Exploring Postsecondary STEM Pathways of Rural High School Students

Dr. Malle R Schilling, Arizona State University

Malle Schilling is an Assistant Professor in The Polytechnic School at Arizona State University. Malle's primary research areas focus on rural engineering education and workforce development, and understanding systemic influences on rural students' education and career pathways.

Felicity Bilow, Virginia Polytechnic Institute and State University

Felicity Bilow is a graduate student at Virginia Tech.

Whitney Elise Hansberry, Arizona State University, Polytechnic Campus
Dr. Sarah Rodriguez, Virginia Polytechnic Institute and State University

Sarah L. Rodriguez is an Associate Professor of Engineering Education and an affiliate faculty member with the Higher Education Program at Virginia Tech. Her engineering education research agenda centers upon engineering and computing identity development of historically marginalized populations at higher education institutions. Currently, Dr. Rodriguez is involved with several large-scale interdisciplinary research projects focused on institutional environments and STEM identity development are sponsored by the National Science Foundation (NSF) and the Kapor Center. In recent years, she was selected as an Early Career Awardee and Faculty Fellow with the American Association of Hispanics in Higher Education (AAHHE) and a NASPA Emerging Faculty Leader. She also received the Barbara Townsend Early Career Scholar Award by the Council for the Study of Community Colleges (CSCC) and gave the distinguished ASHE-CAHEP Barbara Townsend Lecture. To learn more about her current projects, visit http://sarahlrodriguez.com/

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Introduction.

This work-in-progress empirical research paper explores the factors influencing the STEM pathways of rural high school students in the U.S. as they transition to postsecondary education. Rural students pursue higher education [1], [2] and STEM postsecondary education [3] at lower rates than non-rural students. Their limited participation in higher education and STEM postsecondary education is primarily due to systemic challenges and barriers rural school districts and communities encounter because of their location. Rural communities are more likely to be in "education deserts," meaning they are not easily accessible to higher education institutions [4], which may prevent rural students from obtaining and leveraging the benefits these institutions are known to provide. For example, higher education institutions can help local students develop an interest in postsecondary education [4], [5] and provide students with STEM outreach opportunities [6]. Furthermore, rural school districts tend to lack the funding and resources required to provide students with STEM opportunities [6], which can contribute to students' interest in pursuing STEM. Therefore, to understand more about rural students who do go on to pursue STEM, this work-in-progress examines the following research questions:

1. What are the postsecondary STEM enrollment pathways of rural students?
    a. How do math and science interest, identity, utility, and efficacy vary for rural students on different pathways?
2. What are the characteristics of rural students who pursue STEM pathways?

Theoretical Framework.

Social Cognitive Career Theory (SCCT) [7] guided this study. SCCT, a widely used and well-validated theoretical framework in STEM education research, allowed us to explore the social interactions and experiential activities that influenced students' career choices. SCCT is particularly well-suited to studying environmental changes and marginalized groups (e.g., [8]), and has been used widely in engineering education and rural education research (e.g., [1],[9],[10]). SCCT focuses on three main areas: self-efficacy (beliefs about capabilities), outcome expectations (beliefs about the results of actions), and personal goals (intentions guiding behavior). Using SCCT acknowledges the importance of individual characteristics, personal inputs, and learning environments (e.g., rurality, gender, socioeconomic status) as well as socialization processes (e.g., course taking, identity development) in the learning process. This framework also acknowledges that, throughout the learning process, a student's self-efficacy shapes their career interests, goals, and actions, either toward or away from STEM pathways. SCCT was used to inform the formation of research questions and variable selection, which reflect the framework's main focus areas. In addition, SCCT guided the data analysis and the interpretation of findings in alignment with the elements of the theoretical framework.

Methods.

This study leveraged a quantitative approach informed by K-medoids clustering and descriptive statistics. K-medoid clustering is appropriate for handling mixed data types (i.e., categorical, continuous, and Likert data) and weighted survey data [11], [12], and is therefore a suitable analysis technique for the type of data used in this study from the public-use HSLS:09 dataset. HSLS:09 contains STEM-focused data from over 25,000 students about their high school and college experiences and pathways. The sample consisted of rural students in the U.S. as identified by the rural and town NCES [13] locale codes of their most recent high school enrollment. Data included in this study consist of HSLS:09 data collection periods beginning in 2009, when students were in 9th grade, and again in 2012 and 2016 as students progressed through high school and into their postsecondary pathways. The final sample included 4,877 rural students from the U.S. (Appendix A).

