The Role of Social Support and Psychological Well-Being in STEM Performance Trends across Gender and Locality: Evidence from Ghana

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Accepted: 10 October 2019/Published online: 07 January 2020

Abstract
This study focuses on trends in STEM *performance* and *inclusiveness*. We examine performance trajectories in STEM subjects, the predictive role of social support and psychological well-being of students, and variations across student gender and school locality (rural vs urban). We used three waves of data from 135 junior high school students in Ghana. Multilevel growth curve modeling was used to assess the trajectories and the socio-environmental predictors of STEM performance, and posthoc power calculation was used to confirm the adequacy of the sample size. Results show that overall, students' STEM performance improves over time. Minimal gender differences exist but depend on the subject area and evolve with time. We observed a nuanced "urban advantage," with rural students starting well but declining over time. Among various indicators of social support and psychological well-being, teacher support was the strongest positive predictor of STEM performance. The study highlights the need to focus on the structural and cultural impediments to STEM education at the lower levels of education in order not to risk excluding marginalized groups early in the education system. Further, STEM interventions may do well to incorporate long-term measures to sustain girls' interest, motivation, and efforts in STEM.

Keywords Gender inequality · Ghana · Multilevel growth curve modeling · Social support · STEM

1 Introduction

Education ensures a skilled workforce, higher earnings, steady investments, and sustained political stability (Berger & Fisher 2013). With Switzerland as the only

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exception, no high-income country has ever advanced without a highly educated workforce or a university enrollment rate of at least 50% (Mundia 2017; Bloom et al. 2006). Not only have the high-income countries made significant investments in education, but many have prioritized specific areas such as science, technology, engineering, and mathematics (STEM) in part because such targeted investments come with even greater returns to individuals and society at large. The Sustainable Development Goals (SDGs), which comprise 17 global goals set by the United Nations, recommend that low-income countries leverage technological advancements and invest in greater access to quality STEM education due to the vital role STEM plays in advancing economic, social, and environmental justice (United Nations 2015; Blom et al. 2015). STEM education drives technical and scientific innovation, a dual engine of economic growth, competitiveness and national development (Breiner et al. 2012). Skills in STEM-related fields are touted as a viable solution to perennial youth unemployment in low-income countries (World Economic Forum 2017).

In response to this established negative consequence of long-lasting youth unemployment, many low-income countries' strategic approach is the focus on STEM Education as a solution to youth unemployment. In the case of Ghana, international development organizations and the government have made concerted efforts to narrow disparities in the pursuit of STEM education. These efforts include the establishment of the Science, Technology, and Mathematics Education (STME) clinics in the 1980s (Lindsay et al. 2017), the Girls' Education Unit (GEU) in the late 1990s, and the Science Resource Centre Project (SRCP). The SRCP has equipped over 300 urban and rural high schools with modern laboratories and equipment for effective teaching and learning of science. More recently, UNESCO has collaborated with the Ghana Education Service's GEU to revamp the STME clinics with the goal of expanding access to more districts, both rural and urban.

Although these steps are laudable, we argue that a more integrated approach involving a three-pronged framework—access to STEM education (*participation*), quality of STEM learning (*performance*), and inclusive STEM education (*inclusiveness;* UNESCO 2016)—ought to be part of the solution to the often leaky education systems in low-income countries. Included in this framework is an evaluative agenda to assess how countries fare in the three identified areas of *participation, performance,* and *inclusiveness.* It is an evidence-based model measured on outcome considerations. Recognizing the overwhelming emphasis on STEM *participation*, this study purposely focuses on the underemphasized areas of STEM *performance* and *inclusiveness*. Using Ghana as an example, we examine changes in junior high school students' performance in four STEM-related subjects namely, math, basic design and technology (BDT), information and communication technology (ICT), and integrated science. We also examine two dimensions of inclusiveness—gender (boys vs girls) and locality (rural vs urban)—to address the problem of gender discrimination that still plagues education systems, and the problem of the rural-urban divide prevalent in most low-income countries.

1.1 Gender and Locality Differences (or Lack Thereof) in STEM Outcomes

Studies that focus on STEM participation are unequivocal about the underrepresentation of girls and women in STEM education programs and careers (Broadley 2015;

Chavatzia 2017; UNESCO 2018). At the secondary school level, Ghanaian boys' participation in STEM subjects has consistently remained higher than that of girls. Beyond schooling, the gender gaps in STEM careers are wider. Data from the UNESCO Institute for statistics, for example, show that only 35% of researchers in Africa are female, and the number is worse in countries like Ghana (18%) (UNESCO 2018).

While the level of gender disparities in STEM education and career participation often favor boys, that is not the case with performance in STEM subjects. A global-level assessment suggests that where gender differences exist in science and math performance at the primary and secondary school levels, girls typically perform better than boys. For instance, the 2015 Trends in International Mathematics and Science Study (TIMSS) assessed 49 high-income, middle and low-income countries and found no gender differences in secondary school-level science achievement in 51% of the countries. In 49% of the countries where gender differences were observed, girls performed better in two-thirds of the countries (Mullis et al. 2016). In mathematical achievement, girls outperformed boys in 18% of the countries, and boys performed better in 15% of the countries (Mullis et al. 2016). In the remaining 67%, there was no gender difference in math performance. These global trends are mimicked at the state level; for example, in Ghana, Kwame et al. (2015) found that among 1528 final-year senior high school students from Central and Western Ghana, girls outperformed boys in *elective* math.

In the STEM literature, we do not know as much about rural-urban disparities (or lack thereof) as we do about gender disparities. At the 2015 Luncheon Declaration and Framework for Action for the SDG implementation, over 160 countries committed to integrating STEM education to make sure all youth, including rural or urban residents, succeed in STEM fields (UNESCO 2016). In most low-income countries, gender differences are often connected to the rural-urban divide. In Ghana, for instance, the rate at which boys enroll in and complete school exceeds that of girls, and this is especially true in rural and in the socioeconomically disadvantaged areas (Nguyen and Wodon 2014). As Senadza (2012) observed, it was not unusual for families in these underprivileged areas to only send boys to school due to scant resources.

