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STEM Pathways: Examining Persistence in Rigorous Math and Science Course Taking

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Abstract From 2006 to 2012, Florida Statute §1003.4156 required middle school students to complete electronic personal education planners (ePEPs) before promotion to ninth grade. The ePEP helped them identify programs of study and required high school coursework to accomplish their postsecondary education and career goals. During the same period Florida required completion of the ePEP, Florida's Career and Professional Education Act stimulated a rapid increase in the number of statewide high school career academies. Students with interests in STEM careers created STEM-focused ePEPs and may have enrolled in STEM career academies, which offered a unique opportunity to improve their preparedness for the STEM workforce through the integration of rigorous academic and career and technical education courses. This study examined persistence of STEM-interested (i.e., those with expressed interest in STEM careers) and STEM-capable (i.e., those who completed at least Algebra 1 in eighth grade) students ($n = 11{,}248$), including those enrolled in STEM career academies, in rigorous mathematics and science course taking in Florida public high schools in comparison with the national cohort of STEM-interested students to measure the influence of K-12 STEM education efforts in Florida. With the exception of multi-race students, we found that Florida's STEM-capable students had lower persistence in rigorous mathematics and science course taking than students in the national cohort from ninth to eleventh grade. We also found that participation in STEM career academies did not support persistence in rigorous mathematics and science courses, a prerequisite for success in postsecondary STEM education and careers.

Keywords Career academies · Electronic personal education planner · Persistence · Rigorous math and science course taking · STEM-capable

Introduction

The USA is at a crossroads as it seeks to maintain its global leadership in science and technology innovation amid challenges with globalization (e.g., declines in H1-B visa allocations), and policy debates concerning perceived surpluses or shortages in the science, technology, engineering, and mathematics (STEM) workforce (Committee on Prospering in the Global Economy of the 21st Century 2007; National Science Board 2015). According to the latest Global Competitiveness Report (Schwab and Sala-i-Martín 2015), the USA has sustained its placement, behind Switzerland and Singapore, but some argue the STEM workforce shortage remains (Locke 2009; National Economic Council 2011). However, most agree it is critical for the USA to produce an innovative and robust STEM workforce to sustain its global leadership and competitiveness (Carnevale et al. 2011; Committee on

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Underrepresented Groups and the Expansion of the Science and Engineering Workforce Pipeline 2010; National Academy of Sciences, National Academy of Engineering, and Institute of Medicine 2007; National Research Council 2011; National Science Board 2015). As a result, USA policymakers, researchers, administrators, and educators at all levels are seeking effective interventions in K-12 STEM education to stimulate early interest in STEM careers and strengthen STEM career pathways for all students (Carnevale et al. 2011; Locke 2009). In this paper, we focus our attention on Florida's response to this national issue.

From 2006 to 2012, Florida Statute § 1003.4156 (2006) required students who entered the sixth grade to create an electronic personal education planner (ePEP) on the Florida Academic Counseling and Tracking for Students website (FACTS.org) before promotion to ninth grade. Most students created ePEPs during the eighth grade while enrolled in a required course (FACTS.org 2010). The assumption is that a clearly defined programs of study, such as the ePEP, will help facilitate successful navigation through education and career pathways (Trusty et al. 2005). In 2010, over half (57.6 %) of all students enrolled in Florida's secondary schools had created an ePEP (FACTS.org 2010). The ePEP served as a means to facilitate career exploration as students selected their desired programs of study and career pathways, by identifying career interests based on the national 16 career clusters framework (National Association for State Directors of Career and Technical Education Consortium 2014) and related high school coursework (FACTS.org 2012). The intent of the ePEP requirement was to provide students with a 'plan of record' for their postsecondary education and career goals, high school course taking, and fulfillment of graduation requirements as they matriculated from ninth to twelfth grades. Students with expressed interests in STEM careers in eighth grade (hereafter referred to as STEM-interested students) developed STEM-focused ePEPs, which included various levels of rigorous or advanced mathematics and science courses based on their intended goals and academic achievements. During the same period that Florida required completion of the ePEP for promotion to ninth grade, Florida's Career and Professional Education Act stimulated a rapid increase in the number of statewide high school career academies (Florida Department of Education 2014). The career academy is a national instructional model, facilitated by an interdisciplinary team of teachers, that is intended to provide a nurturing and supportive environment for small learning communities of students (Stern et al. 1992). Amid other career options, students may choose to enroll in STEM-focused career academies that offer career planning and hands-on experiences while integrating academic (i.e., mathematics and science) and career and technical education (CTE) courses (Kemple and Willner 2008; Stern et al. 1992).

This study examined STEM-interested students' persistence in rigorous mathematics and science course taking in Florida, in comparison with national cohort of STEM-interested students to measure the influence of K-12 STEM education efforts in Florida. Florida's ePEP requirement and increased availability of STEM career academies offered a unique opportunity to improve students' preparedness for the STEM workforce. In light of these efforts, we were interested in the following questions: What proportion of the STEM-interested students enroll in STEM-related career academies? Are there differences in course taking patterns among STEM-interested students who do or do not enroll in such academies? How do the course taking patterns of STEM-interested students in Florida compare with other students in the USA?

Review of Literature

To further explore factors related to the questions identified above, we first examined the extant literature to determine influences on early STEM interests and aspirations, rigorous mathematics and science course taking, and participation in STEM career academies on persistence in rigorous course taking, and postsecondary STEM education and careers.

Early STEM Interests and Aspirations

Students who indicate interests in STEM, as soon as eighth grade, are most likely to earn an undergraduate degree in a STEM field (Maltese and Tai 2011). Among these students, African American and low-income students are more likely than their affluent White counterparts to develop STEM aspirations, although fewer of them attain STEM postsecondary degrees (Lichtenberger and George-Jackson 2013; Riegle-Crumb et al. 2011). Regardless of race or ethnicity, students' aspirations in STEM postsecondary education and careers are developed based on their intrinsic interests and extrinsic experiences in rigorous mathematics and science course taking, as early as middle school (Maltese and Tai 2011; Sadler et al. 2014; Tai et al. 2006). Moreover, male students are 2.9 times more likely to develop interests in STEM careers than female students during high school (Sadler et al. 2012).