K-medoids clustering was used to identify clusters based on rural students' STEM engagement, affective characteristics, and enrollment patterns. Variables were selected and included in cluster analysis based on their relevance to the theoretical framing and purpose of this study, and based on having lower degrees of missing data for the sample (Appendix B). Descriptive statistics were used to explore the clusters identified through cluster analysis, with analyses conducted in R (v4.1.1; [14]) using the *Weighted Cluster* and *srvyr* packages [15], [16] and applying HSLS:09 replicate weights (W4W1STU).

This research has a few limitations. First, the role that transferring from a two-year to a four-year institution plays in rural students' STEM postsecondary pathways was not examined because this information is not included in the dataset. Additionally, the public-use HSLS dataset has substantial missing data due to various reasons, making it difficult to perform certain analyses when sample sizes are small and hindering our preliminary analyses.

Preliminary Results.

Results of the cluster analysis suggested three clusters within the rural student sample, determined by visual analysis of the silhouette plot, which showed small silhouette widths (average width of 0.04), suggesting overlap between clusters. Though not ideal, this is perhaps not surprising given the nature of the data and the sample. The three clusters may be characterized in the following ways: Cluster 1 generally demonstrated stronger STEM characteristics and often first enroll in four-year institutions; Cluster 2 may be described as a STEM-focused group of students who first enroll in a variety of pathways, though their STEM characteristics decreased throughout high school; and finally, Cluster 3 may be described as a group of students not as focused in STEM who pursue a variety of institutional pathways. The following results should be interpreted with caution given the exploratory nature of the study.

RQ1: Pathways and STEM Characteristics for All Rural Students.

Race and gender demographics across the clusters are mostly similar to those of the overall sample, with some differences (Appendix C, Table 1). For example, Cluster 2 seemed to have greater representation of Asian, Hispanic, and multiracial students than the overall sample.

Almost half of all rural students did not enroll in a STEM degree at the time of the second data collection (Appendix C, Table 2). Cluster 1 had a higher percentage of students enrolled in science, engineering, and math degrees, and psychology and other social sciences. Cluster 2 had a higher percentage of students enrolled in health and medicine compared to Clusters 1 and 3.

Furthermore, business and health professions were consistently the degrees with the highest first-time enrollment for students in this sample (Appendix C, Table 3). Engineering was one of the more popular degrees, but not nearly as popular as others across all clusters (e.g., 5.32% engineering enrollment compared to 17.81% enrollment for health professions in Cluster 2).

Cluster 1 consisted primarily of students who first enrolled in four-year institutions (Appendix C, Table 3). Cluster 2 represented a mix of student enrollment across institution types. Cluster 3 was more balanced between students who first enrolled in four-year and two-year institutions. Looking at patterns of institutional selectivity (Appendix C, Table 4, defined by the 2016 Carnegie Classifications) for all rural students, Cluster 1 represented students who first enrolled in four-year institutions that were moderately selective. Cluster 2 represented a mix of enrollment in highly and moderately selective four-year institutions, which was about equivalent to enrollment in two-year institutions within this cluster. Cluster 3 represented greater degrees of enrollment in two-year institutions compared to highly selective and moderately selective four-year institutions.

For math affective characteristics of all students (Appendix C, Table 5), students in Cluster 1 demonstrated more positive developments over time as indicated by the positive increase in weighted means for math utility, efficacy, and interest, whereas math identity remained unchanged. Cluster 2 students' weighted means trended negatively, showing decreased math identity, utility, efficacy, and interest. Weighted means for math affective characteristics for Cluster 3 students were the most negative, and trended negatively, except for math utility and efficacy, which increased over time. The overall averages for math affective characteristics were greater for students in Cluster 1 compared to students in Clusters 2 and 3.

Students in Cluster 1 demonstrated positive developments in science identity, efficacy, and interest, though utility remained unchanged (Appendix C, Table 6). Again, the characteristics of Cluster 2 students trended negatively, indicating decreased science identity, utility, efficacy, and interest. Cluster 3 students' characteristics showed positive trends across all science affective characteristics, except for science identity, which remained unchanged. The averages for science affective characteristics were greater for students in Cluster 1 than those in Clusters 2 and 3.

