gender differences in self-perceptions are a potential source of gender differences in STEM outcomes both in the short and long run.

Furthermore, the underlying theories of intelligence, or the mindset a student possesses can also have significant positive effects on STEM-related outcomes. We define growth mindset in math ability as the extent to which individuals believe that their math abilities can be improved over time with effort, as opposed to being unchangeable. Individuals who more strongly ascribe to the later view are said to have a fixed mindset. Prior work suggests that a growth mindset could enhance academic achievement and other mediating factors such as perseverance and effort (Dweck, 2008; Yeager & Dweck, 2012). For example, Nix et al. (2015) find that individuals, especially women, who have higher levels of growth mindset are slightly more likely to major in health-related or hard-sciences field at the postsecondary level. Furthermore, several experimental evaluations of interventions designed to foster growth mindset also demonstrate that students with higher levels of growth mindset are on average more likely to undertake more challenging material, exert more effort, and succeed in their math coursework both in the US (Aronson et al., 2002; Blackwell, Trzensniewski, Dweck, 2007; Dweck, 2007; Paunesku et al., 2015) and elsewhere (Alan, Boneva, & Ertac, 2016).

2.2 Intergenerational Transmission of Mindsets

While previous research shows that student's mindsets can be altered and can influence student's non-cognitive skills, such as persistence and self-efficacy in math, as well as subsequent math achievement, the role that parents play in fostering student growth mindset is less clear. Some research demonstrates that non-cognitive skills are often transmitted from parents to their children (Mendez, 2015; Mendez & Zamarro, 2015; Figlio et al., 2016). However, research has generally not found a strong link between a parent's mindset and their children's mindset, in part because the relationships has rarely been tested (Gunderson et al., 2013). Haimovitz and Dweck (2016) suggest that parent mindset does not appear to influence student mindset because parent mindset is not readily observable by children. Instead, children more readily observe their parent's reaction to failure, which can, in turn, affect their mindset. Indeed, the authors find that children are more likely to exhibit fixed mindsets when their parents view failure as harmful rather than a learning experience or an opportunity to improve.

That said, there is evidence that parents with particular mindsets may engage with and react to their children in ways that alter other outcomes (Gunderson et al., 2013). For example, mothers with a fixed mindset are found more likely to be performance-oriented rather than learning-oriented. That is, these parents are more likely to emphasize the attainment of end goals rather than the learning process to attain that end (Moorman, & Pomerantz, 2010). In contrast, children with parent's who exhibit higher levels of growth mindset were found to exhibit higher levels of persistence and lower levels of learned helplessness (Jose & Bellamy, 2012). Thus, parent mindset certainly appears consequential for student outcomes. We investigate these patterns with respect to STEM-related outcomes and reexamine the extent to which parent mindsets appear to influence their children's own mindsets.

2.3 Adult Role-Modeling and STEM Gender Gaps

In addition to parents transmitting their growth mindset to their children, parents could also shape their child's STEM outcomes through other forms of role modeling that are independent of mindset. Currently, most research has focused on the influence of adults besides parents on children. In this area of study, scholars have hypothesized that a female student seeing successful female STEM professionals promotes confidence, positive self-perceptions and could curb attitudes that may hinder success in a typically male-dominated field (Dasgupta & Stout, 2014). Gunderson et al. (2012) theorize that parents' and teachers' personal feelings and attitudes about math and science are apparent in their discussion of these topics and manifest in the ways they discuss math and science with children. They report that children are especially sensitive to the behavior of same-gender adults, and could attempt to emulate those choices as they move through their education. Indeed, Beilock et al. (2010) found that when female elementary school teachers have higher math anxiety, student achievement in math among girls decreases while math achievement among boys remains unchanged. On the other hand, Stout et al. (2010) show that girls who are experimentally assigned to women professionals and experts in STEM not only become more connected to these role models but exhibited more self-efficacy, self-concept and positive attitudes towards STEM. It is possible, then, that experiencing a math-anxious female role model inadvertently confirms gender stereotypes that negatively affects girls, while experiencing positive role models could help girls overcome the debilitating effects of such stereotypes.

Notably, the theory of same-gender role models puts mothers engaged in a STEM profession in a unique position to influence their daughters' math and science choices as they move through school. Using The Childhood and Beyond longitudinal data from Detroit, U.S., Jacobs and Bleeker (2004) found that when children observe their mother engaging in mathematics activities they also presented increased math and science involvement two years later. Additionally, parents could influence their children through the choice of activities and toys to engage in with them. Jacobs and Bleeker (2004) found that children students who participated in math and science activities outside of the classroom with their parents, and whose parents have purchased math- and science-related toys, also presented increased involvement in these courses. We further investigate the influence of mothers on their daughters in our analysis by comparing outcomes for students with and without parents employed in the STEM field.

There is no hesitation to accept that there is a gender gap in STEM education and STEM occupation, as it is considered a “leaky pipeline” (Blickenstaff, 2006), whereby females tend to sort out of educational trajectories and paths that lead to entry into the STEM field. Evidence suggests that this leak can be attributed to the gender differences in self-perceptions and growth mindsets. These differences are seen primarily in math and science courses, and the literature demonstrates that girls could benefit from role-modeling effects. Our paper contributes to the current body of literature by examining the extent to which student mindsets are influenced by their parents’ mindset and how this dynamic contributes to the student’s STEM outcomes. We pay particular attention to the differences between males and females. Additionally, we examine whether parent growth mindset has a separate effect than potential parental role modeling effects through parental occupation, specifically whether or not the parent has a STEM job or not.