Rigorous Mathematics and Science Course Taking

Students who participate in increased numbers of rigorous courses (i.e., advanced placement—AP) develop stronger interests in STEM careers (Sadler et al. 2014). Several studies have defined rigorous mathematics and science course taking experiences according to the Burkam and

Lee (2003) mathematics and science pipeline classifications (see Figs. 1, 2) (Castellano et al. 2004; Choy 2001; Gottfried et al. 2014; Maltese and Tai 2011; Sadler et al. 2014; Teitelbaum 2003; Tyson et al. 2007). These classifications were developed based on transcript data extracted from the National Educational Longitudinal Study of 1988 (US Department of Education 1992). These transcript data were analyzed and constructed into three course taking pipelines for mathematics, science, and foreign language, which aligns with the National Assessment of Educational Progress[1] (NAEP) classifications (NCES 2016). In this paper, we focus on the mathematics and science pipelines.

Algebra 1 is used as a benchmark to ascertain high school students' trajectory along the mathematics pipeline (Fig. 1) as defined by Burkam and Lee (2003). The mathematics pipeline consists of eight levels of mathematics course taking experiences of forty-seven mathematics courses or classifications, which are further categorized into four sub-categories (non-academic, low-academic, middle academic, and advanced academic) to define students' rigorous mathematics course taking experiences in secondary education. According to Burkam and Lee (2003), high school students most commonly complete mathematics courses at levels 4 (22.7 %) and 5 (20.7 %), followed by the lowest three levels (21.5 %). The remaining distribution of high school students (34.9 %) complete courses in the top three levels, including 11 % of students who complete Calculus or greater. Furthermore, students who complete Algebra 1 before high school (e.g., seventh grade) have notable persistence in rigorous mathematics course taking during high school and beyond (National Mathematics Advisory Panel 2008). Mathematics course taking also affects students' likelihood to choose a mathematics or science-intensive undergraduate major (Federman 2007).

Similar to the mathematics pipeline classification, the science pipeline (Burkam and Lee 2003) identifies possible science course taking experiences in secondary education. The science pipeline classification (Fig. 2) consists of six levels comprised of four broad categories (no science, primary physical sciences, secondary physical sciences, and secondary life sciences) to define students' rigorous science course taking experiences in secondary education. Biology 1 (68 %) is the most common science course completed by high school students, followed by Chemistry (41 %), Physical Science (39 %), Earth Science (18 %), and Physics (18 %). Upon further analysis by level, the majority of high school students only complete up to level 1 (35.4 %), and collectively levels 2 and 3 (19.5 %). Twenty-five percent of students achieve level 4 by completing Chemistry 1 or Physics 1. Nearly 12.2 % may complete both Chemistry 1 and Physics 1 to attain level 5, and a small percentage (7.1 %) achieve level 6 upon completion of Chemistry 2 or Physics. Overall, high school science course taking predicts attainment of a STEM undergraduate degree (Adelman 1999; Tyson et al. 2007), and Biology course taking is an indicator of students' trajectory along the science pipeline (Burkam and Lee 2003; Finkelstein et al. 2012).

White and Asian students take more advanced levels of rigorous courses than Black and Hispanic students (Maltese and Tai 2011; Tyson et al. 2007). Although Black and Hispanic students may have a higher interest in STEM careers upon entering high school, they often lack access to advanced levels of rigorous courses due to limited resources and funding at their schools (Lichtenberger and George-Jackson 2013).

Participation in STEM Career Academies

CTE offers multiple delivery systems and programmatic structures, such as STEM-themed high schools, specific programs of study, schools within schools, and comprehensive high schools to provide students with rigorous mathematics and science course taking experiences (Stone 2011). These targeted interventions, including career academies, are designed to prepare students for postsecondary STEM education and career pathways through the integration of academic (i.e., mathematics and science) and CTE courses (Kemple and Willner 2008; McCharen and High 2010; Stern et al. 1992; Stone 2011). Career academies have mostly targeted minority students (Fletcher and Cox 2012), and Black and Hispanic students have historically had high participation rates in CTE (Fletcher and Zirkle 2009; Gordon 2014). Research indicates participation in STEM career academies positively influences rigorous mathematics and science course taking and persistence in secondary STEM education (Association for Career and Technical Education 2009; Castellano et al. 2004; McCharen and High 2010; Stone 2011).

Persistence in High School Rigorous Course Taking

Students' persistence in STEM pathways is impacted by numerous factors such as early aspirations in STEM careers (Maltese and Tai 2011), rigorous mathematics and science course taking (Maltese and Tai 2011; Sadler et al. 2014; Tai et al. 2006), high achievement scores (Schneider et al. 1998), and race and gender (Maple and Stage 1991; Trusty 2002; Tyson et al. 2007; Ware and Lee 1988). High school is a critical time frame for students to leave (e.g., attrition), enter or stay (e.g., persistence) in the STEM pipeline,

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[1] NAEP is a nationally representative and continuing assessment that is managed by the US Department of Education's National Center for Education Statistics (NCES) (NCES 2016).

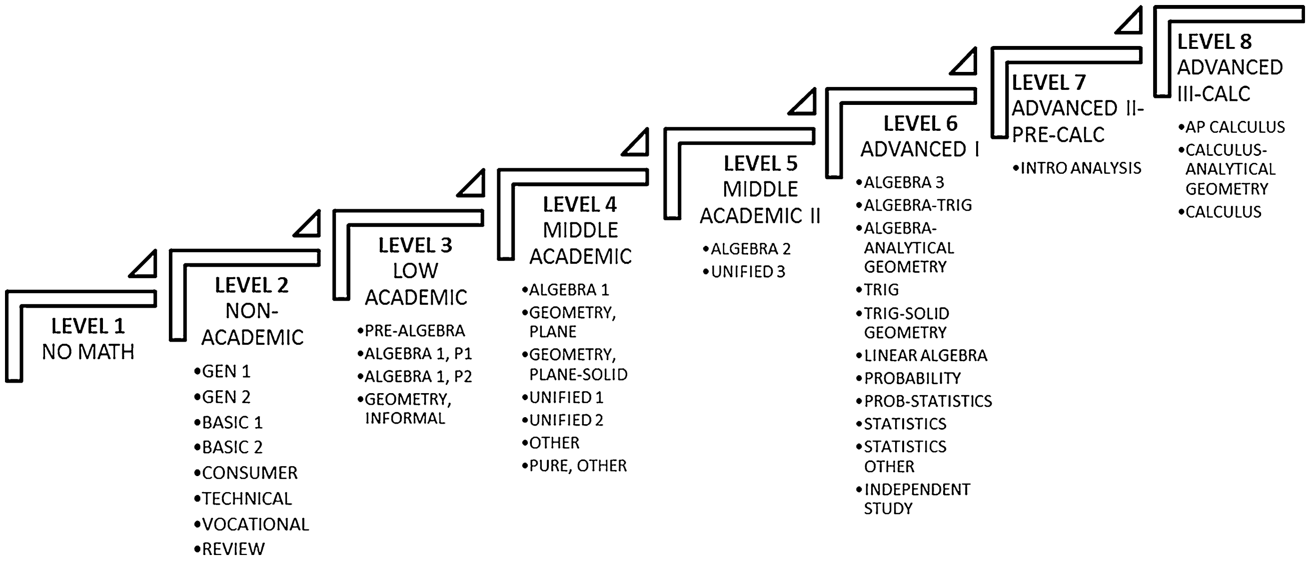

Fig. 1 Mathematics pipeline classification adapted from Burkam and Lee (2003)