RQ2: STEM Characteristics for Rural STEM Students.

Rural STEM students were further defined using the NSF STEM designation, focusing on those students who pursued a degree in science, engineering, or math. Race and gender demographics differ slightly when comparing rural STEM students to all rural students, but are overall comparable in terms of patterns of representation for race and ethnicity and gender compared to the sample of all rural students (Appendix C, Table 7).

Rural STEM students in all three clusters first attended four-year institutions at greater rates compared to other institution types (Appendix C, Table 3). The patterns of institutional selectivity for rural STEM students are similar to those of all rural students; rural STEM students in Cluster 1 attended moderately selective four-year institutions at greater rates than other clusters, and Cluster 2 and Cluster 3 were split between first-time student attendance at four-year and two-year institutions. STEM degrees in medical pathways were still among the most popular enrollments for rural STEM students, but so were degrees in engineering, biology and related sciences, and computer information sciences.

For math affective characteristics of rural STEM students (Appendix C, Table 10), patterns differed slightly when compared to all rural students. Weighted means for math identity and interest trended upward while math utility and efficacy trended downward for Cluster 2. Additionally, math utility, efficacy, and interest trended positively over time for students in Cluster 3, while math identity decreased. Weighted means for rural STEM students were all positive compared to those for all rural students, suggesting that rural STEM students tend to always have more positive math affective characteristics.

For affective science characteristics of rural STEM students (Appendix C, Table 11), Cluster 1 generally showed positive development in science identity, efficacy, and interest, though utility decreased over time. Weighted means for science utility and efficacy in Cluster 2 generally trended negatively, while identity and interest increased. Weighted means for science identity trended positively over time across all clusters. The weighted means for rural STEM students were all positive compared to those for all rural students, suggesting that rural STEM students tended to have more positive science affective characteristics.

Preliminary Discussion.

Results suggest that rural students who had stronger math and science affective characteristics that developed positively in high school were more likely to pursue postsecondary education at four-year institutions. This could be for a number of reasons, such as greater access to four-year institutions and to academic preparation in high school. In addition, the results suggest that institution type and institutional selectivity may influence rural students' overall postsecondary enrollment and their specific STEM enrollment. Notably, some rural students tend to pursue their educational pathways through moderately selective four-year institutions, while many others pursue pathways through two-year institutions (i.e., community colleges). Though institutional selectivity is not currently used as an institutional characteristic in Carnegie classifications, this is not surprising given existing literature suggesting that rural students are likely to pursue their education through community colleges [17] and that there are universities with broader access missions that are rurally located and/or rural-serving [18]. Results also suggest that many rural students likely experienced some decline in their affective STEM characteristics throughout high school, which may have been more detrimental to those who decided not to pursue STEM than to those students who did and generally had stronger math and science affective characteristics.

This work-in-progress explores the potential for cluster analysis with national datasets as a useful method for understanding differences in rural student postsecondary enrollment pathways and pre-college characteristics. Future research will build on the preliminary results to examine differences between STEM disciplines to the extent possible and examine differences between pathways of rural and nonrural students. Additionally, future research will also consider more specific personal characteristics related to socioeconomic status (SES) and parental levels of education, as well as other indicators of STEM engagement through high school extracurriculars and course-taking, and the extent to which these factors influence rural students' STEM postsecondary pathways.

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Appendices.

Appendix A - Total Sample Demographics

Sample Description, Race and Gender as Percent of Total Sample (% of N=4,877 students)

	Male	**Female**
Amer. Indian/Alaska Native, non-Hispanic	0.33	0.47
Asian, non-Hispanic	4.00	4.26
Black/African-American, non-Hispanic	4.18	4.65
Hispanic, no race specified	0.33	0.25
Hispanic, race specified	4.80	5.64
More than one race, non-Hispanic	3.98	4.68
Native Hawaiian/Pacific Islander, non-Hispanic	0.14	0.14
White, non-Hispanic	28.40	33.75