3. Methods

3.1 Data

Data for our analysis come from the Education Longitudinal Study of 2002 (ELS, 2002). During the initial wave of data collection in 2002 (*Wave 0*), the US Department of Education surveyed a nationally-representative sample of 10th graders in the country. At the time, students completed standardized tests in math and English and responded to questionnaires in a predetermined session during a school day. These questionnaires queried students on a variety of topics such as their future plans, opinions about their school, extracurricular activities, and family background. Of particular importance for this present analysis, students were also asked to complete various psychometric scales measuring constructs such as growth mindset, self-efficacy, and effort in their math courses. The initial sample consisted of over 15,000 students.

The US Department of Education also surveyed each student's parent, Math teacher, English teacher, and school principal. Parents were asked to provide information about the student, their family background, and family life. Teachers likewise reported their perceptions of the student and their own personal background information, while school principals provided basic information about school characteristics, policies, and climate. In our analysis, we rely primarily on parent surveys for a variety of demographic control variables, their reported occupation, and measures of their self-reported growth mindset. Only one of the parents was requested to complete the parental survey. In 80 percent of the cases the reporting parent was the student's mother and so our measure of parent growth mindset refers to maternal growth mindset in most of the cases.[1]

Three subsequent waves of data collection occurred to follow up with these students into early adulthood. The first follow-up (*Wave 1*) occurred in 2004 when most of the students were in the 12th grade. Students completed a questionnaire similar to the questionnaire administered in the initial year of data collection and again took standardized tests in Math and English. The second follow-up (*Wave 2*) occurred in 2006 when most of the students were second-year college students. In this wave, students reported information such as their future educational and employment goals. The final follow-up (*Wave 3*) took place in 2012, which among other items, queried students about their employment histories and current families. Parents and school personnel generally did not participate in these final two waves of data collection.

[1] Our analysis focuses on growth mindset measures as reported for either the mother or the father. We also estimated models restricting the sample to only those cases where mothers were reporting and the results we present here still hold.

3.2 Measures of Non-cognitive Skills

We concentrate on three different measures of student non-cognitive skills for our analysis, namely, growth mindset, self-efficacy, and effort. Items for these scales have been adopted from other validated questionnaires (Burns et al., 2003). It is important to note that Likert-type items that were used to construct measures of self-efficacy and mindset were designed to capture them in the context of the student's experiences with math, while the effort scale is a measure of general effort. For instance, the growth mindset scale did not simply ask whether a student believed that general intelligence is something fixed at birth. Instead, students indicated the extent to which they agreed with the statement: "You have to be born with the ability to be *good at math*" (emphasis added). The parent responding to the parent's questionnaire was also asked the same questions concerning growth mindset in math. These are the base of our measure of parent growth mindset. All items used to construct measures of the three student non-cognitive skills are shown in the Appendix. We construct scale scores for each non-cognitive skill measure by coding and averaging responses to items within each scale. The effort and self-efficacy scales exhibited reasonable levels of reliability ($\alpha = 0.88$ and $\alpha = 0.93$, respectively). However, scales for mindset exhibited much lower levels of reliability for students ($\alpha = 0.46$) and parents ($\alpha = 0.51$), which must be considered when interpreting the results.

3.3 Measures of STEM Outcomes

The longitudinal nature of our data allow us to focus on a variety of student outcomes over a long duration of time. From *Wave 1,* we have student test scores in math, which are standardized to have mean equal to 0 and standard deviation equal to 1. Students also self-reported future career plans in this wave and do so again in *Wave 2*. We use this information to create a dichotomous variable indicating whether a student plans to have a job in the STEM field based upon classifications established by the Bureau of Labor Statistics (Ingels et al., 2014). We also created additional dichotomous variables to indicate whether the student plans to have a job in the hard sciences (e.g., engineering, information technology, math, or life or physical sciences) or soft sciences (social science, health, architecture). In addition to reporting career plans, students during *Wave 2* indicated the most advanced high school math course they completed. We also created a dichotomous variable indicating whether or not a student has completed an advanced math course in high school.[2] Finally, we use employment and educational background information in *Wave 4* survey to create a series of dichotomous variables indicating whether the student majored or is currently working in the STEM field. Again, we are able to explore whether students are working in the hard or soft sciences for those in a STEM field.

3.4 Empirical Strategy

We utilize information provided in all waves of data collection of the ELS 2002 survey, as described above, to examine the relationship between student STEM outcomes (i.e. math test scores in 12th grade, STEM job plans in 12th grade and two years after interviewed in 12th grade, completion of advanced math courses in high school, degree completion in a STEM field, and employment in a STEM field at age 25-26) and student and parent non-cognitive skills (i.e. student and parent growth mindset, student self-efficacy and reported effort).

We first estimate models to predict each student STEM outcome as a function of student non-cognitive skill measures, after controlling for a vector of background variables. Our models are based on a version of the following specification:

[2] We consider a student to have taken an advanced math course if he has completed at least a pre-calculus or equivalent course in US secondary schools which typically require a fourth year of math coursework for the typical student.

$$Y_i^{STEM} = \beta_0 + \beta_1 StNonCog_i + \beta_2 X_i + \varepsilon_i \quad (1)$$

Where Y_i^{STEM} represents a STEM related student outcome and $StNonCog_i$ represents a specific student non-cognitive skill (i.e. growth mindset level, self-efficacy or effort). Different models are estimated including each of these different student non-cognitive skills separately. X_i represents a set of socio-demographic controls including: student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. For school urbanicity, we use a set of three dummy variables indicating if the schools is in an (1) urban, (2) suburban, or (3) rural area, while for census region, we a set of four dummy variables indicating if the school is in the (1) Northeast, (2) Midwest, (3) South, or (4) West according to the classifications provided by the US Census Bureau. We use linear regression models for models using student test scores as dependent variable and logit regressions for all other binary STEM outcomes.

