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Parental Occupation and the Gender Math Gap: Examining the Social Reproduction of Academic Advantage among Elementary and Middle School Students

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Abstract: Math proficiency is considered a critical subject for entry into most science, technology, engineering, and math (STEM) occupations. This study examines the relationship between parental occupation and gender differences in students' math performance, that is, the gender math gap. Using insights from theories of social and gender reproduction, we hypothesize that daughters of STEM-employed parents, and especially STEM-employed mothers, will score higher on standardized math tests than their peers with non-STEM parents. Multiple waves of panel data from the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS–K) featuring students in third, fifth, and eighth grades are used to examine these hypotheses. Results from random effects regression models confirm these hypotheses while also revealing support for STEM-employed father-to-son and father-to-daughter transmission of a math performance advantage. Also, regardless of parental occupation, a gender math gap remains evident. We conclude by discussing implications, study limitations, and directions for future research.

Keywords: gender; education; school; math gap; standardized test; STEM; occupation

1. Introduction

The U.S. is expected to add over one million jobs in STEM (science, technology, engineering, and math) fields in the foreseeable future (President's Council of Advisors on Science and Technology 2012). Yet, gender disparities in degree attainment may influence who is able to take advantage of job growth in this important sector of the economy. Bachelor degrees awarded to women increased in many fields between 1998 and 2008, but no such change occurred in STEM fields (U.S. Department of Education 2012a, 2012b). Women currently earn less than 20 percent of all the mathematics, physical sciences, engineering, and computer science degrees in the U.S., and roughly two thirds of STEM jobs fall within these last two fields (Fayer et al. 2017; Landivar 2013; U.S. Department of Commerce 2010, 2011).

This study aims to advance research on average differences in mathematical performance between male and female students during elementary and middle school. This phenomenon, sometimes described as the gender math gap, is the tendency for male students to outperform their female peers in mathematics courses and standardized tests (College Board 2013; U.S. Department of Education 2012a, 2012b). The gender math gap has been well documented among high school students for several decades, but is generally more muted prior to high school (e.g., College Board 2013; Downey and Yuan 2005; Hyde et al. 1990; Sohn 2010; U.S. Department of Education 2012b). Early inquiries suggested that stereotyping discouraged young women from enrolling in advanced math courses (e.g., Conway et al. 1996; Elliot and Church 1997; Schmader 2002; Sherman 1981; Spencer et al. 1999), but more recent empirical studies, including meta-analyses, have suggested that stereotyping is not a consistent factor (Flore and Wicherts 2015; Stoet and Geary 2012). Consequently, our study is among those that aim to explore other, more structural explanations for the gender math gap (e.g., Young and Fisler 2000).

Our study investigates how structural processes of social and gender reproduction within families may influence the gender math gap. Extant studies have examined the influence of social antecedents other than household factors (e.g., race-ethnicity, culture, socioeconomic status) on the gender math gap (e.g., Entwisle et al. 1994; Lewis et al. 2012; Shih et al. 2007). We examine the intergenerational transmission of math proficiency and possible pathways whereby the math gap might be diminished. Specifically, we investigate the role of parental occupation in STEM fields on the math performance of these parents' sons and daughters. In doing so, our study enlists panel data on standardized math test scores from third, fifth, and eighth grade students. Consequently, this investigation sheds new light on possible math gap trajectories, and could delineate practical steps to ameliorate this gap.

2. Literature Review

Despite women's increased presence in the broader workforce, they are three times more likely to be employed in lower paying administrative occupations than higher paying STEM professions (Firestone et al. 1999; Moen 2011). The average woman employed in a STEM field earns 38 percent more than her female counterpart in a non-STEM occupation; yet, men hold more than three quarters of all STEM jobs in the United States (U.S. Department of Commerce 2011). Mathematical acumen is widely considered a foundational and essential skill for success in most STEM fields even though mathematical scientists and those in related fields make up less than 4 percent of all STEM employment (Fayer et al. 2017). Of course, there are different types of STEM occupations, ranging from professional careers as computer scientists, engineers, and natural scientists to the teaching of these subjects in school settings. Moreover, various types of health professions are often considered STEM occupations, but some rely more heavily on science than others. Women are often differentially represented within these internally heterogeneous STEM sectors (Ceci et al. 2014). Moreover, definitions of STEM occupations vary somewhat even among federal government offices (see Fayer et al. 2017). For example, nursing—composed of 83 percent women (Kaiser Family Foundation 2017)—is considered a scientific field in some but not all definitions of STEM careers (Fayer et al. 2017).