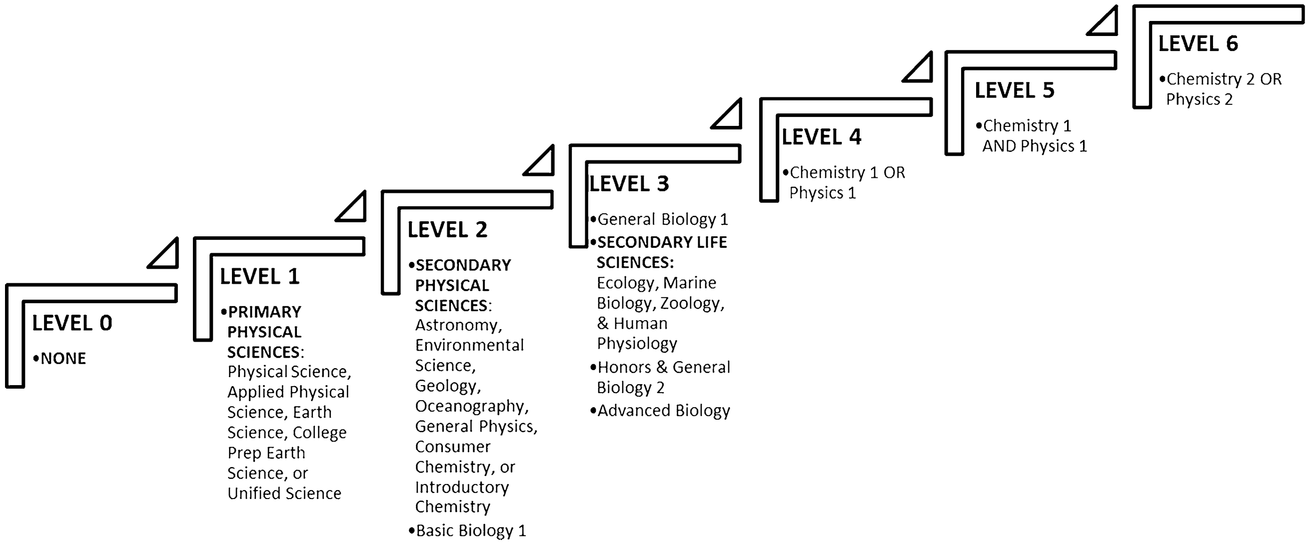

Fig. 2 Science pipeline classification adapted from Burkam and Lee (2003)

because 80 % of STEM college graduates enter the pipeline in high school or college (Hilton and Lee 1988; Maltese and Tai 2011; Tai et al. 2006). In high school, males are more likely than females to choose a STEM major (Lichtenberger and George-Jackson 2013; Maltese and Tai 2011; Seymour et al. 1997). Moreover, Black and Hispanic students who engage in advanced levels of rigorous mathematics and science course taking are more likely than White students to persist in obtaining a STEM degree.

Extant research has investigated the positive influence of students' interest on rigorous course taking (Burkam and Lee 2003), early STEM interests and aspirations on rigorous mathematics and science course taking (Maltese and Tai 2011; Sadler et al. 2014; Tai et al. 2006), and rigorous course taking on STEM degree attainment (Schneider et al. 1998), and has revealed clear connections between students' early STEM interests and aspirations, rigorous mathematics and science course taking patterns, and persistence in postsecondary STEM education and careers. However, the absence of studies about students' rigorous course taking patterns and persistence while enrolled in STEM career academies warranted further study (McCharen and High 2010; Stone 2011). One might conclude from the literature that students who indicate early interests in STEM and have access to career planning tools, such as the ePEP, which provides guidance about courses to complete in preparation for college and careers, would be more likely to take advantage of STEM education opportunities, which includes participation in STEM career academies and engagement in rigorous coursework, to support their preparation for postsecondary STEM education. This study is an attempt to test our hypothesis and to measure the effect of Florida's STEM education efforts on STEM-interested students.

The Study

In this study (Kersaint and Kromrey 2012), we investigated the rigorous mathematics and science course taking patterns of Florida's STEM-interested high school students who created STEM-focused ePEPs in eighth grade during the 2009–2010 academic year. In particular, we examined their persistence in rigorous mathematics and science course taking from ninth to eleventh grade while enrolled in public high schools and STEM career academies, which are intended to provide rigorous coursework and career guidance for students at all achievement levels, regardless of race or gender (Fletcher and Cox 2012; Stern et al. 1992). We used Burkam and Lee (2003) mathematics and science pipeline classifications to define their rigorous course taking patterns. Moreover, we used propensity score methods to measure their overall persistence in taking rigorous mathematics and science courses, which is an indication of their preparedness for postsecondary STEM degree programs and the STEM workforce. STEM-interested students were classified as STEM-capable if they completed at least Algebra 1, Geometry, or Physical Science by the eighth grade. STEM-capable student outcomes in Florida were compared to the outcomes of a national sample of STEM-capable students to determine the extent to which Florida's proactive efforts in career planning and STEM career academy implementation provided a useful model for increasing rigorous mathematics and science course taking based on the following research questions.

1. To what extent did a national cohort of STEM-capable high school students persist in rigorous mathematics and science course taking in grades 9–11 during the 2010–2011 to 2012–2013 academic years?
2. To what extent did a cohort of STEM-capable high school students enrolled in Florida's public schools persist in rigorous mathematics and science course taking while enrolled in grades 9–11 and STEM career academies during the 2010–2011 to 2012–2013 academic years?
3. To what extent did the mathematics and science course taking trends of Florida's STEM-capable students compare to the mathematics and science course taking trends of a national sample of STEM-capable students?

Data Sources

To compare outcomes of Florida's STEM-interested students with national student outcomes, we identified both national and statewide secondary data sources that are described below.