1.2 Explanations for Disparities in STEM Outcomes

Consistent with neuroscience research, existing gender gaps in STEM performance are not related to sex differences, innate ability, genetics, or brain structure (Spearman and Watt 2013). If no one gender is particularly predisposed to stronger performance in STEM subjects, what then explains the differences when they exist? Ruling out biological explanations for variations in STEM performance (Hyde 2005; Hyde and Mertz 2009) elevates the focus on psychosocial and environmental influences. Thus, we explore socio-environmental influences and how they manifest in the short and medium-term.

The STEM literature offers evidence of the socio-environmental and psychological influences on educational outcomes irrespective of gender. The socio-environmental factors include teacher's influence (Hatch 2018; Jones et al. 2013) and classmate roles (Lohbeck et al. 2017). Sex-differentiated socialization in the classroom privilege boys over girls and reinforces stereotypical gender norms (Sefa Dei et al. 2006). Ajayi and Buessing (2015) found that over 25% of girls list home economics as their first program of choice compared to less than 2% of boys. Moreover, males tend to dominate girls in the classroom, meaning that female and male students' classroom participation is not equal (Dunne 2007). The habit of jeering when peers attempt to participate in lessons or answer questions may cause some girls to limit their participation in classroom discussions. Dunne (2007) observed that female students are active participants in the maintenance of this gendered hierarchy. There are times when teachers step in to address such gendered issues, but this is less common among male teachers.

Socialization in the home and school community also plays a critical role in informing career choices and other student outcomes (Cheryan et al. 2011; Xie et al. 2015). These communities teach girls obedience, cooperation, and other skills that may help them to fit into the school routines and cultural gender expectations (Hill and Tyson 2009; Hyde 2005; Legewie and DiPrete 2014; Riegle-Crumb and Humphries 2012). Similar to socialization, psychological barriers can limit female students' STEM participation (Andam et al. 2013). Self-efficacy, or belief in one's ability to succeed in specific situations, may predict adolescent girls' performance in STEM subjects (Adedokun et al. 2013; Beilock et al. 2010).

Time is another variable to consider in evaluating STEM performance. The influence of social and psychological factors on educational outcomes can be immediate (e.g., drop out of school after parent withdraws support) or manifest over time (e.g., performance when parents fail to supervise homework). Examining secondary school level data from the 1980s, Anamuah-Mensah (1995) hints that girls' edge over boys' in the General Certificate of Education (GCE) Ordinary Level (O-Level) exams, but reverses at the GCE Advanced Level (A-Level) exams. Similarly, Mwinkume's (2013) review of the performance of 6164 senior high school students in the Central region of Ghana from 2003 to 2005 found that gender differences in math and science were primarily a function of the year in which students sat for the West African Examinations Council (WAEC) exams.

1.3 The Current Study

To help build on what we know from the extant research, this article addresses the following three questions to better understand other ways that STEM gaps persist besides access and participation, particularly in resource limtied countries:

(a) What is the trajectory of students' performance in STEM subjects, particularly before senior high education?
(b) To what extent do gender and location differences exist in STEM performance trajectories, and how do they evolve with time?
(c) To what extent do the social environment (e.g., parent, teacher, and peer support) and psychological factors (e.g., self-efficacy) explain longitudinal trends in STEM performance?

By addressing the above questions, this study could help fill gaps in the STEM body of work. First, it matters to know the performance trajectory before senior high school because research shows that students rule themselves in or out of a career in STEM before completing junior high school (Archer et al. 2013; Kiwana et al. 2011). Findings regarding STEM performance across time and in subpopulations of gender and locality could inform the development and implementation of targeted interventions. Second, results from this study may inform the appropriate targeting and interventions for effective resource optimization. Policymakers and educators can, over time, determine where to invest more resources to open the way for a change.

2 Methods

2.1 Study Design and Sample

The study used longitudinal data (three waves) from junior high school students ($N = 135$) from three schools in Greater Accra, one of the ten administrative regions of Ghana. The 16 districts, metropolis, and municipalities that make up the region were divided into urban (metropolis and municipalities) and rural clusters. The Dangme West District was randomly selected from the rural cluster and the Ashaiman district from the urban cluster. Two public junior high schools were chosen from Dangme West and one from Ashaiman. All final year students were offered the opportunity to participate in the study. Out of the approximately 150 final year students in the three schools, 135 agreed to participate in the research and provided valid responses to the questions used in the current study. In addition to collecting two waves of survey data nine months apart, we also tracked participants' academic records at three different measurement occasions over a period of one year. All research procedures and protocols were pre-approved by the district offices of the Ghana Education Service and the Institutional Review Board at the University of North Carolina at Chapel Hill. For the majority of the students who were below 18 years, parents and guardians had to consent to their children's participation in addition to the children's assent. A handful of students at the age of majority provided their own consent.

2.2 Measures

Outcomes Junior high school education in Ghana is based on a nine-subject curriculum. In the present study, we focus on the four STEM-related subjects: math, basic design and technology (BDT), information and communication technology (ICT), and integrated science. Data on all four subjects were collected at three different time points. The Wave 1 outcome data, referred to as continuous assessment scores, represent a global score for students' performance during the first academic term (i.e., during a 15-week period). The scores were originally measured on a 50-point scale. The Wave 2 outcome data, originally measured on a 70-point scale, represents students' performance on the end-of-academic term exam, which is 15 weeks after Wave 1 data collection. The Wave 3 data, collected 10 weeks after Wave 2, came from the Basic Education Certificate Examination (BECE), which is a national standardized exam that students sit for at the end of junior high school. The WAEC administers the exams and measures students on a 9-point scale. The *time* variable, centered at the mid-point (Wave 2), indicates the measurement occasion for each of the three waves of outcome data. A quadratic term for the time variable was also created to account for growth over time. The Proportion of Maximum Scaling (POMS) method (discussed under the *Analytical Strategy* section) was used to address possible inherent differences in the three measurement units (Denissen et al. 2007; Moeller 2015; Moreira et al. 2018).