Since advanced math is the gateway subject for nearly all STEM majors (Bybee 2011), the gender gap in mathematical performance is a significant problem (College Board 2013; U.S. Department of Education 2012a, 2012b). Math test score disparities favoring male students have been observed prior to high school (Fryer and Levitt 2010; Robinson and Lubienski 2010; Robinson et al. 2011; Schweinle and Mims 2009). However, such disparities typically become more pronounced with age. For example, even quite recently, the average SAT math score for male high school students (531) was significantly greater than that of their female peers (499) (College Board 2013). And while female students' math test scores have increased over time, some research indicates that the gender math gap has remained intact for over a decade or longer (U.S. Department of Commerce 2011; see (Schafer and Gray 1981) for an early study). However, other studies paint a somewhat more optimistic picture. There is some evidence that the gender math gap has diminished over time or, in some circumstances, may favor girls (Hyde et al. 1990; Hyde et al. 2008; Voyer and Voyer 2014). Disparate findings with respect to the gender math gap reflect the variability of this gap among diverse samples of students, such as the general population versus more selectively sampled groups (e.g., gifted students) (see (Voyer and Voyer 2014) for a meta-analysis). Where evidence for male students' higher scores in mathematical reasoning has been documented, they have been shown to influence career trajectories beyond graduation, including entrance into higher paying fields such as engineering, physical sciences, mathematics, and computer science (Cheema and Galluzzo 2013; College Board 2013; Paglin and Rufolo 1990; Sohn 2010).

Empirical literature on suspected causes of a gender math gap favoring male students is diverse. Some research underscores the influence of gendered expectations among teachers (Gunderson et al. 2012; Kloosterman et al. 2008; Li 2004; Robinson et al. 2011), while other studies point to academic peer pressure that negatively sanctions math proficient female students (Fischer and Massey 2007; Schmader 2002). Test anxiety and related factors have also been examined (Hannon 2012). Early research surmised that boys' putatively superior spatial skills manifest themselves in a gender math gap and produce disparate consequences across educational trajectories (Benbow and Stanley 1981, 1982). However, more recent scholarship has highlighted the role of family factors in mathematical aptitude (Casad et al. 2015; Entwisle et al. 1994; Frome and Eccles 1998), an influence that had been noted in some early research as well (Benbow and Stanley 1980; Block 1983). Parents' gender ideologies influence their children's self-confidence with respect to math (Muller 1998), and parents with traditional gender attitudes tend to have daughters with diminished mathematical self-efficacy (Frome and Eccles 1998; Jacobs and Eccles 1992; Jacobs 1991; Parsons et al. 1982; Schafer and Gray 1981). Parents with lower mathematical expectations for their daughters tend to have daughters with less ambition in math (Casad et al. 2015; Frome and Eccles 1998; Parsons et al. 1982). Moreover, because parents of daughters may underestimate the importance of math skills for long-term professional development, they often (1) provide less positive verbal reinforcement related to math; (2) rationalize their daughters' sub-par math performance; and (3) offer less homework assistance (Muller 1998). Parental influence can also boost the math performance of female students. Young women who receive positive support from their parents, especially their father, tend to persevere in college STEM courses (Frome and Eccles 1998; Scott and Mallinckrodt 2005). Such support may be one key to fostering positive self-assessments, which have been shown to be quite important in women's pursuit of a STEM occupation (e.g., Correll 2001; Sáinz and Eccles 2012). Family factors have been shown to have a more muted influence among students who are academically talented (Raymond and Benbow 1986), but may operate differently and with greater effect in the general population.

Among research studies that bear directly on our investigation, one study analyzed science course performance of high school students in relation to parental occupation, and found a smaller gender performance gap for female students with a mother employed in a STEM field (Riegle-Crumb and Moore 2014). That study added to a growing body of literature on the social reproduction of educational proficiencies across generational lines (Frome and Eccles 1998; Scott and Mallinckrodt 2005; Tenenbaum and Leaper 2003). In fact, another study using ECLS–K data examined social influences on the gender math gap among students, but focused on the employment of parents in math-intensive occupations (Fryer and Levitt 2010). That investigation detected no benefit for elementary school-age students who had a parent employed in a math-intensive field. However, that study's narrow definition of parental employment in a math-intensive field minimized variation in the key independent variable. Moreover, Fryer and Levitt (2010) only focused on elementary school students despite the commonly observed widening of the math gap beyond elementary school. It is also possible that larger structural elements present within societies influence gender and math performance outcomes. Although counterintuitive, a far-reaching cross-national comparative examination revealed that having more mothers employed in a STEM occupation was associated with parental valuation of sons'—but not daughters'—mathematical performance; in that same study, societal gender inequality was not related to gender differences in mathematical performance or anxiety (Stoet et al. 2016). Still others have found an inconsistent relationship between the gender math gap and greater societal gender equality in cross-national comparisons (Fryer and Levitt 2010). In short, a mix of findings has emerged, but the critical role of parental occupation and other structural elements have begun to attract sustained attention among those interested in explaining and, where possible, reducing the gender math gap. Our study focuses quite pointedly on the potential influence of parental STEM employment on gender differences in math performance. Moreover, our study features panel data from students in elementary school through middle school. Analyzing student data along the educational trajectory is important because, as noted, mathematical acumen disparities generally widen as young people move toward high school.