Next, we estimate models to examine whether parent growth mindset helps us predict student non-cognitive skills following this type of specification:

$$StNonCog_i = \gamma_0 + \gamma_1 PNonCog_i + \gamma_2 PNonCog_i * Female_i + \gamma_3 F\_STEM\_Job_i + \gamma_4 M\_STEM\_Job_i + \gamma_5 F\_STEM\_Job_i * Female_i + \gamma_6 M\_STEM\_Job_i * Female_i + \gamma_7 X_i + \varepsilon_i$$

(2)

Where $StNonCog_i$ represents the different student non-cognitive skills measures, i.e. growth mindset, self-efficacy and effort. $PNonCog_i$ represents parent self-reported growth mindset which is included in the model along with its interaction with a dummy for the student being female to test if the role of parent non-cognitive skills differs for boys and girls. Although only one of the parents answers the parent survey, in most cases the mother, and parent growth mindset is only available for one parent, we do have information on type of occupation for both the mother and the father of the student. We then created two separate dummy variables indicating whether the father and the mother, respectively, had an occupation in a STEM related job ($F\_STEM\_Job_i$ and $M\_STEM\_Job_i$). We also added interaction terms of these parental occupation variables and the student gender to capture differential effects for boys and girls. Finally, X_i includes socio-demographic control variables as described in (1) above. Note that our regressions already include controls for mother's educational attainment and household income. Therefore, we interpret parental occupational variables as capturing any remaining role modeling effects that parents might have above the direct economic and educational effects. We then are interested in testing whether parent growth mindset and role modeling effects, captured by parental type of occupation, are separately predictive of student non-cognitive skills.

Finally, we estimate models to study the direct effect of parent growth mindset and role modeling effects through occupation type on student STEM outcomes, after controlling for maternal education attainment and household income among other socio-demographic information. Empirical models in this case are similar to the one described in (2) above but include STEM student outcomes as dependent variable (Y_i^{STEM}).

Some amount of sample attrition occurred in each wave of data collection. From the initial wave of data collection in 2002 (*Wave 0*) to *Wave 1* two years later 9 percent of the initial sample of students left the study, from *Wave 1* to *Wave 2* the attrition rate was 4 percent and finally, from *Wave 2* to *Wave 3*, 11 percent of students in the sample left the study. To ensure that our results remain nationally representative, we employ the use of sampling weights in our analysis. In future versions of this paper, we will further explore the reasons for this attrition and employ alternative methods to correct for it. Also, standard errors are clustered at the school level to take into account the fact that we have multiple students in the sample that come from the same schools.

4. Results

4.1 Descriptive statistics

Tables 1 and 2 present descriptive statistics for the students in our sample, overall and by gender, for key variables in the analysis, respectively. Our sample is equally divided by gender with exactly 50 percent of the students being female. Reflecting other census data on the racial composition of the US in 2002, 60 percent of the students in our sample are White, 14 percent are Black, 16 percent are Hispanic, 4 percent are Asian and another 5 percent are coded as other race (Aud et al., 2010). All regions of the U.S are represented in our data with 19 percent of the sample coming from the Northeast of the country, 24 percent from the South, 34 percent from the Midwest and 23 percent from the West. Most of the students in our sample, 49 percent, study in a school located in a suburban area, while 30 percent study in an urban school and 21 percent in a rural school.

Math test scores are standardized by wave and so they present a mean of 0 and a standard deviation of 1. However, as shown in Table 2 girls have on average significantly lower test-score performance in 12th grade than boys. These differences were already present at baseline with 0.1 standard deviations differences in performance between boys and girls when tested in 10th grade. Concerning plans to have a STEM job, 10 percent of students planned to have a STEM job in the hard sciences when asked in 12th grade, 9 percent planned to two years later and only 6 percent actually had one at age 25 or 26. Similarly, 27 percent of students planned to have a STEM job in the soft sciences when asked in 12th grade, 23 percent planned to two years later and only 7 percent actually had one at age 25 or 26. However, there are significant differences across gender on their plans to have a STEM job. In 12th grade, 17 percent of boys report having plans to have a STEM job in the hard sciences while only 5 percent of girls do so. Two years later, in *Wave 2*, the comparisons are 14 percent of boys as compared to 4 percent of girls. Finally, at ages 25 or 26, 9 percent of men actually had a STEM job in the hard sciences as compared with only 3 percent of women. Finally, overall, 43 percent of the students in our sample completed advanced math courses in high school. Despite being significant, the difference between girls and boys on this percentage was only 1 percentage point, with girls this time being the ones who most often completed advanced math courses in high school.

Concerning measures of non-cognitive skills, on a scale of 1 to 4, students scored on average a 2.87 in growth mindset in math, 2.50 in self-efficacy in math, and 2.74 in student effort in math. Significant differences were also observed in these measures of non-cognitive skills among boys and girls. Boys scored higher than girls on growth mindset and self-efficacy measures, 2.89 versus 2.85 and 2.62 versus 2.39, respectively. Girls, however, scored higher on self-reported effort 2.82 was the effort reported by girls versus 2.66 reported by boys. Finally, on average parents scored 2.91 on a scale from 1 to 4 on growth mindset in math.