High School Longitudinal Study of 2009 (HSLS:09)

We obtained access to the US Department of Education's National Center of Education and Statistics HSLS:09 restricted-use dataset (Ingels et al. 2009) and follow-up studies (HSLS:11 and HSLS:13). These datasets included demographic, school, career aspiration, mathematics and science course taking, and achievement variables for individual students in the USA. Ninth graders enrolled in public high schools (weighted $n = 12{,}299$) were selected for the analysis. HSLS STEM-capable students in public high schools at baseline were identified by enrollment in rigorous (Burkam and Lee 2003) eighth-grade math courses with a grade of C or better and intent to enroll in rigorous ninth grade math courses or enrollment in rigorous eighth-grade science courses with a grade of C or better and intent to enroll in rigorous ninth grade science courses (Table 1). STEM-capable[2] persistence for the first follow-up (2011) was defined by enrollment in either rigorous math or science courses (Table 2). In addition to enrollment in rigorous math or science courses, a student must have participated in the baseline survey and attended a high school at the time of the follow-up survey.

Florida Department of Education Data Warehouse (EDW)

Data were obtained from the Florida Academic Counseling and Tracking for Students site (FACTS.org 2012) on Florida eighth-grade students from 2009 to 2010 who created a STEM-focused ePEP survey, which was used to identify the initial STEM-interested (ePEP) sample. FACTS.org (2012) was a student advising site of the Florida Center for Advising and Academic Support, which became a part of the new Florida Virtual Campus during the 2012 Legislative Session. We obtained raw data files[3] from the EDW (FLDOE 2016). The EDW files were linked by an anonymized identifier that permitted the merging of mathematics, science, and vocational course transcripts and student demographics. Student demographic and transcript files were used to develop a description of the ePEP sample to identify their STEM and non-STEM attributes ($n = 11{,}238$). The baseline sample for

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[2] See Table AI.1 in the electronic supplementary material, which contains the demographic distribution of the HSLS and EDW STEM-capable cohorts.

[3] See Table AI.2 in the electronic supplementary material, which contains a listing of the EDW raw data files.

Table 1 Baseline criteria for HSLS STEM-capable cohort

Course[a]	Level (Burkam and Lee 2003)
Eighth grade[a]	
Advanced or Honors Math 8 (excluding Algebra)	4
Algebra I (including 1A and 1B)	4
Algebra II or Trigonometry	5
Geometry	4
Biology	3
Life Sciences	3
Pre-AP or pre_IB Biology	3
Chemistry	4
Environmental Science	2
Physics	4
Ninth grade[a]	AND
Geometry	4
Algebra II	5
Trigonometry	6
Statistics/Probability	6
Analytic Geometry	6
Advanced Math	6
Physics I	4
Chemistry I	4
Anatomy/Physiology	3
Advanced Biology	3
Advanced Chemistry	6
Advanced Physics	6

[a] With grade of C or better

Table 2 Follow-up criteria for HSLS STEM-capable persistence

Course[a]	Level (Burkam and Lee 2003)
Algebra III	6
Analytic Geometry	6
Trigonometry	6
Pre-calculus or Analysis and Functions	7
AP Calculus AB or BC	8
Other Calculus	8
AP Statistics	8
IB Mathematics, standard level	8
IB Mathematics, higher level	8
IB Biology	6
Anatomy or Physiology	3
Chemistry II	6
AP Chemistry	6
IB Chemistry	6
AP Environmental Science	6
IB Environmental Systems and Societies	6
Physics I	4
Physics II	6
AP Physics B or C	6
IB Physics	6
AP Computer Science	6
IB Design Technology	6
Engineering (general, robotics, aeronautical, mechanical, or electrical)	6

[a] With grade of C or better

Table 3 Baseline criteria for EDW STEM-capable cohort in eighth grade

Course[a]	Level (Burkam and Lee 2003)
Algebra I	4
Algebra I Honors	4
Algebra IA	3
Algebra IB	3
Algebra II Honors	5
Geometry	4
Geometry Honors	4
IB Geometry	5
Pre-AICE Mathematics	5
Pre-Calculus Honors	7
Anatomy and Physiology	3
Biology I	3
Biology I Honors	3
Chemistry I Honors	4
Earth/Space Science	1
Earth/Space Science Honors	1
Marine Science	2

propensity score analysis consisted of STEM-capable students ($n = 4913$) who were identified by rigorous math and science course taking in eighth grade (Table 3). For the outcome measures of STEM-capable persistence in ninth, tenth, and eleventh grades, we used the successful completion of rigorous mathematics and science courses (with a grade of C or better) compatible with grade level.[4]

We further identified STEM career academy students by their participation in STEM career academies. For this study, we initially classified career academy programs as STEM and non-STEM. Then, we combined multiple STEM classifications into one STEM career academy classification in part due to small frequencies of classifications.

Propensity Score Analysis

The propensity score is a statistic used to reduce selection bias in observational studies (Rosenbaum and Rubin 1983). The propensity score method attempts to mimic the balance

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[4] See Tables AI.3-5 in the electronic supplementary material for baseline criteria of the EDW STEM-capable cohort in grades 9–11.

Table 3 continued

Course[a]	Level (Burkam and Lee 2003)
Physical Science	1
Physical Science Honors	1

[a] With grade of C or better

that occurs in randomized studies which guarantee that two groups, on average, are balanced at the start of an experiment and therefore provide unbiased estimates of the average treatment effect. In observational studies, groups are not probabilistically similar, and the effect of the observed treatment may be due to unobserved, unmeasured baseline differences. Propensity scores predict an individual's probability for being assigned to the treatment group and can be used to create equivalent groups in observational studies. When units from the treatment and control group have the same propensity score, it is assumed that the probability of being assigned to the treatment group is the same for each of the individual units, conditional on the observed covariates, and the assumptions of SUTVA (stable unit treatment value) and strong ignorability (Stuart 2010). The purpose of using propensity score modeling for this research was to create treatment and control groups that were probabilistically similar at baseline so that effect of the observed treatment would be due to the difference between the 2 similar groups matched on the propensity scores.

Table 4 Covariates used to predict the propensity score in the Florida EDW dataset

Covariates	
Binary	Continuous
Asian	Achievement Level
Black	AL_Achv_Level
Hispanic	AL_Scale_Score
Multi-race	BI_Achv_Level
Female	BI_Scale_Score
Algebra1	Credit Attempted
Algebra1Honor	Credit Earned
Algebra2Honor	GE_Achv_Level
Biology1Honor	GE_Scale_Score
EarthSpaceHonor	Lunch
Geometry	Math8Ach_Lev
GeometryHonor	Math8DSS
IntegratedScience1Honor	Math8Score
PhysicalScienceHonor	Read8Ach_Lev
SLD	Read8DSS
	Read8Score
	SCALE_SCORE_2_0
	Sci8Ach_Lev
	Sci8Score
	Attempted8
	Earned8
	Grade_point8
	Mngradepoint8
	Sdgradepoint8

For the Florida EDW data, we used the propensity score method to compare students' persistence in STEM course taking from grades eight to 11 between STEM career academy students (treatment group) and regular STEM high school students (control group). The propensity score estimated the probability of being a STEM career academy student. For the HSLS data, we used the propensity score method to compare students' persistence in STEM course taking from grades nine to 11 between STEM high school students (treatment group) and non-STEM high school students (control group). The propensity score estimated the probability of being a STEM high school student. The steps used in the propensity score method included:

(a) Selection of covariates,
(b) Multiple imputations of missing data,
(c) Common support and balance diagnostics,
(d) Propensity score estimation,
(e) Propensity score conditioning, and
(f) Sensitivity analysis.