Appendix B - Variables in Analysis

Variables	**Description**	**SCCT Connection**
X1MTHID and X2MTHID; X1SCIID and X2SCIID	Math and Sci Identity Composite in BY (X1) and F1 (X2)	Self-efficacy, interest
X1MTHUTI and X2MTHUTI; X1SCIUTI and X2SCIUTI	Math and Sci Utility Composite in BY (X1) and F1 (X2)	Outcome expectations
X1MTHEFF and X2MTHEFF; X1SCIEFF and X2SCIEFF	Math and Sci Efficacy Composite in BY (X1) and F1 (X2)	Self-efficacy
X1MTHINT and X2MTHINT; X1SCIINT and X2SCIINT	Math and Sci Interest Composite in BY (X1) and F1 (X2)	Interests
X1STU30OCC_STEM1 and X2STU30OCC_STEM1	Expected occupation at 30 in STEM domain (BY and F1)	Goals
X3THIMATH and X3THISCI	Highest level of math and science taken (HS transcripts)	Learning experiences, context
X4REFLEVEL, X4REFSELECT	Institution level and selectivity (F2)	Attainment
X4RFMJSTNSF	Degree/major enrolled by NSF STEM domains (F2)	Attainment
X4OCC1STEM1	First job after high school in STEM (F2)	Attainment
X4STU30OCC2	Expected occupation at 30 (F2)	Attainment
DERMTHEXTRA1, DERSCIEXTRA1, DERMTHEXTRA2, DERSCIEXTRA2	Derived variables combining original variables about participation in science and math extracurriculars (BY and F1)	Learning experiences, context
S2ANYDUAL	Taken any dual enrollment course (F1)	Learning experiences, context
S2FFA, S2HOSA, DERCLGPREP	Participated in other programs (FFA and HOSA) and other college prep (derived variable) (F1)	Learning experiences, context
DERHSMTHTAKING1, DERHSSCITAKING1	Derived variables combining original variables about influences on math and science course taking in high school (F2)	Learning experiences, context
DERMENJOYS1, DERMCHALLENGE1, DERMTHENC1, DERMTHNEED1; DERSENJOYS1, DERSCHALLENGE1, DERSCIENC1, DERSCINEED1	Derived variables combining original variables about enjoyment of math and science and enjoying challenges, and reasons taking math and science in high school (BY)	Learning experiences, context

NOTE: Base year (BY), first follow up (F1), second follow up (F2)

Appendix C - Results Tables

Table 1

Race and Gender Demographics as Percents of the Cluster Sizes

	Cluster 1 (n = 1,486)		Cluster 2 (n = 2,482)		Cluster 3 (n = 909)	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Amer. Indian/Alaska Native, non-Hispanic	0.54	0.61	0.12	0.32	0.55	0.66
Asian, non-Hispanic	3.70	4.17	4.23	4.71	3.85	3.19
Black/African-American, non-Hispanic	3.70	4.24	3.71	4.03	6.27	7.04
Hispanic, no race specified	0.47	0.13	0.24	0.24	0.33	0.44
Hispanic, race specified	3.97	5.25	5.28	5.96	4.84	5.39
More than one race, non-Hispanic	3.70	4.51	4.07	4.79	4.18	4.62
Native Hawaiian/Pacific Islander, non-Hispanic	0.07	0.20	0.20	0.08	0.11	0.22
White, non-Hispanic	29.61	35.13	28.32	33.68	26.62	31.68

Table 2

NSF Field of Study for First Enrollment by Cluster, represented as % of total cluster size

	Cluster 1 (n = 1,486)	Cluster 2 (n = 2,482)	Cluster 3 (n = 909)
Science, Engineering, Math	29.21	27.44	20.46
Psychology and Other Social Sciences	9.62	6.16	5.72
Health and Medicine	7.27	9.55	7.92
Other Field of Study (Not STEM)	45.56	44.20	50.06
NA	8.34	12.65	15.84

Table 3
Popularity of Degrees for First Time Post-secondary enrollment, % of total cluster size