3. Theory

We enlist insights from Bourdieu's social reproduction theory and more recent insights from gender reproduction paradigms to examine the influence of parental occupation on youngsters' mathematical ability. Social reproduction theory is organized around the premise that advantages enjoyed by parents are often transmitted to their children. Cultural capital—that is, valued knowledge, skills, and behaviors that can be translated into educational and economic advantage—is a key conduit for the intergenerational transmission of privilege and inequality (e.g., Bourdieu 1977, 1991, 1996; Bourdieu and Wacquant 1992; see also Kraaykamp and van Eijck 2010; Tzanakis 2011). Within much of this research, structural factors such as family organization and educational background are considered core generators of cultural capital. Families are particularly adept at generating cultural capital, as those in positions of privilege can employ practical strategies related to marriage, language, fertility, and education to establish and maintain their status (Bourdieu 1996).

Initial variants of social reproduction theory paid some attention to the gendered dimensions of cultural capital, although such insights have been expanded with the rise of gender reproduction theory (Eccles et al. 2000; Frome and Eccles 1998; Huppatz 2012; Parsons et al. 1982; Ridgeway 2011; Tenenbaum and Leaper 2003). Gender segregation within family relationships is a foundational medium through which children learn and internalize the hidden nuances of gender (e.g., Bourdieu 1989, 1996), and these gendered habits often gain additional reinforcement as youngsters transition from home to school (Bourdieu 1962; see also Kraaykamp and van Eijck 2010; Ridgeway 2011; Swartz 1977). Therefore, while social reproduction pays attention to the transmission of inequality regimes writ large (e.g., class position), gender reproduction theory focuses more pointedly on how differences between boys and girls as well as men and women are structured and sustained (e.g., deeply gendered patterns of housework, child care, educational achievement, and occupational pursuits) (Ridgeway 2011).

How might gender reproduction operate with respect to math proficiency? Students are often exposed to messages about gendered forms of academic proficiency through social networks, and the internalization of these messages can have consequences for later life trajectories (Hill et al. 2014). Parents, in particular, may directly convey expectations or provide messages about academic proficiency. However, as noted, stereotype threat and related factors have not proven to be a consistent influence on math performance (Flore and Wicherts 2015; Stoet and Geary 2012). So, structural factors emerge as a likely antecedent. Given the power of what some gender reproduction theorists and researchers call "gender capital"—that is, gendered forms of cultural capital (Huppatz 2012)—parents may not so much overtly discourage daughters against the pursuit of math achievement or STEM careers. Rather, structured patterns of gender difference and inequality found in workplaces can be transposed into family life and sustained across generations. Specifically, parents may model sex-differentiated competencies in math and other subjects in a manner that strikes parents and, quite importantly, their sons and daughters, as "natural" and "normal" based on their occupations. Hence, capacities that are structurally embedded in social institutions such as the workplace and the home need not be articulated but rather can present themselves as the "natural order of things." In this way, social institutions are "structuring structures" and gendered patterns can exhibit remarkable persistence. In short, theories of social reproduction—and their variant, gender reproduction—are valuable inasmuch as they are able to explain the structural—even institutional—character and persistence of social stratification and gender inequality. Gendered math performance and the gender math gap may be subject to these dynamics of structural influence. If so, we would expect to find evidence for this pattern in linkages between parental occupation and children's math achievement.

Our study also examines a potential upside of social reproduction for students—and especially female students—in elementary and middle school. Specifically, we seek to determine if children who have at least one parent employed in a STEM occupation exhibit greater mathematical ability. Consequently, we augment conventional theories of social reproduction and research on the intergenerational transmission of occupation by examining the prospects for gender reproduction in the home (e.g., Oren et al. 2013). We anticipate both male and female children to receive a cultural capital benefit from the employment of either or both parents in a STEM field. Given the social and familial prominence of gender, we also expect gender-specific patterns of social reproduction to be evident. In this regard, we anticipate observing mother-to-daughter and father-to-son transmission of math proficiency, respectively, when mothers and fathers are employed in STEM fields. Such homes may provide more positive role modeling and reinforcement, whether transmitted consciously or not, along gender-specific lines. The mother-to-daughter transmission of math proficiency would counter the gender math gap, while father-to-son proficiency would reinforce it. In this way, we follow other researchers who have pointed to the value of exploring how social reproduction can be gendered (Eccles et al. 2000; Frome and Eccles 1998; Parsons et al. 1982; Tenenbaum and Leaper 2003). We propose a series of hypotheses based on these theoretical perspectives.

4. Hypotheses

Having reviewed research on the gender math gap while introducing our theoretical framework, we advance three hypotheses. All hypotheses are stated net of confounding factors for which we control in our statistical analyses.

- H1: Children with one or both parents employed in a STEM field are expected to exhibit significantly higher standardized math test scores than children with no parent employed in a STEM field.
- H2: Among female students, those with a STEM-employed mother are expected to exhibit significantly higher math test scores than their female counterparts with a mother not employed in a STEM field.
- H3: Among male students, those with a STEM-employed father are expected to exhibit significantly higher math test scores than their male counterparts with a father not employed in a STEM field.

5. Research Methods

5.1. Data

To conduct this study and test these hypotheses, we enlist data from the public-use file for students assessed through the Early Childhood Longitudinal Study, Kindergarten Cohort of 1998–1999 (ECLS–K). These data follow the cohort of children for nine years, from kindergarten through eighth grade. The ECLS–K allows researchers to study how a variety of family, school, community, and individual factors are potentially linked to school performance. Students were assessed periodically for their cognitive, social, emotional, and physical development. Information about the children's home, educational activities, school type and environment, classroom curriculum, and teacher qualifications was also collected. The first wave of the ECLS–K was nationally representative. The child's gender and race were ascertained in the original round, while the family type, household income, parental education, and parental occupation were collected from each subsequent round.