Discrete-time survival analysis provided the survival and hazard estimates for STEM persistence between the career academy and STEM high school students (Singer and Willett 1993). The probability of persistence in rigorous course taking among the HSLS:09 STEM high school students was reported with the Florida persistence probabilities to compare the Florida data with national trends in eleventh grade.

Selection of Covariates

Variables were selected to predict the propensity to be a STEM student (HSLS) or a STEM career academy student (Florida EDW) during high school. The variables for the HSLS:09 data were selected from the student, school, and parent surveys. In total, 227 covariates were selected for propensity score estimation with 156 binary and 71 continuous variables in the HSLS dataset.[5] For the Florida EDW dataset, covariates were selected based on demographic, math and science achievement scores, and eighth-grade math and science course taking (Table 4). A total of

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[5] See Tables AI.6-11 in electronic supplementary material, which provide the 227 covariates selected in the HSLS dataset.

Table 5 Reduced sample size after removal of observations with ≥50 % covariates missing

	Observations with ≥50 % covariates missing					
	Before removing			After removing		
	FL EDW STEM career academy[a]	FL EDW STEM high school[a]	HSLS STEM[c]	FL EDW STEM career academy[b]	FL EDW STEM high school[b]	HSLS STEM[c]
N	603	4310	3079	603	4310	2853

[a] Frequency missing = 30

[b] Frequency missing = 2

[c] Normalized weighted frequencies

15 binary and 24 continuous covariates for propensity score estimation were selected in the Florida EDW dataset.

Multiple Imputation of Missing Data

Variables in the HSLS and Florida EDW datasets were evaluated for missing values. Observations with 50 % or greater covariates missing were removed from the dataset, resulting in a reduction of sample size (Table 5). Multiple imputation was then performed using SAS PROC MI (SAS Institute 2010, which created five datasets with imputed values for the variables with incomplete data. The missing data for the covariate predictors was imputed prior to the estimation of the propensity score based on findings from a simulation study that indicated this sequence provided the least statistical bias for missing data patterns, i.e., missing completely at random (MCAR) and missing at random (MAR) (Rodriguez de Gil et al. 2015a).

Common Support and Balance Diagnostics

To assess common support (overlap) of the propensity score distribution between groups, box plots were examined before and after trimming.[6] To assess the balance between the groups on the selected covariates, we computed Cohen's *d* (standardized mean difference) for each continuous variable. A standardized mean difference smaller in magnitude than 0.25 (Stuart 2010) was used as our criterion for acceptable balance. Balance for dichotomous and discrete ordinal covariates was evaluated using odds ratios. Equivalent values of effect sizes for the odds ratio for a Cohen's *d* standardized mean difference of <0.25 ranged from ≥0.40 to ≤1.60 (Chen et al. 2010).

Propensity Score Estimation

A normalized survey weight for the HSLS dataset was included as a predictor for the propensity to be STEM. It was calculated by multiplying the student survey weight included in the baseline dataset by the quotient of sample size over the sum of weights (Eq. 1).

$$\text{Normalized student weight} = \text{student survey weight} \\ * (\text{sample } N/\text{sum of weights}) \tag{1}$$

Logistic regression was used to estimate the outcome for the propensity to be STEM in the national dataset or the propensity to be STEM career academy in the Florida EDW dataset for each imputation (Eq. 2). The outcome was predicted by the 39 covariates for the Florida dataset and 227 covariates and the normalized student weight (DuGoff et al. 2014) for the national dataset. The linear estimate XBETA was used as the propensity score measure.

$$\text{Logit}\,(Z-1) = \left[\frac{\text{Log e}^{x}}{1-\text{e}^{x}}\right] = \beta_0 + \beta_p X_p \tag{2}$$

Propensity Score Conditioning

In preparation for propensity score conditioning, normalized longitudinal weights for the HSLS datasets were calculated for each imputation using the longitudinal student weight provided in the follow-up dataset. Propensity scores for each imputation were conditioned using PS ANCOVA (Austin 2011; Lanehart et al. 2012; Shadish and Steiner 2010). The model outcome, STEM persistence, was predicted by the STEM cohort group and the linear propensity score. In the HSLS dataset, the linear propensity score was weighted by the normalized longitudinal weight. Also, the balanced repeated replication weights, or BRR weights, from the baseline survey were used as replicate weights. The odds of persistence (OR) was reported for the outcome measure.

The conditioning method, PS-ANCOVA, was chosen based on results from a simulation study that indicated this procedure, after caliper matching, had the least Type I error rate, mean bias, and confidence interval coverage in the presence of covariate measurement error (Rodriguez de Gil

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[6] See Figures AI.1a-d in the electronic supplementary material, which contains the propensity score distributions before and after trimming.

et al. 2015b). PS_ANCOVA retains greater generalizability than caliper matching due to loss of sample in caliper matching.

PS-ANCOVA and Model Specification

Several authors (see Austin 2011; Chen and Kaplan 2015) note the fact that the use of propensity score adjustment as a conditioning method can be hindered by possible model misspecification. The credibility of propensity score analysis is based on the assumption of "strongly ignorable treatment assignment" where it is assumed that all of the relevant covariates are included in the treatment assignment and that the bias due to *unmeasured* covariates is ignorable (see Lanehart et al. 2012, p. 8). The unmeasured covariate bias is reflected in the error of the model. Our research team has published a Monte Carlo simulation study that examined the effect of measurement error in seven different conditioning methods (see Rodriguez de Gil et al. 2015b). The selection of the conditioning method PS-ANCOVA for this research was based on the results of the simulation which indicated that caliper matching and PS-ANCOVA were the conditioning methods least likely to be impacted by Type I error rate, mean bias, and confidence interval coverage in the presence of covariate measurement error. Also, PS-ANCOVA has greater generalizability than caliper matching due to loss of sample in caliper matching (see Propensity score conditioning).