4.2 Determinants of STEM outcomes

Given the gender differences in STEM related outcomes and non-cognitive skills measures described above, in this section we study their determinants and the role that both parent's growth mindset and role modeling through type of occupation could have in these outcomes.

Table 3 presents estimates of models that predict each student STEM outcome as a function of student non-cognitive skill measures, following the empirical model in (1) described in previous section. The table presents regression coefficient effects for math test scores and marginal effects for the rest of binary outcomes. In the short term, we observe that overall student's non-cognitive skills measured in 10th grade have a significant effect on math test performance in 12th grade, although the effect seems largest for self-efficacy in math. Increasing self-efficacy by one standard deviation leads to an estimated increase of almost 0.6 standard deviations in math test scores, keeping income, mother's education and other socio-demographic information constant. Similarly, an increase of one standard deviation in the effort scale leads to an increase of 0.4 standard deviations in math test scores. In contrast, although significant, an increase of one standard deviation on student's growth mindset only leads to an increase in test scores of 0.1 standard deviations.

Panel B in Table 3 shows the estimated effects in the probability of having completed advance math courses two years after 12th grade (*Wave 2*). Again, in this case, we observe that all student non-cognitive measures have a significant effect on this probability. However, the effect seems to be higher and more significant for measures of self-efficacy and student reported effort than for measures of student growth mindset. A one-standard-deviation increase in self-efficacy or reported effort leads to almost a 5 percentage point increase in the probability of completing advance math courses in high school, all else equal. In contrast, an equivalent increase in reported growth mindset only leads to an increase of 1 percentage point.

Panel C in Table 3 shows the estimated effects on the probability of having earned a college degree in a STEM field at age 25 or 26. In this case, we observe that only self-efficacy and effort are significantly associated with the probability of having a STEM degree and the effect is greater for self-efficacy. A one-standard-deviation increase in the self-efficacy scale is associated with an increase of 4.5 percentage points in this probability while a similar increase in effort is associated with an increase of 3 percentage points.

Concerning job plans, student's non-cognitive skills are also associated with higher probabilities of planning to have a STEM job. Increasing the self-efficacy or effort measures by one standard deviation leads to an increase in the probability of planning to work in a STEM job in the future of about 4 percentage points. An equivalent increase in student's growth mindset is associated with an increase in the probability of desiring to work in a STEM job of 2 percentage points. Interestingly, most of the effect of student growth mindset is concentrated on increasing the probability of working in the hard sciences while self-efficacy affects both the probability of working in the hard and soft sciences. Finally, student reported effort only has a significant effect on the probability of planning to work in the soft sciences and not in the hard sciences. Similar results are observed in the medium-run outcomes, reported in Panel B of Table 3, based upon student reports in *Wave 2*, two years after 12^{th} grade.

In contrast, when looking at the long term results from *Wave 3*, reported in Panel C of Table 3, we observe that student growth mindset loses its predictive power with respect to the actual probability of working in a STEM job. Self-efficacy and effort maintain their predictive power and also lead to increases to the probability of actually working in a STEM job at age 25 and 26, although the estimated effects are smaller. A one-standard-deviation increase in the self-efficacy scale leads to an increase in the probability of working in a STEM job of 2 percentage points with most of this increase happening through the probability of working in a hard science STEM job. Finally, an increase of one standard deviation in the student self-reported effort scale leads to a 2.5 percentage-point increase in the probability of working in a STEM job but most of this effect is due to an increase in the probability of working in a soft science STEM job.

Our next set of results, presented in Table 4, study the determinants of student non-cognitive skills, especially the influence that parent growth mindset and role modeling through occupation might have. These results follow the empirical specification (2) described above. As we can see in this table we find that parent growth mindset has a small but significant effect on the level of non-cognitive skills of her child. Increasing parent growth mindset by one standard deviation is associated with a 0.08 increase in boys' growth mindset, a 0.04 increase in boys' self-efficacy and a 0.04 increase in boys' effort. This effect does not seem to be different for girls in the case of growth mindset but it doubles in size for the case of self-efficacy and effort. Increasing parent growth mindset by one standard deviation is associated with a 0.08 increase in girls' self-efficacy and a 0.06 in girls' effort, though estimates are imprecise. Finally, concerning role modeling effects through the parental occupation, in general, we do not find significant effects. The only marginally significant effects we find are of father's occupation in a STEM job on growth mindset of girls but that effect seems to be compensated by a negative effect of mother's occupation in a STEM job.

Finally, Tables 5, 6 and 7 present the direct effects of parent growth mindset and role modeling effects through occupational type on student STEM outcomes measured in the short-term (*Wave 1*), two years after 12^{th} grade (*Wave 2*) and at age 25 or 26 (*Wave 3*). These results are obtained following the empirical specification described in section 3.4 above. Short-term effects are presented in Table 5. As we can see in this table, we find a limited association between parent growth mindset and STEM outcomes in *Wave 1* (12^{th} grade). Parent growth mindset only seems to have a significant positive effect on the reported probability of planning to have a soft science STEM job. This effect, however, doubles in size for girls as compared with boys. A one-standard-deviation increase in parent growth mindset leads to an increase in the reported probability of planning to have a job in the soft sciences of 2.3 percentage points for boys and 4.6 percentage points for girls. We also do not find many significant associations between parental role modeling effects and student STEM outcomes in the short-term. The only exception is the case of math test scores, in this case we do find a positive and significant effect of fathers having a STEM job on test scores. However, the effect seems to be compensated by a negative and significant effect of equivalent size if the mother has a STEM job also.