The data collection in fall 1998 of the original cohort yielded direct child assessments of 19,173 kindergarten students and a parent interview sample size of 18,097. Attrition occurred in subsequent waves, but the sample size remained robust. The ECLS featured 14,470 direct child assessment and 13,489 parent interviews for the third-grade cohort, 11,346 child assessments and 10,996 parent interviews for the fifth-grade cohort, and 9296 child assessments with 8755 parent interviews for the eighth-grade cohort). The size of our study sample (14,374 third-graders, 11,274 fifth-graders, and 9285 eighth-graders) is truncated somewhat by the available standardized test scores. Multiple imputation was conducted on independent variables to retain as many cases as possible. Multiple imputation of the dependent variable was avoided because it would produce invalid values (inaccurate test scores).

5.2. Dependent Variable

The ordinal standardized math test scores of both male and female students from three waves of the ECLS–K data are the focus of this study. Students' math achievement was measured on a scale that was prepared for secondary analysis by an internal team of ECLS researchers. Each test examined age-appropriate mathematical skills and featured a broad range of items designed to examine mastery across various math performance domains. For example, the eighth-grade test examined (1) number sense, properties, and operations, (2) measurement, (3) geometry and spatial sense, (4) data analysis, statistics, and probability, and (5) patterns, algebra, and functions (Najarian et al. 2009). Every math test used by ECLS was carefully field tested to ensure valid measurement, and the ECLS team ensured sufficient parity across waves to generate a longitudinal scale score (Najarian et al. 2009).

Analysis using ECLS standardized test data focuses on student performance as determined by math Item Response Theory (IRT) scores examined in three separate waves, including the spring semester of the child's third grade (ECLS wave 5 with an alpha coefficient = 0.95), fifth grade (ECLS wave 6 with an alpha coefficient = 0.95), and eighth grade (ECLS wave 7 with an alpha coefficient = 0.92) in school. The ECLS team recalibrated cognitive math assessments for each round using IRT procedures. The consistent use of IRT scoring permits the measurement of gains in achievement over time and across grade levels (Najarian et al. 2009; Tourangeau et al. 2009a, 2009b). The IRT provides a test using patterns of correct and incorrect answers to establish estimates that are comparable across different groups (Tourangeau et al. 2009a, 2009b). For the current study, the IRT scaled scores for math are included in the model for academic achievement. The IRT is designed to solve practical problems otherwise associated with the assembly, administration, scoring, and analysis of large-scale aptitude tests (Reise and Waller 2009). The results can be compared between students and throughout each administration of the test for the same student, regardless of when tests were administered (Tourangeau et al. 2009a, 2009b).

Our dependent variable is composed of math test scores produced by students from all three waves of the survey used in this study. We use random effects models (also known as panel regression) to analyze merged data from all of these waves and then include survey wave as a control variable in our regression models. Conducting panel regression of merged data permits us to examine score changes exhibited by students across the educational trajectory, that is, from third grade to fifth grade to eighth grade. Our analytical procedures are described in more detail below yet warrant mentioning here to clarify the nature of our dependent variable. We do not pool or average math test scores because such an approach would truncate variation in our dependent variable. Our data merging procedure preserves each dependent variable data point from every survey wave, thereby permitting us to examine the full range of variation in math performance (gain or losses) exhibited by students over time. In short, our use of math test scores treats these data points as a time-varying dependent variable.

5.3. Independent Variables

Parental occupation and gender are the two key categorical independent variables used in this study. To test the proposed hypotheses, maternal and paternal occupations from all waves were used. Parental occupation was the proxy for measuring the process of social reproduction in general (i.e., influence of STEM-employed parent on child) and in gender-specific forms (e.g., influence of STEM-employed mother on daughter). The gender-specific hypothesis is examined by focusing primarily on the magnitude of the maternal influence on female students, with gender coded as male = 1 and female = 0 and the latter serving as the reference category.

Maternal and paternal occupation variables were dummy-coded into three time-varying variables: 1 = male parent in a STEM occupation (Dad STEM) with male parent not in a STEM occupation (Dad non-STEM) serving as the reference, 1 = female parent in a STEM occupation (Mom STEM) with female parent not in a STEM occupation (Mom non-STEM) serving as the reference, and 1 = both parents in a STEM occupation (Both parents STEM) with neither parent in a STEM occupation serving as the reference (Both non-STEM). It is important to note that we do not treat these dummy variables as static measures. Because parents can migrate into and out of STEM professions over each survey wave, we treat parental occupation as a time-varying variable in our random effects models. We are therefore able to test not only for the influence of parental occupation, broadly conceived, but can also account for specific changes in parental occupation (migration into or out of STEM fields) over time. Our combination of dummy-coding and random effects models offers these advantages.