A sensitivity analysis was performed based on methods described by Hong 2004 and Lanehart et al. 2012. Results indicated that the lower and upper treatment effects adjusted for hidden bias, 0.30587 and 0.36245, respectively, with lower and upper adjusted CI (0.30135, 0.36697) had a minimal impact on altering the statistical inference of the unadjusted treatment effect estimate of 0.3342 (0.3277, 0.3406) which can be considered an unbiased estimate.

In another simulation study, our research team found that imputing the missing values of the covariates before estimating the PS resulted in the least amount of bias (see Rodriguez de Gil et al. 2015a). The authors feel that the imputation of missing values for the measured covariates does not contribute to the misspecification of the PS model but instead strengthens the estimate of the propensity score model (see multiple imputation of missing data).

Discrete-Time Survival Analysis

Survival of STEM persistence was analyzed using the discrete survival method (Allison 1995; Singer and Willett 1993). Discrete survival methods are desirable for educational data where events occur in discrete blocks of time, i.e., the school year. According to Singer and Willett (1993: 168), each student in the sample will persist through each sequential discrete-time period until the student experiences the "event of interest" or is "censored" at the end of the study. In this study, the event of interest was dropping out of rigorous STEM course taking.

Equation 3 represents the population hazard model where h_i defines the probability that individual i, identified by their specific predictor values, z_{1ij}, z_{2ij}, ... z_{pij}, will experience the event in time period j, given that they survived throughout the prior time periods (Singer and Willett 1993:164).

$$h_{ij} = \Pr\left\{T_{i=j} \parallel T_i \geq j, \quad Z_{1ij} = z_{1ij}, \quad Z_{2ij} = z_{2ij}, \ldots, Z_{pij} = z_{pij}\right\} \tag{3}$$

The chronology of each student's event history was recorded using a sequence of dummy variables, Y_{ij}, that were defined as:

$Y_{ij} = 0$ if student i does not drop out of rigorous STEM course taking in period j or 1 if student i does drop out of rigorous STEM course taking in period j.

Censoring was used to separately record whether each student's rigorous course taking was ended by the event of interest or by censoring. A student was censored (value of 1) in each discrete-time period if the student persisted in STEM course taking. If the student had dropped out of STEM course taking, then the student was not censored (value of 0). Also, the last time period that a student was enrolled in rigorous course taking was recorded. The event indicator, dummy variable Y, was created using the last time period and censoring information.

The interrelationship between the three parameters, censoring, last time period, and the event indicator, was used to construct the maximum likelihood function of survival. The likelihood of observing the data was derived from two sources: (1) for uncensored students, the probability that the event occurs in time period j_i; and (2) for censored students, the probability that the event occurs after time period j_i (Singer and Willett 1993, pp. 169, 171).

$$L = \prod_{i=1}^{n} \prod_{j=1}^{j_i} h_{ij}^{y_{ij}} \left(1 - h_{ij}\right)^{\left(1 - y_{ij}\right)} \tag{4}$$

Logistic regression was used to obtain the likelihood parameter estimates that were then used to estimate the discrete-time survival and hazard probabilities.

Survival probabilities of STEM persistence were estimated for the STEM-capable HSLS cohort in grade 11 and the STEM-capable Florida EDW career academy and high school students in grades 9, 10, and 11 for each imputation (Singer and Willett 1993: 177).

$$\hat{S}_j = \prod_{k=1}^{j} \left(1 - \hat{h}_k\right) \tag{5}$$

Table 6 Sample sizes before and after trimming for the HSLS and Florida EDW datasets

	Before trimming			After trimming		
	HSLS STEM*	FL STEM career academy	FL STEM high school	HSLS STEM*	FL STEM career academy	FL STEM high school
n	2853	605	4310	2832	603	4304

* Analytical sample *n* calculated using normalized weight

SAS PROC MIANALYZE was used to combine survival estimates across imputations. Persistence was also assessed by race and gender in both the HSLS and Florida EDW datasets.

Results

Propensity Score Comparisons

Common support (areas of overlap) for the propensity score distribution was evaluated, and areas of non-overlap were trimmed. Sample sizes before and after trimming are provided below (Table 6).

Balance of Covariates

For the HSLS[7] dataset, only three binary covariates, math competition (1.86), offsite Algebra II (1.71), and ninth grader enrolled in any Honors course (3.81), failed to meet the criteria for balance after conditioning. The binary balance estimates for the Florida EDW[8] dataset after conditioning were within the odds ratio (OR) effect size range for all of the predictors, i.e., range ≥ 0.40 to ≤ 1.60 ~Cohen's *d* of 0.25 (Chen et al. 2010). For the continuous covariates in the Florida EDW dataset, all standardized mean differences were <0.25 in absolute value.

Estimates of Treatment Effects

The odds of persistence for the HSLS STEM high school students are reported in Lanehart et al. 2014. The results of conditioning on the propensity score indicated that STEM career academy students, on the average, were 7 % less likely to persist in STEM course taking than STEM high school students[9] (Table 7).

Survival Analysis

In response to our research questions (a) we provide the estimated survival probabilities of STEM persistence for the national sample of STEM-capable students in grade 11, (b) we also provide the estimated survival probabilities of STEM persistence for the Florida STEM-capable students enrolled in STEM career academies and public high school cohorts from grades 9 to 11, and (c) we compare estimated survival probabilities of Florida STEM-capable students, including those who did or did not enroll in STEM career academies, with a national sample of STEM-capable students.

Persistence in rigorous course taking in grade 11 was equivalent between males and females (0.87) from the *national sample of STEM-capable students* (Table 8). Asian students (0.91) had the greatest probability of persistence in rigorous course taking in grade 11 followed by Multi-race (0.88), White (0.87), Hispanic (0.85), and Black (0.79) students (Table 8).

In Florida, female *STEM-capable students* began with lower probabilities of persistence in ninth grade than males but had higher persistence by grade 11 in both STEM career academies and public high schools (Table 8). Asian and White students (0.73) had the greatest probabilities of persistence in both career academies and high schools followed by Multi-race (0.67), then Black and Hispanic students (0.50) by grade 11 (Table 8). The probability of persistence in rigorous course taking in grade 11 by race indicated that Multi-race students (0.77) had the greatest probability of persistence in STEM career academies followed by White (0.68), Asian (0.53), Black (0.43), and Hispanic (0.38) students by grade 11 (Table 8). With the exception of Multi-race students, all ethnic minorities in

Table 7 Odds of STEM persistence for STEM career academy (Florida EDW dataset)

Imputation	Odds ratio	Lower CI	Upper CI
1	0.93	0.78	1.11
2	0.94	0.78	1.12
3	0.92	0.77	1.10
4	0.94	0.79	1.13
5	0.91	0.76	1.09
Overall	0.93	0.78	1.11

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[7] See Tables AI.6-11 in electronic supplementary material, which describe the HSLS covariates balance before and after conditioning results.