Similar effects are found two years after 12^{th} grade (*Wave 2*) as reported in Table 6. Also in this case, we find a limited association of parent growth mindset and student STEM outcomes. Concerning parent role modeling effects we now find that having a father in a STEM occupation has a positive significant effect of 5.2 percentage points on the probability of completing advanced math courses in high school and of 4 percentage points in the reported probability in planning to have a job in a hard-sciences field. These effects are found to be bigger for girls than for boys, although the difference is not statistically significant.

Larger and more significant role modeling effects on student STEM outcomes at age 25 and 26 (*Wave 3*), as presented in Table 7. In this case both having a father or a mother working in a STEM occupation have a significant positive effect on the probability of the student actually earning a college degree in a STEM field. Effects are again higher for girls than for boys. Having a father with a STEM occupation increases this probability by almost 10 percentage points for boys and 17 percentage points for girls. Additionally, having a mother in a STEM occupation increases this probability by 7 percentage points for boys and by almost 10 percentage points for girls. Also, having a father or a mother working in a STEM occupation increases the probability of the student having a hard science STEM job by 3 percentage points if the father has a job in STEM and by 4 percentage points if the mother has a job in STEM and the student is a boy. The effect of the mother having a job in STEM is doubled if the student is a girl with an increase in the probability of 7.5 percentage points in this case.

5. Discussion Conclusion

According to the U.S Bureau of Labor Statistics, employment in STEM occupations such as science, technology, engineering and mathematics are expected to grow by about one million jobs between 2012 and 2022 (Bureau of Labor Statistics, 2014). As a result, introducing and better-preparing students to enter the STEM fields is a first order concern. However, despite efforts to do so, a gender gap persists with women being significantly underrepresented among STEM jobs and STEM college degree completion.

In this paper, we study the role of student's non-cognitive skills and specifically the mediating effect that parental mindsets and role modelling could have on the development of student's skills and their impact on STEM outcomes. To do so, we use longitudinal data from the ELS 2002 study that collected information on a nationally-representative sample of about 15,000 10^{th} grade students. Students were then followed in 12^{th} grade, two years after, and at age 25 and 26. Our dataset contains information of student growth mindset, self-efficacy in math and academic effort along with math test scores in 12^{th} grade and baseline, job plans, advanced math courses taken, degree completion and actual employment at age 25 or 26. Parent growth mindset reported by one parent, mostly the mother, father and mother type of occupation, along with important socio-economic information is also available and used in the analysis.

Our descriptive analysis of the data shows significant gender differences in student STEM outcomes and non-cognitive skills in this sample. Girls have, on average, significantly lower math test score performance both in 10^{th} and 12^{th} grade than boys. Overall, boys plan to enter a STEM profession and actually earn a STEM degree at higher rates than girls, although girls plan on having a soft science STEM job and actually work in this field in higher proportions than boys do. Smaller differences across genders were observed in the probability of having completed advanced math courses, although the difference remained statistically significant. Concerning measures of non-cognitive skills, boys reported higher levels of growth mindset and self-efficacy in math than girls, while girls reported higher levels of effort.

We then studied the relationship between student non-cognitive skills levels and STEM outcomes and, similarly to previous literature, found significant associations, although effects were bigger and more persistent for student self-efficacy and reported effort than for student growth mindset. Growth mindset was only significantly associated with outcomes in the short or medium term but not long term. Self-efficacy also was found to promote the predicted and actual probability of working in a hard science STEM job while reported effort increased the predicted and actual probability of working in a soft science STEM job. However, given the low levels of reliability for the mindset scale, the results might have been attenuated due to measurement error. In this case, it is even more striking that we find any relationship at all between student mindset and other measures.

Our second set of analysis focused on the potential effects of parent growth mindset and role modeling on student non-cognitive skills. In this respect, parent growth mindset was found to have a small but significant effect on the level of non-cognitive skills of her child. This effect doubled in magnitude for girls in the case of their self-efficacy and reported effort. Again, it is striking that we have detected such relationships given the low reliability of the mindset scales in our data. Concerning role modeling effects through the parental occupation, we generally did not find significant effects on student non-cognitive skills.

Finally, we studied direct effects of parent growth mindset and role modeling on student STEM outcomes. Role modeling effects were found to gain importance with time as they were more significant and stronger in long-term outcomes. In this case, both having a father or a mother working in a STEM occupation had a significant positive effect on the probability of the student actually earning a college degree in a STEM field. Effects were also higher for girls than for boys. Having a father with a STEM occupation increased this probability by almost 10 percentage points for boys and 17 percentage points for girls. Additionally, having a mother in a STEM occupation increases this probability by 7 percentage points for boys and by almost 10 percentage points for girls. We failed to find direct effects of parent growth mindset on student STEM outcomes.

Having parents working in the STEM fields increased the probabilities that students entered a profession in the hard sciences but not the soft sciences. However, women seem to benefit more when they have parents, especially mothers, in a STEM profession. In fact, our estimates presented in Table 7 reveal a gender gap in the hard-sciences professions of about 8 percentage points, whereas females who have mothers in a STEM profession are about 7 percentage points more likely to enter a profession in the hard-sciences. In other words, a maternal role-modelling effect appears to virtually close this gender gap. Such a result is worth more investigation. What, exactly, about the mother-daughter relationship explains these patterns?