We used a set of occupational categories with the definition of STEM workers as those employed in computer and mathematical occupations, engineers, engineering technicians, life scientists, physical scientists, social scientists, and science technicians for STEM largely based on the 2012 Standard Occupational Classification Policy Committee (SOCPC) recommendations from the U.S. Department of Labor 2010 Standard Occupational Classification system. The following are considered STEM occupations based on the SOCPC framework: natural scientists and mathematicians; engineers, surveyors, and architects; registered nurses, pharmacists, dieticians, therapists, and physician's assistants; health technologists and technicians; technologists and technicians, except health; and physicians, dentists, and veterinarians. We adapted this coding framework to exclude nurses from the STEM occupational category in our study. There are different approaches to defining STEM (see Fayer et al. 2017), and nursing as a profession is not consistently classified as a STEM occupation. Nursing is also, of course, a gendered profession (Kaiser Family Foundation 2017). Given our interest in gender reproduction and the fact that more than 8 in 10 nurses are women, it is safest to exclude nursing from our STEM category rather than introduce measurement error into this category. Of course, some nursing degrees (e.g., nurse practitioner) are clearly more science-based than others, but we have no way of distinguishing among them. Moreover, the argument could be made that nursing is certainly not among the most math-intensive STEM professions, thereby providing little opportunity for social or gender reproduction in terms of mathematical acumen. In the ECLS data, nurses were grouped with pharmacists. Therefore, anyone in these two occupations was classified as non-STEM, as were those in occupations other than the SOCPC STEM-designated professions featured above.

5.4. Control Variables

Control measures for students' sociodemographic characteristics and parent/household attributes were applied. Several variables were dummy-coded for analysis to capture the students' family and school background. Student-level controls for race-ethnicity were recoded into groups of interest (Non-Hispanic White, Non-Hispanic Black, Hispanic, Non-Hispanic Asian, Non-Hispanic other), and are treated as dummy variables in the analysis. Other race refers to American Indians, Pacific Islanders or those identifying with more than one race, which were not assessed due to small sample sizes. White is the reference group. For family type, single-parent families and other families were compared with married parents as the reference category. Maternal and paternal education was measured, respectively, on an ordinal scale ranging from 1 (eighth grade or below) to 9 (doctorate or professional degree). To account for the ways in which different school climates and community contexts could affect students (Riegle-Crumb and Moore 2014), school-level measures of Census regions were examined (coded as 1 = South versus other [Northeast, Midwest, West = 0]), as were city type (urban = 1, rural/suburban = 0), and school type (public = 1, private = 0). With the exception of race-ethnicity and gender (time invariant characteristics), all other control variables are time-varying covariates that are capable of changing across data collection waves. Our analytical technique (described below) permits us to control for changes in these time-varying covariates. It is also worth noting that the three waves of data were stacked to produce the results presented here. Given this data-stacking procedure, grade level is entered into all regression models as a control variable, such that fifth and eighth grade were dummy-coded with third grade as the reference. Stacking the data economizes and simplifies the presentation of results while providing ample statistical power.

5.5. Statistical Methods

Descriptive statistics for all variables were first generated to determine the frequency distribution of the data for each wave of the ECLS–K study. To capitalize on the panel design features of the data, a series of random effects regression models were estimated to evaluate the effect of parental occupation and gender on student math scores. In each random effects model, the individual-specific effect is a random variable that is uncorrelated with explanatory variables. Therefore, time invariant variables such as race–ethnicity and gender can be included in the regression models. Each of these regression models determines the statistical significance of each predictor variable on the dependent variable (student math test scores). Given the focus of this study, special attention is paid to the effect of parental occupation on math scores for students across three grades. Math scores from the third, fifth, and eighth grade waves of the survey were merged and regressed on their dummy-coded parents' occupation in a STEM field and gender net of statistical controls. As noted, this merging technique preserves maximum variation in math scores across time because merging these data points permits them to be treated as a time-varying dependent variable.

Our panel regression results were replicated using linear growth curve modeling using Stata software. Very broadly, growth curve modeling "refers to statistical methods that allow for the estimation of inter-individual variability in intra-individual patterns of change over time" (Curran et al. 2010). One of two growth curve modeling strategies is commonly utilized by social scientists: (1) linear growth curve modeling (using multilevel models); and (2) latent growth curve modeling (using SEM software). Given the nature of our key independent variables as well as our covariates, we utilized linear growth curve modeling. Methodologically, in our random effects models, individuals and time serve as multilevel variables (repeated measures nested within each individual). This approach is consistent with how these variables are analyzed as linear growth curves within the multilevel modeling framework. The results using linear growth curve modeling were nearly identical to the findings we present using random effects models utilized for this study. The key difference between these approaches relates to the modeling of the time variable. In our random effects models, we used two dummy-coded time variables, each representing a specific survey wave. Using linear growth curve modeling, we specified time (survey wave) as a metric variable to estimate the rate of change. Results of this replication are available by request.