[8] See Tables AI.12-13 in electronic supplementary material, which describe the Florida EDW covariates balance before and after conditioning results.

[9] See Table AI.14 in electronic supplementary material, which provide the frequencies of persistence for the Florida and HSLS STEM-capable students.

Table 8 Survival probabilities of persistence in rigorous course taking among national (HSLS) and Florida (EDW) STEM-capable students

	Group									
	National (HSLS) STEM-capable high school students			Florida (EDW) STEM-capable STEM career academy students			Florida (EDW) STEM-capable high school students			*p* value
Grade	9	10	11	9	10	11	9	10	11	
Cohort			0.87	0.78	0.66	0.57	0.82	0.72	0.65	<.001
Race										
Multi-race			0.88	0.94	0.83	0.77	0.91	0.75	0.67	0.37
White			0.87	0.88	0.78	0.68	0.90	0.81	0.73	0.10
Asian			0.91	0.70	0.61	0.53	0.84	0.78	0.73	0.01
Black			0.79	0.70	0.54	0.43	0.75	0.60	0.50	0.24
Hispanic			0.85	0.57	0.45	0.38	0.67	0.56	0.50	0.004
Gender										
Female			0.87	0.78	0.69	0.62	0.81	0.72	0.66	0.36
Male			0.87	0.78	0.65	0.55	0.83	0.72	0.64	<.001

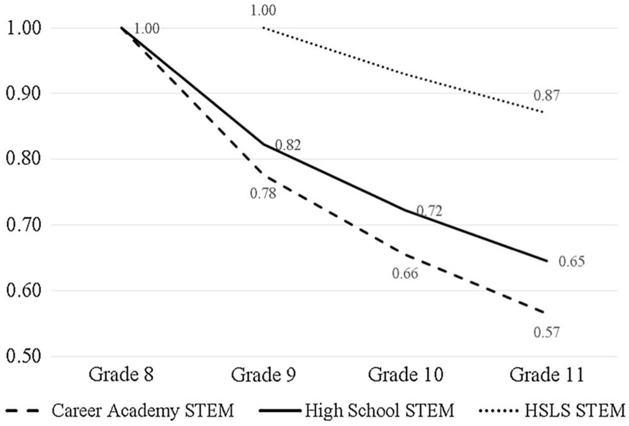

Fig. 3 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) STEM-capable students

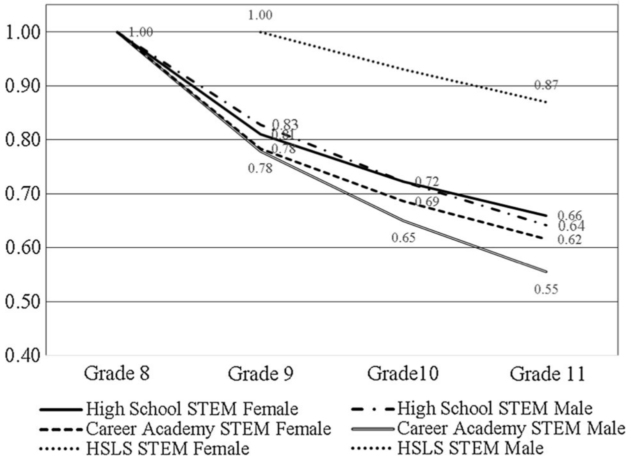

Fig. 4 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) STEM-capable students by gender

STEM career academies had lower probabilities of persistence in rigorous mathematics and science course taking than high school students by grade 11 (Table 8).

National Trends Versus Florida Trends of STEM Persistence

Persistence probabilities for all racial categories in the national sample of STEM-capable high school students were higher than both Florida's STEM-capable students who were enrolled in STEM academies and public high schools (Table 8; Figs. 3, 4, 5, 6, 7, 8, 9). The survival probabilities indicated that persistence[10] in rigorous course taking was higher among Florida STEM-capable students enrolled in public high schools than similar students enrolled in STEM career academies by grade 11 ($p < 0.001$) (Table 8), but lower than the national sample of STEM high school students (Fig. 3).

Discussion

This study builds upon the limited knowledge about the impact of students' participation in STEM career academies on their persistence in rigorous mathematics and science course taking and compares the rigorous STEM course taking patterns of Florida and national high school students. It sheds light on outcomes related to strategies used in Florida to develop STEM pathways and to adequately prepare students for the STEM workforce through career exploration tools, such as the ePEP, and career-

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[10] See Table AI.14 in electronic supplementary material, which provide the frequencies of persistence for the EDW and HSLS.

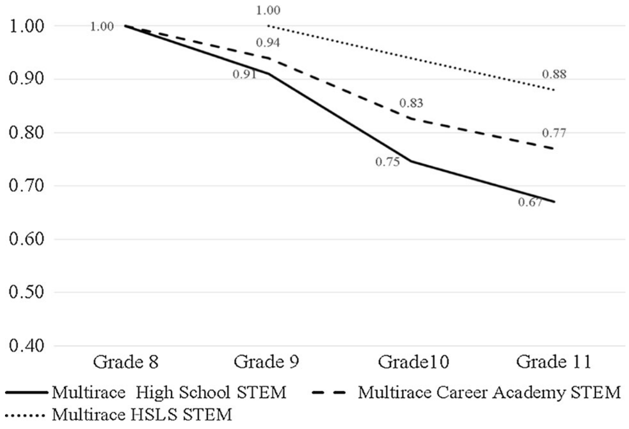

Fig. 5 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) Multi-race STEM-capable students

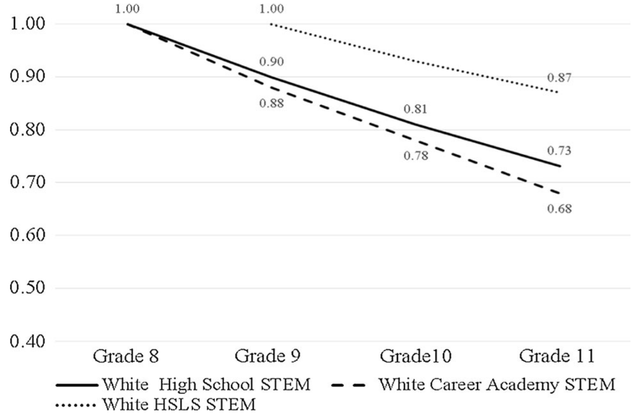

Fig. 6 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) White STEM-capable students