There are some limitations to our analysis, however. For instance, we only have information on growth mindset for one of the parents, mostly the mother. It could be that parental mindset becomes more important if effects of the other parent mindset are taken into account. Finally, it would be valuable to study the potential effect that teacher mindset could have on student non-cognitive skills and STEM outcomes. Unfortunately, our data does not contain information about growth mindset of all students' teachers. We do have information of growth mindset levels of one math teacher and have performed an analysis to estimate their potential effect. However, our limited evidence in this respect, suggests that parents are the stronger sources of influence on student non-cognitive skills and STEM outcomes. More research is needed though to fully understand the separate influence that parents and teachers could have on students.

Overall, our work shows evidence that parent growth mindset could have a significant effect on student self-efficacy, reported effort and growth mindset in math and these effects seem to be bigger for girls than for boys. However, role modeling effects, independent of any effect of non-cognitive skills, ultimately seem to be the more important channel for changing STEM outcome decisions in the long-term. More research is needed to understand how these role modeling effects operate if one wishes to pursue the policy goals not only of closing the gender gap in STEM but encouraging students -- boys and girls, alike – to enter the STEM fields.

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Table 1 Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum
Student Outcome Variables				
Wave 1				
Math Test Scores	0.00	1.00	-3.02	3.00
Plans to have a STEM Job in the Hard Sciences	0.10	0.31	0	1
Plans to have a STEM job in the Soft Sciences	0.27	0.44	0	1
Wave 2				
Completed Advanced Math Courses in High School	0.43	0.50	0	1
Plans to have a STEM Job in the Hard Sciences	0.09	0.29	0	1
Plans to have a STEM job in the Soft Sciences	0.23	0.42	0	1
Wave 3				
Earned a Degree in a STEM Field	0.16	0.37	0	1
Employed in a STEM Job in the Hard Sciences	0.06	0.24	0	1
Employed in a STEM Job in the Soft Sciences	0.07	0.26	0	1
Independent Variables				
Student Non-cognitive Skills				
Student Growth Mindset in Math	2.87	0.62	1	4
Student Self-Efficacy in Math	2.50	0.84	1	4
Student Effort in Math	2.74	0.74	1	4
Parent Occupation Type				
Mother has a STEM Job	0.13	0.34	0	1
Father has a STEM Job	0.12	0.32	0	1
Parent Growth Mindset in Math	2.91	0.54	1	4
Female	0.50	0.50	0	1
Baseline Math Test Scores	0.00	1.00	-3.06	3.67
Student Race				
White	0.60	0.49	0	1
Black	0.14	0.35	0	1
Hispanic	0.16	0.37	0	1
Asian	0.04	0.20	0	1
Other Race	0.05	0.22	0	1
Mother’s Educational Background				
Less than High School	0.13	0.34	0	1
High School	0.28	0.45	0	1
Some College	0.35	0.48	0	1

Table 1 Summary Statistics (*Continuation*)

	Mean	Standard Deviation	Minimum	Maximum
Bachelor's Degree	0.17	0.37	0	1
Post Baccalaurate Degree	0.08	0.27	0	1
Annual Household Income				
Less than $20,000	0.15	0.36	0	1
$20,000 to 34,999	0.19	0.39	0	1
$35,000 to $49,999	0.2	0.4	0	1
$50,000 to $74,999	0.21	0.41	0	1
$75,000 to $99,000	0.13	0.34	0	1
More than $100,000	0.13	0.33	0	1
School Locale				
Urban	0.3	0.46	0	1
Suburban	0.49	0.5	0	1
Rural	0.21	0.41	0	1
US Region				
Northeast	0.19	0.39	0	1
South	0.24	0.43	0	1
Midwest	0.34	0.47	0	1
West	0.23	0.42	0	1

Table 2: Summary Statistics of Key Independent Variables by Gender

	Boys		Girls	
	Mean	Standard Deviation	Mean	Standard Deviation
Student Outcome Variables				
Wave 1				
Math Test Scores	0.07	1.04	-0.06	0.96
Plans to have a STEM Job in the Hard Sciences	0.17	0.38	0.05	0.21
Plans to have a STEM job in the Soft Sciences	0.15	0.36	0.38	0.49
Wave 2				
Completed Advanced Math Courses in High School	0.43	0.49	0.44	0.50
Plans to have a STEM Job in the Hard Sciences	0.14	0.35	0.04	0.20
Plans to have a STEM job in the Soft Sciences	0.12	0.33	0.34	0.47
Wave 3				
Earned a Degree in a STEM Field	0.25	0.43	0.09	0.29
Employed in a STEM Job in the Hard Sciences	0.09	0.29	0.03	0.17
Employed in a STEM Job in the Soft Sciences	0.04	0.19	0.10	0.30
Independent Variables				
Student Non-cognitive Skills				
Student Growth Mindset in Math	2.89	0.62	2.85	0.61
Student Self-Efficacy in Math	2.62	0.84	2.39	0.83
Student Effort in Math	2.66	0.75	2.82	0.73
Baseline Math Test Scores	0.05	1.04	-0.05	0.96

Note. Independent t-tests indicate that all differences in means are statistically significant at the 0.01 level. Sampling weights included.