	Cluster 1 (n = 1,486)		Cluster 2 (n = 2,482)		Cluster 3 (n = 909)	
	Degree	**%**	**Degree**	**%**	**Degree**	**%**
Most Popular (top 5)	Business, Management, Marketing, and Related Support Services	14.47	Health Professions and Related Clinical Sciences	17.81	Health Professions and Related Clinical Sciences	16.5
	Health Professions and Related Clinical Sciences	14.2	Business, Management, Marketing, and Related Support Services	11.85	Business, Management, Marketing, and Related Support Services	14.19
	Biological and Biomedical Sciences	7.34	Education	5.92	Education	7.04
	Engineering	5.85	Biological and Biomedical Sciences	5.92	Visual and Performing Arts	3.96
	Education	5.85	Engineering	5.32	Engineering	3.41
Least popular (bottom 5)	Residency Programs	0.20	Architecture and Related Services	0.24	Residency Programs	0.22
	Architecture and Related Services	0.34	Natural Resources and Conservation	0.32	Transportation and Materials Moving	0.22
	Construction Trades	0.34	Legal Professions and Studies	0.36	Foreign languages, literatures, and Linguistics	0.33
	Mechanic and Repair Technologies/Technicians	0.40	Multi/Interdisciplinary Studies	0.40	Natural Resources and Conservation	0.44
	Precision Production	0.40	Foreign languages, literatures, and Linguistics	0.44	Communications Technologies/Technicians and Support Services	0.55

Table 4

Institutional Level by Cluster, represented as % of total cluster size

	All Rural Students			Rural STEM Students		
Institutional Level	**Cluster 1 (n = 1,486)**	**Cluster 2 (n = 2,482)**	**Cluster 3 (n = 909)**	**Cluster 1 (n = 1,486)**	**Cluster 2 (n = 2,482)**	**Cluster 3 (n = 909)**
4 year	87.35	55.72	47.19	27.05	19.70	11.44
2 year	11.37	39.20	47.30	2.15	7.37	8.80
Less than 2 year	1.21	4.83	5.17	NA	0.36	0.22
NA	0.07	0.24	0.33	*NA*	*NA*	*NA*

Table 5

Institutional Selectivity by Cluster, represented as % of total cluster size

	All Rural Students			Rural STEM Students		
Selectivity	**Cluster 1 (n = 1,486)**	**Cluster 2 (n = 2,482)**	**Cluster 3 (n = 909)**	**Cluster 1 (n = 1,486)**	**Cluster 2 (n = 2,482)**	**Cluster 3 (n = 909)**
	19.04	19.14	10.67	6.26	8.66	3.30
	53.90	18.69	21.89	16.42	6.16	5.61
Inclusive, 4yr	7.81	9.79	8.58	2.49	2.50	1.87
	6.59	8.10	6.05	1.88	2.38	0.66
	11.37	39.20	47.30	2.15	7.37	8.80
	1.21	4.83	5.17	*NA*	0.36	0.22
NA	0.07	0.24	0.33	*NA*	*NA*	*NA*

Table 6

Average Weighted Means of Math Affective Variables by Data Collection

		Cluster 1	Cluster 2	Cluster 3
	Grade 9 (2009)	0.200	0.301	-0.452
Math - Identity	Grade 12 (2012)	0.191	0.233	-0.729
	Change	-0.009	-0.068	-0.277
	Grade 9 (2009)	-0.117	0.141	-0.534
Math - Utility	Grade 12 (2012)	0.091	0.119	0.051
	Change	0.208	-0.021	0.585
	Grade 9 (2009)	0.130	0.170	-0.377
Math - Efficacy	Grade 12 (2012)	0.208	0.082	-0.319
	Change	0.078	-0.088	0.058
	Grade 9 (2009)	0.025	0.232	-0.208
Math - Interest	Grade 12 (2012)	0.112	0.076	-0.379
	Change	0.086	-0.157	-0.171

Table 7

Average Weighted Means of Science Affective Variables by Data Collection

		Cluster 1	Cluster 2	Cluster 3
	Grade 9 (2009)	0.40	0.07	-0.13
Science - Identity	Grade 12 (2012)	0.44	0.01	-0.12
	Change	0.04	-0.06	0.01
	Grade 9 (2009)	0.03	0.03	-0.33
Science - Utility	Grade 12 (2012)	0.02	0.00	0.01
	Change	-0.01	-0.03	0.34
	Grade 9 (2009)	0.29	0.04	-0.11
Science - Efficacy	Grade 12 (2012)	0.33	-0.02	0.34
	Change	0.04	-0.07	0.45
	Grade 9 (2009)	0.19	0.04	-0.13
Science - Interest	Grade 12 (2012)	0.30	-0.11	0.05
	Change	0.11	-0.14	0.18