Moderators and Predictors The study examined whether two time-invariant variables—*gender* and *locality*—moderated students' STEM performance trajectories. *Gender* is a binary variable; 1 denotes female and 0, male. The *rural* variable is a binary measure of whether a school was located in a rural (coded 1) or urban area (coded 0). Based on the reviewed STEM literature and a forerunner study in Ghana that shows that student support systems matter for their schooling outcomes (Ansong et al. 2017), we controlled for teacher, peer, and parental support. The 7-item *parental support* scale was originally developed by Ames et al. (1993) and adapted to the Ghanaian context using a 5-point response set from 1-*never* to 5-*always*. The multi-item scale measures the level of parents' involvement in their children's schooling in the form of assisting with homework, ensuring completion of homework, communicating expectations, participation in school meetings and events, and engagement with school teachers (See Ansong et al. 2017 for psychometric validation results).

The three-item classmate support construct assessed the extent of perceived support from peers based on emotional support from classmates, the ability to work with classmates, and availability of help when needed. The three-item *teacher support* construct assessed students' perception of the level of support from their class teachers based on the teachers' interest in their success, their availability when students needed help, and fair treatment from the teacher (See Ansong et al. 2017 and Torsheim et al. 2000, 2012 for scale items and psychometric validation results for the classmate and teacher support construct). Both scales were rated on a 5-point response set (i.e., 1-*strongly disagree* to 5-*strongly agree*). The study also accounted for students' *academic self-efficacy beliefs* based on evidence of its association with Ghanaian youth's academic performance (Ansong et al. 2019). The eight-item academic self-efficacy construct, which refers to students' ability to complete schoolwork successfully, was scored on an 11-point response scale (i.e., 0-*cannot do at all* to 10-*highly certain can do*). The items for each scale—parental, classmate, teacher support, and self-efficacy beliefs— were averaged to form composite scores for each construct because all four scales have been psychometrically validated and deemed appropriate for Ghanaian youth (See Ansong et al. 2016; Ansong et al. 2017). The items are listed in Table 1.

2.3 Analytical Strategy

Rescaling of Outcome Variables Following best practices, the Proportion of Maximum Scaling (POMS) method was used to transform the outcome data into the same metric ranging from a minimum possible value of 0 to a maximum possible value of 1 (Moeller 2015; Moreira et al. 2018). This rescaling was necessary because the STEM subjects were scored on different scales (0–50, 0–70, and 1–9) at each of the three measurement occasions. As shown in Eq. 2, POMS is calculated as the difference between the observed and minimum values divided by the difference between the maximum and minimum values for each outcome variable.

$$POMS = \frac{Observed - Minimum}{Maximum - Minimum} \tag{1}$$

Table 1 Descriptive sta tistics

Construct	Items	Mean(SD)	Range
Classmate support	1. The students in my class enjoy being together	3.63(1.29)	1–5
	2. Most of the students in my class are kind and helpful	3.73(1.18)	1–5
	3. When a classmate is upset, other students comfort him	3.72(1.37)	1–5
	Overall classmate support score	3.82(0.79)	2–5
Teacher support	1. Our teachers treat us fairly	4.15(1.01)	1–5
	2. When I need extra help, I can get it	4.13(0.87)	1–5
	3. My teachers are interested in me as a person	4.50(0.66)	2–5
	Overall teacher support score	4.38(0.55)	2.75–9.88
Parental support	1. Attend Parent-Teacher Association (PTA) meetings at your school	3.85(1.29)	1–5
	2. Discuss your school progress with your teachers	2.78(1.15)	1–5
	3. Attend your school events such as sporting activities, speech and prize giving events	3.06(1.65)	1–5
	4. Volunteer at your school	1.68(1.08)	1–5
	5. Make sure you do your homework	3.84(1.43)	1–5
	6. Talk with you regarding their expectations for your school work	3.98(1.20)	1–5
	7. Motivate you to try harder when you make a poor grade	4.20(1.24)	1–5
	Overall parental support score	3.28(0.85)	
Academic self-efficacy beliefs	1. How well can you get teachers to help you when you get stuck on school work?	7.48(2.61)	1–10
	2. How well can you study when there are other interesting things to do?	6.42(2.25)	1–10
	3. How well can you study a chapter for a test?	8(2.16)	3–10
	4. How well do you succeed in finishing all your homework every day?	7.88(2.25)	1–10
	5. How well can you pay attention during every class?	8.39(1.98)	3–10
	6. How well do you succeed in passing all subjects?	7.17(1.89)	1–10
	7. How well do you succeed in satisfying your parents with school work?	8.45(1.95)	1–10
	8. How well do you succeed in passing a test?	8.19(1.76)	4–10
	Overall academic self-efficacy score	7.75(1.19)	4.5–9.88

The POMS methods are ideal for longitudinal and nested data (Moeller 2015). They have several advantages over the traditional z-standardization and ipsatization, including (1) maintaining the integrity of the covariance matrix (see Closs 1996; Chan 2003), (2) accurate interpretation of longitudinal profiles mean scores (see Denissen et al. 2007), (3) allowing examination of mean level variations between individuals and across time (Moeller 2015).