Table 3: Student Non-cognitive Skills and STEM Outcomes

Panel A: Short-Run Outcomes (12th Grade)

	Math Test Scores			Job Plans								
				Any STEM Job			Hard Science STEM Job			Soft Science STEM Job		
Growth Mindset	0.090*			0.022**			0.017**			0.006		
	(0.050)			(0.007)			(0.004)			(0.007)		
Self-Efficacy		0.568**			0.041**			0.013**			0.026**	
		(0.057)			(0.007)			(0.005)			(0.006)	
Effort			0.394**			0.043**			0.004			0.040**
			(0.054)			(0.007)			(0.004)			(0.006)
Female	-0.387**	-0.286**	-0.527**	0.109**	0.119**	0.098**	-0.121**	-0.118**	-0.123**	0.229**	0.237**	0.221**
	(0.108)	(0.107)	(0.106)	(0.013)	(0.013)	(0.014)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.013)
Observations	9,990	9,920	9,660	7,140	7,090	6,910	7,140	7,090	6,910	7,140	7,090	6,910

Panel B: Medium-Run Outcomes (Two Years After 12th Grade)

	Completed Advanced Math Courses in High School			Job Plans								
				Any STEM Job			Hard Science STEM Job			Soft Science STEM Job		
Growth Mindset	0.010*			0.017**			0.014**			0.003		
	(0.005)			(0.006)			(0.004)			(0.006)		
Self-Efficacy		0.049**			0.039**			0.023**			0.015**	
		(0.005)			(0.007)			(0.004)			(0.005)	
Effort			0.048**			0.043**			0.004			0.040**
			(0.005)			(0.007)			(0.004)			(0.006)
Female	0.049**	0.060**	0.034**	0.116**	0.125**	0.098**	-0.092**	-0.214**	-0.123**	0.209*	0.088**	0.221**
	(0.010)	(0.009)	(0.010)	(0.012)	(0.012)	(0.014)	(0.008)	(0.012)	(0.009)	(0.012)	(0.008)	(0.013)
Observations	10,740	10,670	10,390	7,650	7,600	7,400	7,650	7,600	7,400	7,650	7,600	7,400

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported for models predicting test scores. Other coefficients are marginal effects computed after estimating logistic regression models. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Table 3: Student Non-cognitive Skills and STEM Outcomes (*Continuation*)

Panel C: Long-Run Outcomes (Age 25-26)

	Degree in a STEM Field			Employment								
				Any STEM Job			Hard Science STEM Job			Soft Science STEM Job		
Growth Mindset	0.010			0.003			0.004			-0.002		
	(0.006)			(0.004)			(0.003)			(0.003)		
Self-Efficacy		0.045**			0.019**			0.012**			0.007**	
		(0.007)			(0.004)			(0.003)			(0.003)	
Effort			0.029**			0.025**			0.008*			0.017**
			(0.006)			(0.004)			(0.003)			(0.003)
Female	-0.130**	-0.114**	-0.019*	0.019*	0.024**	0.010	-0.058**	-0.055**	-0.061**	0.081**	0.083**	0.075**
	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Observations	5,120	5,090	4,960	9,480	9,410	9,170	9,480	9,410	9,170	9,480	9,410	9,170

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported for models predicting test scores. Other coefficients are marginal effects computed after estimating logistic regression models. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Table 4: Parent Growth Mindset and Student Non-cognitive Skills

	Student Growth Mindset			Student Self-Efficacy			Student Effort		
Female	-0.075**	-0.089**	-0.089**	-0.246**	-0.256**	-0.262**	0.228**	0.229**	0.238**
	(0.023)	(0.028)	(0.029)	(0.023)	(0.028)	(0.029)	(0.025)	(0.030)	(0.030)
Parent Growth Mindset	0.076**		0.076***	0.055**		0.039**	0.043**		0.036*
	(0.018)		(0.020)	(0.017)		(0.017)	(0.016)		(0.017)
Parent Growth Mindset*Female	0.004		-0.004	0.051*		0.041	0.041		0.030
	(0.025)		(0.028)	(0.025)		(0.027)	(0.026)		(0.028)
Father has STEM Job		0.066	0.082		0.069	0.070		0.066	0.057
		(0.059)	(0.061)		(0.054)	(0.056)		(0.051)	(0.054)
Father has STEM Job * Female		0.132	0.140†		-0.065	-0.059		-0.012	0.018
		(0.083)	(0.084)		(0.075)	(0.077)		(0.072)	(0.080)
Mother has STEM Job		-0.033	-0.022		0.086†	0.069		-0.028	-0.049
		(0.050)	(0.052)		(0.048)	(0.051)		(0.050)	(0.053)
Mother has STEM Job * Female		-0.162*	-0.140†		-0.042	-0.042		0.021	0.003
		(0.071)	(0.077)		(0.065)	(0.072)		(0.066)	(0.071)
Observations	9,560	8,770	7,700	9,490	8,690	7,630	9,250	8,470	7,440

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Table 5: Parent Influences on Short-Run (12th grade) Student STEM Outcomes

	Math Test Scores			Job Plans					
				Hard Science STEM Job			Soft Science STEM Job		
Female	-0.034** (0.010)	-0.032* (0.013)	-0.034* (0.013)	-0.125** (0.009)	-0.120** (0.011)	-0.118** (0.012)	0.228** (0.011)	0.244** (0.014)	0.239** (0.015)
Parent Growth Mindset	0.006 (0.006)		0.007 (0.007)	0.002 (0.010)		0.000 (0.010)	0.019* (0.008)		0.023** (0.008)
Parent Growth Mindset*Female	-0.014 (0.012)		-0.012 (0.013)	-0.001 (0.011)		-0.008 (0.012)	0.027* (0.014)		0.023 (0.014)
Father has STEM Job		0.063** (0.022)	0.058* (0.024)		0.024 (0.025)	0.017 (0.026)		-0.022 (0.026)	-0.014 (0.026)
Father has STEM Job * Female		0.028 (0.032)	0.020 (0.035)		0.006 (0.027)	-0.003 (0.028)		-0.092* (0.038)	-0.064 (0.039)
Mother has STEM Job		-0.054* (0.024)	-0.058* (0.026)		0.007 (0.022)	0.001 (0.024)		0.015 (0.023)	0.015 (0.024)
Mother has STEM Job * Female		-0.030 (0.034)	-0.034 (0.035)		-0.009 (0.026)	-0.020 (0.028)		-0.059 (0.038)	-0.040 (0.039)
Observations	10,750	9,670	8,640	7,560	6,870	6,110	7,560	6,870	6,110