6. Results

Descriptive statistics for all variables after imputation are presented in Table 1 for the third grade, fifth grade, and eighth grade samples (respective panels). For each variable, the imputed sample size (n) and percentage or mean and the standard deviation are presented. Sample composition is such that 49.29 percent of third graders in the study are female, and 50.71 percent are male. The mean math score for all 14,374 students was 98.72 in third grade, with a standard deviation (SD) of 24.72. The number of students decreased to 11,274 in fifth grade, and their mean math score increased to 123.69 (SD = 24.79). By eighth grade, the number of students was 9285, while the mean math score increased to 142.22 (SD = 22.01). Less than 1 percent (0.86 percent) of third-grade students have both parents employed in a STEM occupation. Households with a mother employed in a STEM occupation peak at 6.83 percent in eighth grade. Both parents employed in a STEM occupation also peaks in eighth grade at 1.03 percent of households. In third grade, the percentage of students with a mother employed in a STEM field was the lowest at 4.25 percent. Descriptive statistics on control variables are also featured in Table 1.

Tables 2 and 3 feature the results of random effects regression models, and display results for the dummy-coded parental occupation variables with gender of the student as a primary predictor variable. In these tables, analyses are conducted for the whole sample of students with primary attention given to the general effects produced by the various parental occupation categories (Mom non-STEM, Mom-STEM, Dad non-STEM, Dad STEM, Both non-STEM, and Both STEM). Table 2 features parental occupation results for all students combined with a gender variable (male) entered into each of the two models. Model 1 estimates effects for children who have one parent employed in a STEM occupation, while Model 2 estimates effects for children with both parents employed in a STEM occupation. Table 3 features a series of gender-specific models whereby effects are estimated first for female students (Models 1–2) and then for male students (Model 3–4).

Recall that H1 predicted that, among the full sample, children with one or both parents employed in a STEM field would exhibit significantly higher standardized math test scores than children with no parent employed in a STEM field. Table 2 examines the relative support for this hypothesis in the full sample of students. The results indicate strong support for this hypothesis. Students with a STEM-employed mother, STEM-employed father, or both parents STEM-employed perform significantly better on standardized math tests when compared, respectively, with children who have a non-STEM mother, non-STEM father, or neither parent STEM-employed. However, an important caveat bears mentioning from Table 2. While the intergenerational transmission of a math performance advantage for children of STEM-employed parents is observed, this advantage does not eliminate the gender math gap. In both models featured in Table 2, the gender variable (male) remains highly statistically significant ($p < 0.001$). Thus, parental STEM occupation employment confers a math performance advantage for children. Yet, regardless of parental occupation, boys generally outperform girls on standardized math tests.

H2 predicted, in gender-specific models, female students with a STEM-employed mother to exhibit significantly higher standardized math test scores than their female counterparts with a mother not employed in a STEM field. This hypothesis is supported by the results featured in Table 3 (Model 1). Daughters of STEM-employed mothers score significantly better on standardized math tests than those with non-STEM mothers ($p < 0.05$). However, this result is accompanied by a finding that warrants an important caveat. Female students with a father employed in a STEM field also outperform their female peers without a STEM-employed father. In fact, this father-to-daughter transmission of a math performance advantage is considerably robust ($p < 0.001$). Thus, while H2 is supported for STEM-employed mother-to-daughter transmission of a math performance advantage, STEM-employed father-to-daughter transmission is especially strong.

H3 predicted male students with a father employed in a STEM field to exhibit significantly higher math test scores than their male peers with a father not employed in a STEM field. As indicated in Model 3 of Table 3, H3 is supported. Male students with a STEM-employed father outperform their male counterparts who do not have a STEM-employed father ($p < 0.001$). An important caveat is again warranted for Model 3. Male students with a STEM-employed mother do not outperform their male peers without a STEM-employed mother. The coefficient representing this relationship is non-significant. Therefore, the father's occupational category but not the mother's occupational category is influential for male students.

In addition to testing the three hypotheses posed in this study, Models 2 and 4 in Table 3 were run to determine the influence of couple employment combinations with STEM. As revealed in Model 2, female students with both parents employed in a STEM field far outperform female students with neither parent employed in a STEM field ($p < 0.001$). Likewise, significantly higher math test scores are achieved by male students with two STEM-employed parents when compared with male students who have neither parent employed in a STEM field ($p < 0.05$). The empirical patterns reported here are summarized in Table 4.

Table 1. Descriptive statistics.