Multilevel Growth Curve Modeling For each of the four STEM outcome measures—math, BDT, ICT, and integrated science—we applied a multilevel growth curve modeling approach to model the structure and the socio-environmental and psychological predictors of STEM performance changes over time. The analytical approach has the added advantage of handling missing data successfully (Luke 2004). Both linear and quadratic components were tested. Because modeling both the linear and quadratic elements of time increased the risk of collinearity, we centered the time variable at the mid-point to address this risk.

For each outcome, we tested four nested models in the following sequence: (1) unconditional model to assess amount of variation explained by difference across time and between individual students, (2) unconditional linear growth curve model to evaluate differences in students' performance over time, (3) conditional growth model with addition of a quadratic term to examine the rate of acceleration or deceleration in STEM performance over time, and (4) a condition growth curve model with moderating variables—gender and locality—to assess growth differences across gender and locality. In this model, the linear slope was modeled as random effects to account for the possibility that changes in performance vary across students. We did not model similar random effects for the quadratic term because of the limited time points (3 waves). We also investigated whether student gender and locality (rural vs urban) were predictive of a student's STEM achievement. Parent, teacher, and classmate's involvement were assessed for their predictive influence on each of the four STEM outcomes. Three two-way interactions between gender and parent involvement, rural locality and time were included in all final models to investigate whether the relationship between gender and STEM performance depended on parents' level of involvement, locality (rural vs urban), or evolved. Another two-way interaction between location and time were included to assess whether the predictive role of location changed over time. The systems of equation for the final mode is:
Level 1:

$$\text{STEM Performance}_{ij} = \beta_{0j} + \beta_{1j}(\text{Time})_{ij} + r_{ij} \tag{2}$$

Level 2:

$$\begin{aligned}
\beta_{0j} &= \gamma_{00} + \gamma_{01}\left(\text{Time}^2\right)_j + \gamma_{02}(\text{Female})_j + \gamma_{03}(\text{Rural})_j + \gamma_{04}(\text{Parent})_j \\
&+\gamma_{05}(\text{Peer})_j + \gamma_{06}(\text{Teacher})_j + \gamma_{07}(\text{Efficacy})_j \\
&+\gamma_{08}(\text{Female*Parent})_j + \gamma_{09}(\text{Female*Rural})_j + u_{0j} \\
\beta_{1j} &= \gamma_{10} + \gamma_{11}(\text{Female})_j + \gamma_{12}(\text{Rural})_j + u_{1j}
\end{aligned} \tag{3}$$

where γ_{00} through γ_{12} are the coefficients of the fixed effects, u_{0j} and u_{1j} error terms represent the variability between measurement occasions, and r_{ij} represent variability between students within a measurement occasion.

The Akaike's Information Criterion (AIC) was used to compare two nested models—one with and another without the random slopes for time—to assess the model that fits the data best. Models with AICs 2 points less the other model was deemed more parsimonious and thus selected as the final model. All statistical models were tested in Stata version 15, and cluster-robust standard errors were used to account for the possibility that the covariance structures vary by the schools that participated in the study.

2.4 Power Analysis

A post hoc power analysis was conducted with an alpha of .05 and three measurement occasions ($math_{delta} = 0.62$, $science_{delta} = 0.12$, $ICT_{delta} = 0.77$, and $technology_{delta} = 0.50$). The estimated power for repeated-measures ANOVA F-test for within subject with Greenhouse-Geisser correction suggests that a sample size of 135 subjects is adequate to maintain power (>. 99) for math, ICT, and BDT. However, the integrated science models are underpowered and may require up to 1000 subjects to maintain adequate statistical power (>.80).

3 Results

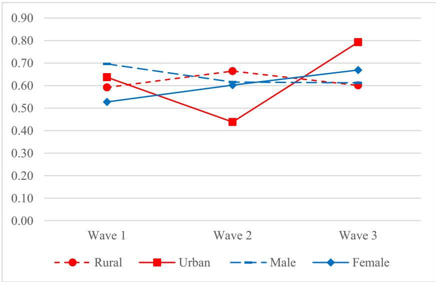
3.1 Descriptive Results

The four graphs in Fig. 1 depict nonlinear growth trends in students' performance. This nonlinear trajectory suggests that on average, students' STEM performance drops during the end-of-academic term exams, but it bounces back by third wave of data collection. This nonlinear growth necessitates the inclusion of a quadratic term ($Time^2$) in the growth curve modeling to account for possible nonlinear growth trajectories in students' performance. Segmentation of the data by gender reveals a more nuanced growth trend. The trends for girls, as shown in Fig. 1, generally shows a relatively stable trajectory in STEM performance over time. Boys, on the other hand, experience a steeper decline across all STEM subjects, but the recovery is tepid (Fig. 1). In the case of rural-urban differences, urban students' performance drops sharply but bounces back by the third wave. Comparatively, rural students' performance is more stable, although they decline marginally over time.

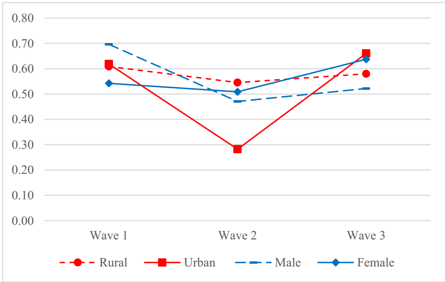
Comparison of the nested models revealed that in the case of math ($\Delta AIC = 29.61$), integrated science ($\Delta AIC = 13.62$), and ICT ($\Delta AIC = 65.35$), the models with the random components for *Time* fit the data best. These models allowed the linear slope to vary by individual students. In the BDT models, the reduced model (model without random effect for time) had the best fit with the data ($\Delta AIC = 2.75$), meaning it was not necessary to assess whether the linear slope depended on individual students.