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported for models predicting test scores. Other coefficients are marginal effects computed after estimating logistic regression models. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Table 6: Parent Influences on Medium-Run (Two Years after 12th grade) Student STEM Outcomes

	Completed Advanced Math Courses in High School			Job Plans					
				Hard Science STEM Job			Soft Science STEM Job		
Female	0.054**	0.043**	0.042**	-0.103**	-0.107**	-0.107**	0.210**	0.224**	0.220**
	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)	(0.011)	(0.010)	(0.013)	(0.014)
Parent Growth Mindset	0.006		0.004	0.003		0.010	0.013*		0.016*
	(0.006)		(0.007)	(0.007)		(0.008)	(0.006)		(0.007)
Parent Growth Mindset*Female	0.001		-0.005	0.003		0.005	0.014		0.013
	(0.009)		(0.011)	(0.009)		(0.010)	(0.012)		(0.013)
Father has STEM Job		0.046*	0.052*		0.048*	0.040*		0.029	0.033
		(0.022)	(0.023)		(0.019)	(0.020)		(0.022)	(0.022)
Father has STEM Job * Female		0.024	0.039		0.026	0.021		-0.023	-0.010
		(0.031)	(0.032)		(0.022)	(0.023)		(0.033)	(0.034)
Mother has STEM Job		-0.011	-0.017		0.009	0.000		-0.002	0.000
		(0.023)	(0.024)		(0.021)	(0.024)		(0.019)	(0.020)
Mother has STEM Job * Female		0.005	0.003		0.005	-0.004		-0.071*	-0.069*
		(0.029)	(0.030)		(0.025)	(0.027)		(0.032)	(0.034)
Observations	11,520	10,290	9,140	8,240	7,390	6,570	8,240	7,390	6,570

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported for models predicting test scores. Other coefficients are marginal effects computed after estimating logistic regression models. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Table 7: Parent Influences on Long-Run (Age 25-26) Student STEM Outcomes

	Earned a Degree in a STEM Field			Employment					
				Hard Science STEM Job			Soft Science STEM Job		
Female	-0.126** (0.012)	-0.158** (0.015)	-0.155** (0.016)	-0.059** (0.007)	-0.085** (0.009)	-0.082** (0.009)	0.078** (0.007)	0.097** (0.008)	0.096** (0.009)
Parent Growth Mindset	-0.007 (0.008)		-0.006 (0.009)	-0.002 (0.005)		0.002 (0.006)	-0.004 (0.003)		-0.003 (0.004)
Parent Growth Mindset*Female	0.006 (0.011)		0.006 (0.012)	0.004 (0.006)		0.006 (0.008)	-0.005 (0.007)		-0.007 (0.007)
Father has STEM Job		0.100** (0.022)	0.099** (0.023)		0.034** (0.013)	0.033* (0.014)		0.005 (0.011)	-0.000 (0.011)
Father has STEM Job * Female		0.069* (0.031)	0.068* (0.032)		0.017 (0.016)	0.018 (0.017)		-0.013 (0.019)	-0.025 (0.020)
Mother has STEM Job		0.069** (0.023)	0.073** (0.024)		0.040** (0.013)	0.037** (0.014)		-0.015 (0.011)	-0.015 (0.011)
Mother has STEM Job * Female		0.033 (0.029)	0.023 (0.030)		0.044** (0.016)	0.038* (0.018)		-0.037* (0.019)	-0.034† (0.020)
Observations	5,410	5,090	4,610	10,090	9,150	8,140	10,090	9,150	8,140

Notes: All models control for student's gender, race, baseline math test scores, mother's educational background, household income, and the urbanicity and US census region of student's school. Linear regression coefficients are reported for models predicting test scores. Other coefficients are marginal effects computed after estimating logistic regression models. Standard errors are clustered at the school level. †p<0.1; *p<0.05; **p<0.01.

Appendix: Items and Scales for Measures of Non-cognitive Skills

Student Mindset and Parent Mindset

Answer options: Strongly agree, Agree, Disagree, Strongly disagree

1) Most people can learn to be good at math.
2) You have to be born with the ability to be good at math.

Student Self-Efficacy

Answer options: Almost never, Sometimes, Often, Almost always

1) I'm confident that I can do an excellent job on my math tests.
2) I'm certain I can understand the most difficult material presented in math texts.
3) I'm confident I can understand the most complex material presented by my math teacher.
4) I'm confident I can do an excellent job on my math assignments.
5) I'm certain I can master the skills being taught in my math class.

Student General Effort and Persistence Scale

Answer options: Almost never, Sometimes, Often, Almost always

1) When I study, I make sure that I remember the most important things.
2) When studying, I try to work as hard as possible.
3) When studying, I keep working even if the material is difficult.
4) When studying, I try to do my best to acquire the knowledge and skills taught.
5) When studying, I put forth my best effort.