	Third Grade				Fifth Grade				Eighth Grade			
Variable	***n***	**Percent**	**Mean**	**SD**	***n***	**Percent**	**Mean**	**SD**	***n***	**Percent**	**Mean**	**SD**
Dependent Variable												
Standardized Math Test Scores	14,374		98.72	24.72	11,274		123.69	24.79	9285		142.22	22.01
Independent Variables												
Gender												
Female (reference)	7085	49.29%			5599	49.66%			4616	49.71%		
Male	7289	50.71%			5675	50.34%			4669	50.29%		
Parents' Occupation												
Mother non-STEM (reference)	13,763	95.75%			10,741	95.27%			8651	93.17%		
Mother STEM	611	4.25%			533	4.73%			634	6.83%		
Father non-STEM (reference)	13,214	91.93%			10,368	91.96%			8310	89.50%		
Father STEM	1160	8.07%			906	8.04%			975	10.50%		
Both Parents non-STEM (reference)	14,251	99.14%			11,162	99.01%			9189	98.97%		
Both Parents STEM	123	0.86%			112	0.99%			96	1.03%		
Control Variables												
Student-level Variables												
Race/ethnicity												
White (reference)	8125	56.53%			6470	57.39%			5707	61.46%		
Black	1889	13.14%			1275	11.31%			955	10.29%		
Hispanic	2598	18.07%			2106	18.68%			1605	17.29%		
Asian	958	6.66%			799	7.09%			514	5.54%		
Other	804	5.59%			624	5.53%			504	5.43%		
Parents' Education												
Mother Education	14,374		4.56	1.87	11,274		4.58	1.85	9285		4.79	1.95
Father Education	14,374		4.68	2.11	11,274		4.62	2.08	9285		4.77	2.08
School-level Variables												
Family Type												
Two Parent Home	11,316	78.73%			8860	78.59%			7388	79.57%		
Single Parent Home	3058	21.27%			2414	21.41%			1897	20.43%		
Census Region												
Non-South (reference)	9667	67.25%			7639	67.76%			6245	67.26%		
South	4707	32.75%			3635	32.24%			3040	32.74%		
Location of School												
Rural (reference)	3194	22.22%			2678	23.75%			2446	26.34%		
Urban	11,180	77.78%			8596	76.25%			6839	73.66%		
School Type												
Private (reference)	2639	18.36%			2055	18.23%			1579	17.01%		
Public	11,735	81.64%			9219	81.77%			7706	82.99%		

Table 2. Random effects models to predict standardized math test scores.

Standardized Math Test Scores		
Variables	**Model 1**	**Model 2**
Intercept	90.55 ***	90.70 ***
Male	3.87 ***	3.87 ***
Mom STEM	1.05 *	-
Dad STEM	2.87 ***	-
Both parents STEM	-	4.60 ***
Black	−19.04 ***	−19.13 ***
Hispanic	−10.60 ***	−10.70 ***
Asian	0.40	0.48
Other	−9.15 ***	−9.21 ***
Single Parent Home	−1.59 ***	−1.73 ***
South	0.66	0.66
Urban	2.83 ***	2.87 ***
Public	−0.25	−0.27
Mothers' Education	1.14 ***	1.14 ***
Fathers' Education	0.79	0.82 ***
Fifth Grade	24.44 ***	24.44 ***
Eighth Grade	41.16 ***	41.22 ***
Wald Chi-squre	97,143 ***	97,069 ***
df	15	14
Person-Grade	34,933	34,933

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 3. Random effects models to predict standardized math scores by gender.

Standardized Math Test Scores by Gender				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Variables	**Female**	**Female**	**Male**	**Male**
Intercept	90.23 ***	90.43 ***	94.64 ***	94.74 ***
Mom STEM	1.45 *		0.55	
Dad STEM	2.99 ***		2.76 ***	
Both parents STEM	-	6.38 ***	-	3.09 *
Black	−18.43 ***	−18.52 ***	−19.67 ***	−19.76 ***
Hispanic	−10.51 ***	−10.62 ***	−10.69 ***	−10.77 ***
Asian	−0.20	−0.15	1.08	1.20
Other	−9.43 ***	−9.58 ***	−8.88 ***	−8.88 ***
Single Parent Home	−1.62 ***	−1.78 ***	−1.51 ***	−1.64 ***
South	1.37 **	1.35 **	0.08	0.09
Urban	2.74 ***	2.78 ***	2.87 ***	2.90 ***
Public	−0.18	−0.21	−0.28	−0.27
Mothers' Education	1.22 ***	1.22 ***	1.07 ***	1.08 ***
Fathers' Education	0.67 ***	0.69 ***	0.92 ***	0.94 ***
Fifth Grade	24.25 ***	24.25 ***	24.62 ***	24.62 ***
Eighth Grade	42.47 ***	42.55 ***	39.85 ***	39.90 ***
Wald Chi-squre	52,453 ***	52,411 ***	45,501 ***	45,478 ***
df	14	13	14	13
Person-Grade	17,300	17,300	17,633	17,633

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 4. Summary of results in relation to hypotheses.

Hypothesis	Level of Support and Findings
H1: Children with one or both parents employed in a STEM field are expected to exhibit significantly higher standardized math test scores than children with no parent employed in a STEM field.	H1 is supported (Table 2). However, the gender math gap persists net of parental occupation.
H2: Among female students, those with a STEM-employed mother are expected to exhibit significantly higher math test scores than their female counterparts with a mother not employed in a STEM field.	H2 is supported (Table 3). However, having a STEM-employed father or both parents STEM-employed is also beneficial for female students.
H3: Among male students, those with a STEM-employed father are expected to exhibit significantly higher math test scores than their male counterparts with a father not employed in a STEM field.	H3 is supported (Table 3). However, having both parents STEM-employed is also beneficial for male students. Having a STEM-employed mother makes no difference.