3.2 Multivariate Results

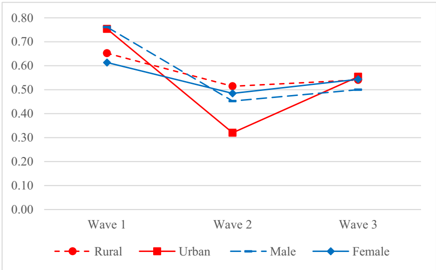
STEM Performance Improves Over Time Tables 2 and 3 show results of the multilevel growth curve modeling. The intercepts for all four models were statistically significant at the .001 significance level. The results show that by the second measurement occasion, the mean score was .56 for math ($SE = 0.06$, $p < .001$), .70 for integrated science ($SE = 0.11$, $p < .001$), .49 for ICT ($SE = 0.01$, $p < .001$), and .53 for BDT ($SE = 0.04$, $p < .001$). Overall, there was a statistically significant ($p < .001$) linear improvement in performance in all four subjects over time (γ_{10}, math = .48, $SE = 0.05$; science = .47, $SE = 0.05$; ICT = .41, $SE = 0.03$, and technology = .42, $SE = 0.02$). This means every time students sit for the end-of-term exam or national standardized exam, their performance goes up in all four subject areas by .41 to .48 points.



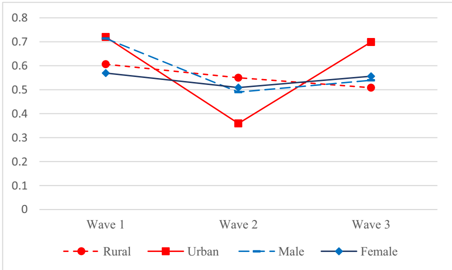
(a) Math



(b) Integrated science



(c) Information and communication technology



(d) Basic design and technology

Fig. 1 Graph of STEM performance trajectories by locality and gender. Note: In this study, time is measured in weeks. The interval between Wave 1 and 2 is 15 weeks, and Wave 2 and 3 is 10 weeks. (**a**) Math, (**b**) Integrated science, (**c**) Information and communication technology and (**d**) Basic design and technology

The quadratic terms were positive and statistically significant in all four models: math ($\gamma_{01} = 0.13$, $SE = 0.03$, $p < .001$), integrated science ($\gamma_{01} = 0.09$, $SE = 0.03$, $p < .001$), ICT ($\gamma_{01} = 0.19$, $SE = 0.03$, $p < .001$), and BDT ($\gamma_{01} = 0.23$, $SE = 0.04$, $p < .001$). These significant quadratic effects suggest that the increase in STEM performance accelerated marginally over time. The accelerated improvement was faster for BDT (0.23) followed by ICT (0.19), math (0.13), and integrated science (0.09).

Linear Growth Varies by Student The linear slope varied significantly across students: Math ($u_1 = .014$, CI, [0.005 0.034]) integrated science ($u_1 = .009$, 95% CI [.001, .045]), ICT ($u_1 = .018$, 95% CI [.009, .039]), and BDT models ($u_1 = .012$, 95% CI [.001, .181]). These significant results suggest different rates of linear increase in STEM subject performance among students.

Some Forms for Social Support Matter Parental involvement was not a significant predictor in any of the models: math ($\gamma_{04} = 0.001$, $SE = 0.03$, $p = .68$), integrated science ($\gamma_{04} = -0.0002$, $SE = 0.006$, $p = .95$), ICT ($\gamma_{04} = -0.002$, $SE = 0.003$, $p = .63$), and BDT ($\gamma_{04} = .0001$, $SE = 0.001$, $p = .08$). Teacher support was a significant predictor in the positive direction in all four models ($\gamma_{05,}$ math = .06, SE = .02, $p < .01$; integrated science = 0.07, $SE = 0.01$, $p < .001$; ICT = 0.03, $SE = 0.01$, $p < .05$, and BDT = 0.03, $SE = 0.01$, $p < .05$). In contrast, peer support was negatively predictive of all four outcomes (γ_{05}, math = −0.04, $SE = 0.01$, $p < .01$; integrated science = 0.04, $SE = 0.02$, $p < .05$; IT = −0.01, $SE = 0.003$, $p < .001$; BDT = −0.04, $SE = 0.01$, $p < .05$).

Table 2 Multilevel growth curve results of student performance in math and integrated science

	Math		Integrated science	
	Conditional growth model	Conditional growth model with random effects	Conditional growth model	Conditional growth model with random effects
Fixed effects	*β*(*Robust SE*)	*β*(*Robust SE*)	*β*(*Robust SE*)	*β*(*Robust SE*)
For Intercept (β_{0j})				
Intercept, (γ_{00})	0.58 (0.04)***	0.56 (0.06)***	0.69 (0.10)***	0.70 (0.11)***
Time^2 (γ_{01})	0.13 (0.03)***	0.13 (0.03)***	0.09 (0.03)**	0.09 (0.03)**
Female (Male = 0) (γ_{02})	0.01 (0.04)	0.03 (0.02)	−0.03 (0.03)	−0.02 (0.03)
Rural (Urban = 0) (γ_{03})	−0.26 (0.08)***	−0.26 (0.08)***	−0.37 (0.09)***	−0.37 (0.08)***
Parents' role (γ_{04})	<−0.01 (<0.01)	<−0.01 (<0.01)	<−0.01 (0.01)	−0.002 (0.01)
Peers' role (γ_{05})	−0.04 (0.01)**	−0.04 (0.01)**	−0.04 (0.02)*	−0.04 (0.02)*
Teachers' role (γ_{06})	0.05 (0.02)**	0.06 (0.02)**	0.07 (0.01)***	0.07 (0.01)***
Academic self-efficacy (γ_{07})	0.01 (0.02)	0.01 (0.02)	<−0.01 (0.02)	−0.001 (0.02)
Female*Parent's role (γ_{08})	<−0.01 (0.01)	<−0.01 (<0.01)	<0.01 (0.01)	<0.01 (0.01)
Female*Rural (γ_{09})	0.02 (0.06)	0.00 (0.05)	0.05 (0.05)	0.05 (0.05)
For Time Slope (β_{1j})				
Time (γ_{10})	0.48 (0.05)***	0.48 (0.05)***	0.47 (0.05)***	0.47 (0.05)***
Female*Time (γ_{11})	−0.07 (0.05)	−0.07 (0.04)	−0.09 (0.05)	−0.09 (0.05)
Rural*Time (γ_{12})	−0.44 (0.01)***	−0.44 (0.01)***	−0.47 (0.01)***	−0.47 (0.01)***
Random effects				
Intercept, u_0	$1.52^{e-25}(5.14^{e-23})$	.003(0.003)	$1.31^{e-23}(5.54^{e-21})$	.001(0.007)
Time slope, u_1		.009(0.004)**		.006(0.005)
Level-1, r_{ij}	.027(0.005)	.015(0.005)**	.030(0.005)***	.024(0.012)*
Cov(Time, Intercept)		−.0004(0.003)		−.0002(0.003)
Model fit indices				
N	307	307	307	307
AIC	−231.25	−260.86	−194.94	−208.56
ΔAIC		29.61		13.62
BIC	−220.07	−253.4	−183.76	−201.11
Log-likelihood	118.62	132.43	100.47	106.28