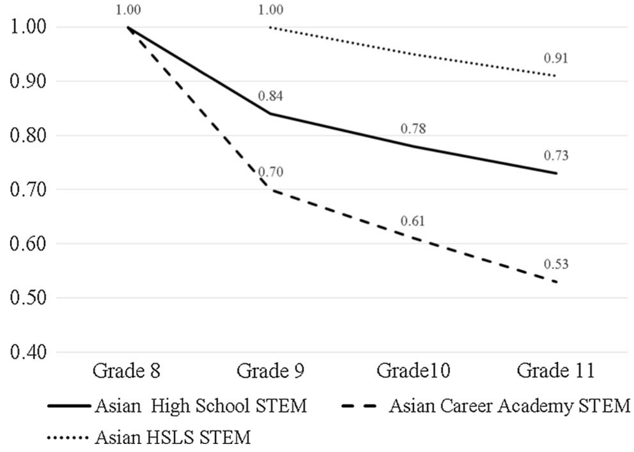

Fig. 7 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) Asian STEM-capable students

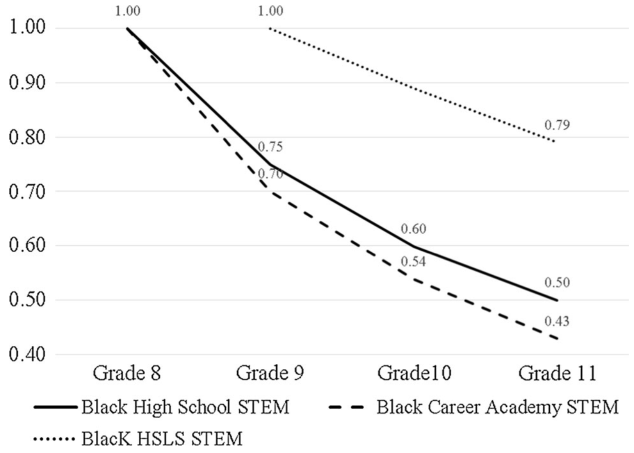

Fig. 8 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) Black STEM-capable students

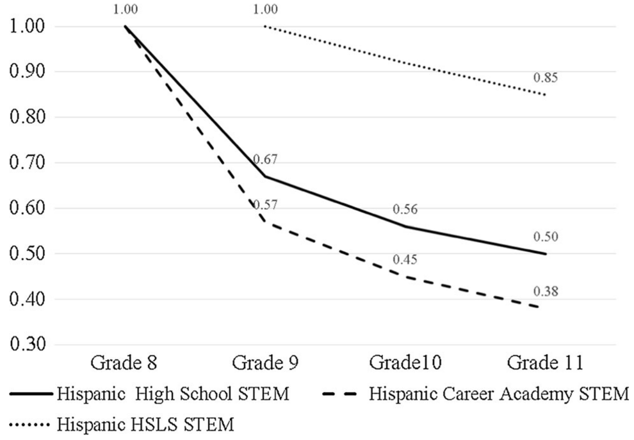

Fig. 9 Probability of persistence in rigorous STEM course taking among national (HSLS) and Florida (EDW) Hispanic STEM-capable students

themed curricula and programs, such as STEM career academies, in high school. If positive outcomes were found, the ePEP tool could be considered a viable possibility for other states to improve STEM pipelines and pathways, as early as middle school, to select STEM courses of study. In particular, the Florida Career and Professional Education (CAPE) Act has the potential to serve as a model for other states to establish legislation to promote rigorous and relevant middle school and high school career-themed curricula to prepare students for critical high-wage and high-demand careers in the STEM workforce. Despite the promise of these Florida initiatives, the results of our study suggest that the outcomes were not as great as intended and did not provide for enhanced outcomes for underrepresented populations of students.

As evidenced by survival probabilities, STEM-capable high school students in Florida had lower persistence in rigorous mathematics and science course taking than similar students in the national cohort, regardless of gender, race, or ethnicity. In contrast to findings in Tyson et al. (2007) study, female students in Florida entered the ninth grade with lower probabilities of persistence in rigorous course taking than their male counterparts, but completed the eleventh grade with higher probabilities of persistence. This finding suggests that female students have similar capabilities as male students to excel in rigorous mathematics and science courses upon entry into Florida's high schools (i.e., public high schools and STEM career academies), but their experiences in these courses may negatively impact their persistence and related academic achievements. Additional studies are needed to investigate the factors that may influence students' rigorous course taking experiences. In the national cohort, male and female students had equivalent but higher probabilities of persistence than students in Florida. Asian and Multi-race students had the highest probabilities of persistence in the national sample of STEM-capable students, but Asian and White (0.73) students had the highest probabilities of persistence in Florida. This finding is consistent with other reports that White and Asian students enroll in more advanced rigorous courses than Black and Hispanic students (Maltese and Tai 2011; Tyson et al. 2007). While Black and Hispanic students in Florida's STEM career academies had lower probabilities of persistence than similar students in the national STEM-capable cohort, Multi-race students had the greatest probability of persistence among ethnic minorities in Florida's STEM career academies. Although these findings contribute to research that examines students' rigorous STEM course taking within STEM career academies (McCharen and High 2010; Stone 2011), additional studies are needed to investigate the influence of ethnicity on students' rigorous course taking in the context of STEM career academies. For instance, researchers may consider research questions such as: *To what extent did ethnicity influence rigorous course taking within STEM career academies?*, and *To what extent did the rigorous course taking trends of Black and Hispanic STEM-capable students compare to the rigorous course taking trends of Multi-race STEM-capable students?* Answers to these questions will contribute to our understandings about the course taking patterns of underrepresented minority students who are participating in STEM career academies and can inform the development of interventions to increase their participation in STEM education and careers.

Although we examined the outcomes of students identified as STEM-capable in Florida, we found it interesting that participation in STEM career academies, often touted as a means to enhance the pipeline to STEM careers, did not support persistence in rigorous mathematics and science courses, a prerequisite for success in STEM postsecondary education and career. Given the important role that course taking plays in postsecondary education, this result warrants further investigation to determine what experiences are provided in STEM career academies and how those experiences influence students' persistence and performance in rigorous mathematics and science course. These results suggest a need for further investigation to determine the factors that might play a role in the identified outcomes. Questions raised included: *What do we know about students' experiences in these programs?*, and *What are the curricular expectations for student engagement in STEM academies (e.g., do they limit or expand students' abilities to take advantage of advanced mathematics and science courses)?* Although this study builds on and extends previous findings about students' rigorous course taking patterns and persistence in rigorous course taking within STEM career academies, we suggest future studies explore students' related high school experiences (Maltese and Tai 2011) in rigorous STEM courses, particularly in the context of STEM career academies and STEM-themed career and technical education (CTE) programs.

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