7. Discussion and Conclusions

This study set out to explore the role of parental occupation as a possible antecedent to students' math performance and, more broadly, the gender math gap. The gender math gap consists of the propensity for male students to outperform their female peers in math courses and standardized tests. In this study, we examined standardized math test scores of students across three grade levels in elementary and middle school. Using insights from social reproduction and gender reproduction theories, we examined the degree to which parental occupation—and, specifically, having a STEM-employed mother, a STEM-employed father, or two STEM-employed parents—affected male and female students' performance on standardized math tests in third, fifth, and eighth grade.

We anticipated that children with either parent or both parents employed in a STEM field would perform better on standardized math tests. We found that students with a STEM-employed mother, STEM-employed father, or both parents STEM-employed perform significantly better on standardized math tests when compared, respectively, with children who have a non-STEM mother, non-STEM father, or neither parent STEM-employed. Thus, an intergenerational math advantage is transmitted from parents to children. At the same time, it is important to note that this advantage does not eliminate the gender math gap. In random effects regression models, the gender variable (male) was consistently and strongly significant in a way that indicated boys' superior overall mathematical performance. Thus, regardless of parental occupation, boys generally outperformed girls on standardized math tests. These findings indicate that a parental math advantage and a gender math gap are not mutually exclusive. We find evidence for both in our statistical models. Despite the consistency of the parental math advantage based on STEM employment, it does bear mentioning that households with two STEM-employed parents are an extremely small minority of families in the study (generally below 1 percent of all study participants). The relatively small number of cases in this category could influence the observed findings. Of course, parents are not the only influence on students' capabilities. Students' course-taking patterns as they transition from elementary school to middle school may have an effect on students' perceptions of their own abilities in mathematics (Sáinz and Eccles 2012). Additional research should be conducted to examine such influences.

A second hypothesized effect was linked to female students' test performance with a STEM-employed mother. We predicted that female students with a STEM-employed mother would achieve significantly higher math test scores than their female peers whose mother was employed in a non-STEM field. This anticipated finding was tied most closely to gender reproduction theory and was observed in the data. Support was also found for our third hypothesis, which was also connected to gender reproduction theory. We found that the boys of STEM-employed fathers consistently fared better on standardized math tests than their peers whose father was not employed in a STEM field.

Thus, gender reproduction in the form of mother-to-daughter mathematical skill transmission was observed even as its opposite—that is, father-to-son transmission—was also evident. In short, having both parents employed in a STEM field can provide broad-based benefits for children's mathematical performance. And sons and daughters with a STEM-employed father consistently score better on math tests, while mothers' STEM employment is relevant only for their daughters (not their sons). Our findings are different than those that emerged from a cross-national comparative study in which mothers' STEM employment was unrelated to gender differences in young people's mathematical performance (Stoet et al. 2016). Our study is only based on U.S. data and focuses on elementary and middle school students. Moreover, because we found evidence of a mother-to-daughter math proficiency effect (but no mother-to-son effect), more research is needed within and outside the U.S. to explore the prevalence of such patterns.

What, then, are the implications of these results, and what directions for future research seem most promising? Social supports designed to bolster math performance may be critical for many different types of students, but may be especially helpful for those whose parents are not employed in a STEM field. Given the persistence of the gender math gap in all of our regression models that controlled for student gender, the targeted recruitment of girls to advanced math courses and math camps may also be beneficial. Relatedly, caregivers in households where one or both parents are not employed in a STEM field might benefit from additional direction in nurturing mathematical acumen among their children and especially their daughters. Based on the findings of this study, the only types of families in which such direction is not urgently needed are those in which both parents are STEM-employed. However, these families make up a small proportion of our sample. Therefore, some caution is warranted in interpreting these findings. Given the probabilistic (not predictive) nature of our investigation and the wide prevalence of the math gap, there is no good reason to withhold math supports from any female students at any point in the educational trajectory. Even if math support benefits may be more muted for girls raised by two STEM-employed parents, such supports may help reverse other potentially adverse social influences on girls' math performance.

Future research could be conducted to address the limitations of this study. Observational research and in-depth interviews could pinpoint the specific strategies that two STEM-employed parents use to foster math achievement so readily in sons and daughters alike, and such strategies may be adapted for use in other homes. Collecting additional survey data from an oversample of households with two STEM-employed parents would be especially helpful given the generally low representation of such families in the general population. And, of course, previous investigations examining the ecological (society-wide) antecedents of the gender math gap could be replicated for the U.S.-based ECLS sample by pairing aggregate-level indicators (e.g., state or county-level gender inequality measures) with survey outcomes (for a cross-national investigation using this approach, see Stoet et al. 2016). Such an analytical approach would entail the use of multiple data sources and multi-level modeling techniques that are beyond the scope of our paper. Finally, the precise mechanisms underlying parental and maternal influence cannot be determined by our investigation due to survey data limitations. Future research should explore the mechanisms for transmitting mathematical competence across generations, including parental expectations for subject-specific skills and abilities (e.g., knowledge of mathematical lexicon or procedures), communication habits (e.g., verbal encouragement), everyday activities (e.g., math and measurement games), and direct support (e.g., homework help). Until such research is conducted, this study has shed important light on parental occupation as an antecedent of gender dynamics associated with math performance.

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