* $p < .05$, ** $p < .01$, ***, $p < .001$; *SE*, Standard error; *AIC*, Akaike information criterion; Δ*AIC*, Change in Akaike information criterion; *BIC*, Bayesian information criterion

Gender Differences Depend on Subject Area and Evolve over Time The main effects for gender were mixed, as the results show that gender is predictive of ICT ($\gamma_{02} = 0.05$, $SE = 0.01$, $p < .001$) and BDT performance ($\gamma_{02} = 0.03$, $SE = 0.01$, $p < .01$), but not math ($\gamma_{02} = 0.03$, $SE = 0.02$, $p > .05$) and integrated science ($\gamma_{02} = -0.02$, $SE = 0.03$, $p > .05$). When gender was significant, it favored girls. Girls scored 0.05 points more in ICT and 0.03 more in BDT than their male counterparts.

The statistically nonsignificant two-way gender interaction terms (gender and parent's role, γ_{08}; gender and locality, γ_{09}; and gender and time, γ_{11}) mean there is no evidence in the data to support a hypothesis of significant gender differences based on the level of parental involvement, locality, and linear trends. However, although the slight gender gap in favor of girls was not significant, it is worth noting that over time,

Table 3 Multilevel growth curve results of student performance in information and communication technology (ICT) and basic design and technology (BDT)

	Information technology		Basic design and technology	
	Conditional growth model	Conditional growth model with random effects	Conditional growth model	Conditional growth model with random effects
Fixed effects	β(*Robust SE*)	β(*Robust SE*)	β(*Robust SE*)	β(*Robust SE*)
For Intercept (β_{0j})				
Intercept, (γ_{00})	0.52 (0.02)***	0.48 (0.01)***	0.61 (0.06)***	0.53 (0.04)***
Time^2 (γ_{01})	0.19 (0.02)***	0.20 (0.02)***	0.22(0.04)***	0.23(0.04)***
Female (Male = 0) (γ_{02})	0.05 (0.01)***	0.05 (0.01)***	0.03(0.01)**	0.03 (0.01)**
Rural (Urban = 0) (γ_{03})	−0.32 (0.04)***	−0.30 (0.05)***	−0.24(0.03)***	−0.24(0.03)***
Parents' role (γ_{04})	<−0.01(<0.01)	−0.002 (0.003)	−0.0003(0.001)	−0.001(0.001)
Peers' role (γ_{05})	−0.03 (0.01)**	−0.01 (0.003)***	−0.04(0.02)*	−0.04(0.01)*
Teachers' role (γ_{06})	0.06 (0.02)**	0.03 (0.02)*	0.04(0.01)***	0.03(0.01)***
Academic self-efficacy (γ_{07})	<−0.01 (0.01)	0.01 (0.01)	0.01(0.02)	0.02(0.02)
Female*Parent's role (γ_{08})	<−0.01 (<0.01)	<−0.01 (<0.01)	−0.0003(0.002)	0.001(0.002)
Female*Rural (γ_{09})	−0.04 (0.02)	−0.04 (0.03)	−0.04(0.02)	−0.04(0.03)
For Time Slope (β_{1j})				
Time (γ_{10})	0.41 (0.03)***	0.41 (0.03)***	0.42(0.02)***	0.42 (0.02)***
Female*Time (γ_{11})	−0.05 (0.02)**	−0.05 (0.02)**	0.08 (0.03)**	0.08(0.02)***
Rural*Time (γ_{12})	−0.48 (0.01)***	−0.48 (0.01)***	−0.56 (0.01)***	−0.56(0.02)***
Random effects				
Intercept, u_0	1.50^{e-25}(4.05^{e-23})	0.006(0.001)***	2.8^{e-18}(7.87^{e-16})	0.015(0.006)**
Time slope, u_1		0.013(0.005)*		0.002(0.001)**
Level-1, r	0.029(0.008)**	0.013(0.003)**	0.029(0.008)**	0.019(0.004)*
Cov(Time, Intercept)		0.006(0.002)**		0.005(0.001)***
Model fit indices				
N	307	307	307	307
AIC	−209.62	−274.98	−185.15	−221.19
ΔAIC		65.36		36.04
BIC	−198.44	−267.53	−129.24	−157.83
Log-likelihood	107.81	139.49	107.57	127.59

*$p < .05$, **$p < .01$, ***$p < .001$; *SE*, Standard error; *AIC*, Akaike information criterion; Δ*AIC*, Change in Akaike information criterion; *BIC*, Bayesian information criterion

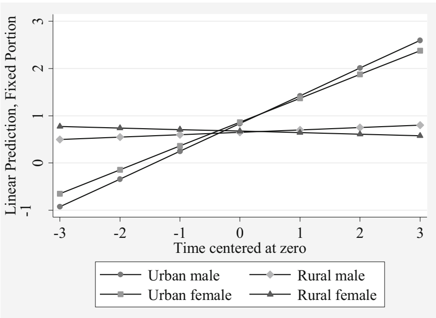
the marginal gender gap flips to favor boys as illustrated by the predictive margins in Fig. 2. Except for BDT, boys start with lower scores, but over time, they outperform girls by a slim margin.