Table 8
Race and Gender Demographics as Percents of the Cluster Sizes, STEM students

	Cluster 1 (n = 1,486)		Cluster 2 (n = 2,482)		Cluster 3 (n = 909)	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Amer. Indian/Alaska Native, non-Hispanic	0.07	0.34	NA	0.08	NA	0.22
Asian, non-Hispanic	2.15	1.01	2.46	1.89	0.99	0.66
Black/African-American, non-Hispanic	0.94	0.94	0.89	0.81	0.88	1.87
Hispanic, no race specified	0.13	NA	0.04	NA	NA	NA
Hispanic, race specified	1.55	1.62	1.41	1.13	0.66	1.10
More than one race, non-Hispanic	1.14	1.28	1.01	1.13	0.88	0.88
Native Hawaiian/Pacific Islander, non-Hispanic	NA	0.20	0.08	NA	NA	NA
White, non-Hispanic	9.35	8.48	7.90	8.62	6.38	5.94

Table 9
Popularity of Degrees for First Time Post-secondary enrollment, STEM students, % of total cluster size

	Cluster 1 (n = 1,486)		Cluster 2 (n = 2,482)		Cluster 3 (n = 909)	
	Degree	**%**	**Degree**	**%**	**Degree**	**%**
Most Popular (top 4)	Biological and Biomedical Sciences	7.34	Health Professions and Related Clinical Sciences	7.86	Health Professions and Related Clinical Sciences	8.03
	Health Professions and Related Clinical Sciences	6.53	Biological and Biomedical Sciences	5.92	Engineering	3.41
	Engineering	5.85	Engineering	5.32	Biological and Biomedical Sciences	2.75
	Computer and Information Sciences and Support Services	2.62	Computer and Information Sciences and Support Services	0.11	Computer and Information Sciences and Support Services	2.31
Least popular (bottom 4)	Natural Resources and Conservation	1.28	Engineering Technologies/Technicians	0.12	Mathematics and Statistics	0.99
	Agriculture, Agriculture Operations, and Related Sciences	1.01	Multi/Interdisciplinary Studies	0.08	Physical Sciences	0.55
	Mathematics and Statistics	0.67	Social Sciences	0.04	Natural Resources and Conservation	0.44
	Multi/Interdisciplinary Studies	0.13	Business, Management, Marketing, and Related Support Services	0.04	Agriculture, Agriculture Operations, and Related Sciences	0.33

Table 10

Average Weighted Means of Math Affective Variables by Data Collection, STEM Students

		Cluster 1	Cluster 2	Cluster 3
Math - Identity	**Grade 9 (2009)**	0.429	0.292	0.210
	Grade 12 (2012)	0.542	0.535	0.184
	Change	0.113	0.243	-0.026
Math - Utility	**Grade 9 (2009)**	0.042	0.444	0.099
	Grade 12 (2012)	0.304	0.321	0.252
	Change	0.262	-0.122	0.153
Math - Efficacy	**Grade 9 (2009)**	0.304	0.461	0.106
	Grade 12 (2012)	0.372	0.336	0.196
	Change	0.068	-0.124	0.089
Math - Interest	**Grade 9 (2009)**	0.204	0.232	0.017
	Grade 12 (2012)	0.389	0.260	0.199
	Change	0.185	0.027	0.182

Table 11

Average Weighted Means of Science Affective Variables by Data Collection, STEM Students

		Cluster 1	Cluster 2	Cluster 3
Science - Identity	**Grade 9 (2009)**	0.601	0.431	0.269
	Grade 12 (2012)	0.784	0.491	0.674
	Change	0.183	0.060	0.405
Science - Utility	**Grade 9 (2009)**	0.200	0.359	NA
	Grade 12 (2012)	0.041	0.026	NA
	Change	-0.158	-0.333	--
Science - Efficacy	**Grade 9 (2009)**	0.535	0.364	NA
	Grade 12 (2012)	0.544	0.273	NA
	Change	0.010	-0.091	--
Science - Interest	**Grade 9 (2009)**	0.336	0.246	NA
	Grade 12 (2012)	0.492	0.265	NA
	Change	0.155	0.019	--