Rural Students Show Promise but their Performance Declines Over Time The main effect of schooling in a rural area was consistently significant in the negative direction for all four STEM subjects: math ($\gamma_{03} = -0.26$, $SE = 0.08$, $p < .001$), integrated science ($\gamma_{03} = -0.37$, $SE = 0.08$, $p < .001$), ICT ($\gamma_{03} = -0.30$, $SE = 0.05$, $p < .001$), and BDT ($\gamma_{03} = -0.24$, $SE = 0.03$, $p < .001$). In each subject area, rural students scored lower compared to students in urban areas.

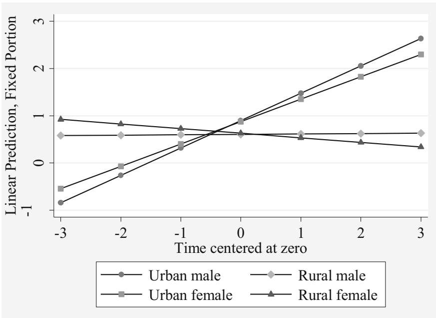
The predictive margins in Fig. 2 show that heterogeneity in STEM performance trends is more pronounced based on locality (i.e., rural vs. urban) than gender (i.e., boys vs girls). As shown in Tables 3 and Fig. 2, the interaction term for rural and time was significant but negative, regardless of the subject area: math ($\gamma_{12} = -0.44$, $SE = 0.01$, $p < .001$), integrated science ($\gamma_{12} = -0.47$, $SE = 0.01$, $p < .001$), ICT ($\gamma_{12} = -0.48$, $SE = 0.05$, $p < .001$), and BDT ($\gamma_{12} = -0.56$, $SE = 0.02$, $p < .001$). These results mean that unlike their urban peers, overall, the average rural student experienced a decline in their performance on all four STEM subjects. In other words, the linear change in STEM performance depends on whether the student attends school in a rural or an urban area. As depicted in the predict margins in Fig. 2, STEM performance in rural areas follow two trajectories over time: they either remain unchanged (i.e., in the case of math and integrated science) or decline over time (i.e., in the case of ICT and BDT). In contrast, performance in urban areas follows only one trajectory: a consistent upward trend.

4 Discussion

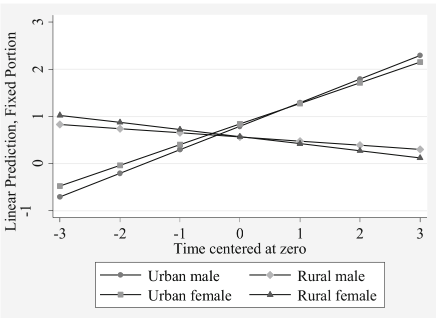
The study's three objectives were to investigate performance trajectories in STEM subjects, determine the predictive role of social support and psychological well-being, and examine the extent to which the trajectories depend on gender (boys vs. girls) and



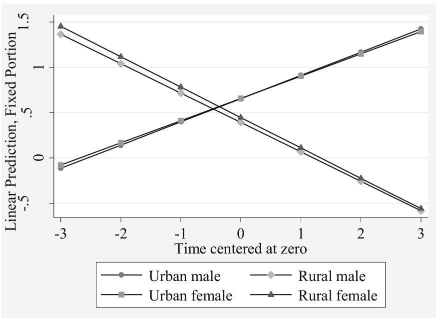
(a) Math



(b) integrated science



(c) Information and communication technology



(d) Basic design and technology

Fig. 2 Graphs showing predictive margins of locality and time interaction by gender. (**a**) Math, (**b**) Integrated science, (**c**) Information and communication technology and (**d**) Basic design and technology location of the school (rural vs. urban). The multilevel growth curve results show that overall, students' STEM performance improves by the time they take the national standardized test. Minimal gender differences exist but depend on the subject area and evolve with time.We observed an urban advantage, with the performance of students in rural areas starting well but declining over time. We also noticed that teacher support was a strong predictor of good performance in STEM subjects.

Findings from this study add to our understanding regarding how girls' STEM performance is promising and consistent across time. Our findings are consistent with studies conducted in the high-income countries where girls' performance in STEM subjects were consistently higher than boys (American Association of University Women Educational Foundation 2008; Voyer and Voyer 2014). In the current study, the direction of the main effect of gender favored girls in all four models, but noteworthy is that only the coefficients for ICT and BDT were statistically significant. In the STEM literature, girls often outperform boys in mathematics and science, but this new finding suggests that they have the capacity to outperform boys in a wide range of STEM areas.

A novel contribution of this study is the growth curve modeling of STEM performance trajectories, which reveals nonstationary findings that should concern STEM education stakeholders. Though there is "a gender similarity" in STEM performance (Hyde 2005; Hyde and Mertz 2009) where boys and girls have the same capabilities to succeed in STEM subjects, girls may be affected by sociocultural contexts over some time (Wang and Degol 2014). As shown in the predictive margins in Fig. 2 and the gender*time interaction term in Tables 2, girls' slight advantage over boys overturns with time. This phenomenon probably reflects how sociocultural influences may be masked in the short-term and manifest in the long run. With a few exceptions, girls around the world are raised to view STEM careers as a masculine profession. Over time, such stereotypes and misconceptions can dampen girls' interests, attitudes, and motivations to pursue STEM careers (Ceci et al. 2014; Diekman et al. 2010). There is a need to sustain girls' interest and motivation for STEM. Targeted empowerment programs that engage, motivate, and expose girls to female STEM career professionals may help sustain girls' STEM interest, but there needs to be greater effort in this regard. In Ghana, the *STME* Clinics initiated in the late 1980s to expose more girls to female scientists may have narrowed the gender gap in the pursuit of STEM careers (Andam et al. 2013). Nonetheless, findings from our predictive margins, which forecast that over time boys overtake girls marginally, should caution educators and policymakers to ensure that STEM interventions such as *STME* Clinics build in long-term measures to sustain girls' interest, motivation, and efforts in STEM.

Consistent with prior research, we found an urban advantage; urban schools perform better than their rural counterparts over the course of time. Students in urban areas have access to infrastructure, financial, and human resources (Ansong et al. 2018), which may facilitate STEM education more than in rural areas. Indeed, the introduction of the Science Resource Centre Project in Ghana in the late 1990s helped narrow the urban-rural gap in access to STEM laboratories and equipment for effective teaching and learning of science, but this program only targeted the senior high level. Given the current study's finding that the urban-rural divide in STEM performance is pervasive at the junior high level, programs like the Science Resource Centre Project may be beneficial at the junior high level to address the locality disparities at the lower levels of education. The need to invest more in STEM education resources at the junior high school level is even more important given the ample evidence that many children decide to pursue STEM career paths at the junior high level (Archer et al. 2013; Kiwana et al. 2011). In the long term, a broader strategy is needed to address the rural-urban disparities in allocation of education resources at all levels of education. Urban areas are exposed to better learning materials and have wide and good facilitation of teachers, attracting the best pool of STEM teachers who are dedicated to student learning. Good teachers might shun joining rural schools that lack computers and laboratories needed to facilitate STEM learning. As a result, students in rural schools may lack role models (Karikari 2015) as they are trained by less motivated teachers who are forced to rely on outdated teaching resources. Yet, research shows that access to role models increases students' interest and performance in STEM subjects (Shin, Levy, & London 2016).

Of the four predictors—role of parents, classmates, teachers, and students' self-efficacy beliefs—the growth curve modeling revealed that teacher's role was the most consistent positive predictor of STEM performance trajectory. Connecting back to the policy implications, governments in low-income countries will have to do more to improve remuneration for teachers, and teacher professional development to improve STEM performance. A UNESCO report on education in four African countries, including Ghana, found that teachers in schools were not utilizing laboratories for practical lessons due to lack of equipment, thus compromising the quality of education. With the changing face of STEM careers, there is a need for teachers to receive professional development that equips them with new ways of teaching and engaging students in STEM learning (Callingham et al. 2016).

We also observed student heterogeneity in STEM performance in the data, but differences in student performance in-and-of-itself are not alarming, particularly if there is an upward trajectory across the board. However, in our sample, we observed widely divergent directions of the trajectories, and that is worrisome and warrants intervention development. To improve STEM performance, particularly for those who experience downward trends, it may be necessary to initiate programs that identify students who are not performing well in STEM subjects and provide them with additional support. We recommend the expansion of the *STME* learning camps and clinics to the lower education levels to allow students who might be struggling in schools to receive early support in a non-threatening environment. In the last two decades, these clinics and camps have served over 40,000 girls and are credited with narrowing the gender gap in STEM at the senior high level in Ghana. The model could be adapted to the junior high level to address the performance gaps.

4.1 Limitations

As with most studies, this study has limitations. The study has weak external validity because even though the participating schools were selected from both rural and urban areas, they may not be heterogeneous enough to reflect the experiences of different students across Ghana fully, and for that matter other low-income countries. Second, the limited statistical power for the integrated science models means readers should exercise caution when drawing conclusions about results from the science model. Third, the study may have missed important predictors of STEM performances such as prior schooling experiences, thus increasing the risk of omitted variable bias and biased coefficients. Lastly, the use of different measurement scales for the three time occasions increases the risk of measurement error. Following best practice in the use of longitudinal and nested data (Denissen et al. 2007; Moreira et al. 2018; Moeller 2015), we used the POMS method to rescale the outcomes measures for comparability.

Notwithstanding these limitations, this study is significant for two reasons: First, the use of administrative data on performance and the advanced analytic approach to rescaling longitudinal data enhance the trustworthiness of the study findings. Second, conceptual and analytic focus on growth trajectories and temporal changes in STEM performance is an improvement over the far too common reliance on cross-sectional snapshot assessment of student performance. Third, the study highlights the need to focus on the structural and cultural impediments to STEM education at the lower levels of education in order not to risk leaving out girls and rural students early in the education system.

4.2 Conclusion

Support for STEM education is growing in low-income countries, but the steady movement towards inclusive STEM education is not only a supply-side issue. There is compelling evidence of excitement on the demand side as well. Children in low-income countries view STEM positively because they see STEM careers as an opportunity to improve their overall quality of life (Gouthier 2005). The above supply-side initiatives (although inadequate) and the favorable view of STEM among young people represent an opportunity to prioritize STEM education in Ghana and other low-income countries. To maximize and reap the benefits of STEM education in low-income countries, all children, regardless of their gender or where they live must not only have access to advanced education in STEM fields but also view of their future selves as STEM career professionals. Advancement of this goal for all children will require a greater emphasis on all three areas of STEM education: participation, performance, and inclusiveness.

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