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How Do Students Experience Choice? Exploring STEM Course-offerings and Course-taking Patterns in Texas Charter and Non-charter Public Schools

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Abstract: Charter schools are positioned by proponents as a key component of reform efforts striving to expand school choice. Proponents argue that charter schools have the flexibility to experiment with novel curricular and instructional models outside the constraints of the traditional public education system, and therefore have the potential to transform students' experiences. Influential reports over the last three decades have highlighted the need to improve students' preparation in STEM, and charter schools have emerged as a reform with the potential to do so.

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This work uses methods from social network analysis and logistic regression to investigate how course-taking patterns in Texas charter and non-charter schools either promote or constrain student engagement within the STEM disciplines by: 1) exploring STEM course offerings in Texas charter and non-charter public secondary schools; and 2) identifying students' STEM course-taking patterns in these schools. Findings suggest charter schools are less likely than non-charter public schools to offer STEM courses tailored for special education students and that charter school students' course-taking patterns tend to be either slightly more advanced or more basic than the course-taking patterns of students in non-charter schools. In addition, students in charter schools tend to be more mobile (e.g., transfer between schools) than students in non-charter public schools.
Keywords: Charter schools; STEM course taking; STEM curricula; School choice

¿Cómo experimentan los estudiantes la elección? Explorando las ofertas de cursos STEM y patrones de curso en las escuelas públicas charter y no charter de Texas
Resumen: Las escuelas charter están posicionadas por los proponentes como un componente clave de los esfuerzos de reforma que se esfuerzan por expandir las opciones de escuelas. Informes influyentes de las últimas tres décadas han destacado la necesidad de mejorar la preparación de los estudiantes en STEM, y las escuelas charter han surgido como una reforma con el potencial de hacerlo. Este trabajo utiliza métodos de análisis de redes sociales y regresión logística para investigar cómo los patrones de cursos en las escuelas charter y no charter de Texas promueven o limitan la participación de los estudiantes dentro de las disciplinas STEM al: 1) explorar las ofertas de cursos STEM en las escuelas charter y no charter de Texas. escuelas secundarias públicas charter; y 2) identificar los patrones de cursos STEM de los estudiantes en estas escuelas. Los hallazgos sugieren que las escuelas charter tienen menos probabilidades que las escuelas públicas no charter de ofrecer cursos STEM diseñados para estudiantes de educación especial y que los patrones de cursos de los estudiantes de escuelas charter tienden a ser un poco más avanzados o más básicos que los patrones de cursos de los estudiantes en escuelas que no son charter. Además, los estudiantes de las escuelas charter tienden a tener más movilidad (e.g., la transferencia entre escuelas) que los estudiantes de las escuelas públicas no charter.
Palabras-clave: escuelas charter; tomando cursos STEM; Currículos STEM; Elección de escuela

Como os alunos experimentam a escolha? Explorando ofertas de cursos STEM e padrões de curso em escolas públicas charter e não charter do Texas
Resumo: As escolas charter são posicionadas pelos proponentes como um componente-chave dos esforços de reforma que buscam expandir a escolha escolar. Relatórios influentes nas últimas três décadas destacaram a necessidade de melhorar a preparação dos alunos em STEM, e as escolas charter surgiram como uma reforma com potencial para fazer isso. Este trabalho usa métodos de análise de rede social e regressão logística para investigar como os padrões de cursos nas escolas charter e não charter do Texas promovem ou restringem o envolvimento dos alunos nas disciplinas STEM ao: 1) explorar as ofertas de cursos STEM no Texas charter e não escolas secundárias públicas charter; e 2) identificar os padrões de cursos STEM dos alunos nessas escolas. As descobertas sugerem que as escolas charter são menos propensas do que as escolas públicas não charter a oferecer cursos STEM adaptados para alunos de educação especial e que os padrões de cursos dos alunos de escolas charter tendem a ser ligeiramente mais avançados ou mais básicos do que os padrões de cursos dos alunos em escolas não charter. Além

disso, os alunos das escolas charter tendem a ser mais móveis (e.g., transferência entre escolas) do que os alunos das escolas públicas não charter.
Palavras-chave: Escolas charter; fazendo cursos STEM; Currículos STEM; Escolha da escola

Introduction

Since charter schools were first established in the United States in the early 1990s, the number of charter schools and the number of students enrolling in them have steadily increased. According to the National Alliance for Public Charter Schools (NAPCS), over 3.2 million students were enrolled in roughly 7000 charter schools operating nationwide during the 2016-2017 school year (NAPCS, 2018). Charter schools are publicly funded schools that in most cases operate independently of local school districts. Charter school proponents argue that independence from the traditional public-school system and autonomy over curriculum, financing, and staffing allow charter schools to innovate and develop novel educational models that promote student achievement more effectively than non-charter public schools (Bierlein & Mulholland, 1994; Guggenheim, 2010). Guided by this notion, charter schools have received bipartisan support. A number of grant programs offered through the Department of Education's Office of Innovation and Improvement, established during Obama's presidency, are geared towards opening and expanding charter schools (Anderson, 2018). More recently, Secretary of Education Betsy DeVos established grant funding guidelines aimed at expanding charter schools and school choice nationally, citing the need to provide families with alternatives to their neighborhood schools and empower families to enroll children in schools best suited to their students' needs (DeVos, 2017). Thus, the growth of charter schools is unlikely to slow any time soon.

Extant quantitative research has explored the impacts of charter schools on student outcomes, focusing on student achievement on standardized exams (Clark et al., 2015; Curto & Fryer, 2014; Gleason et al., 2010; Toma & Zimmer, 2012; Tuttle et al., 2012; Winters, 2012; Zimmer et al., 2012) in addition to college enrollment and labor market outcomes (Dobbie & Fryer, 2016). Qualitative studies have explored how the introduction of market principles and competition to the public education sector has impacted the public education system in unintended ways (Jabbar, 2015, 2016; Lubienski, 2003; Winters, 2012). Despite the breadth of literature on charter schools, there is little consensus about the effects of charter schools on student outcomes. Therefore, scholars advocate investigating the underlying conditions, such as ability grouping practices, that may explain observed differences in student outcomes between charter and non-charter public schools (Berends, 2015; Berends & Donaldson, 2016).

In contrast to comparative studies exploring student achievement differences by school sector, Berends and Donaldson (2016) explored how ability grouping in charter and non-charter schools influenced student performance on standardized math exams. Berends and Donaldson (2016) investigated ability groups by administering a survey to teachers in charter and non-charter schools in which teachers described their instructional practices. The majority of the schools included in their study were elementary and middle schools, and these authors did not investigate course-taking patterns in charter and non-charter secondary schools. Here we extend the research conducted by Berends and Donaldson (2016) by looking at how students enroll in different sets of courses within charter and non-charter public secondary schools in addition to how differences in course offerings by school sector mediate these student course-taking patterns. While Berends and Donaldson investigate the instructional differences between charter and non-charter schools, we explore the programmatic differences in how STEM (science, technology, engineering, and mathematics) is organized in charter and non-charter schools. Specifically, we address the following:

1. What are the programmatic differences between Texas charter and non-charter public schools, specifically in STEM course offerings?
2. What are the differences in STEM course-taking patterns between students enrolled in charter schools and students enrolled in non-charter public schools?

The focus upon STEM course-offerings and course-taking patterns in charter and non-charter public schools is motivated by the fact that the charter movement is positioned as a way to overcome inequity within an "inefficient" United States public education system (Friedman, 2002; Goals, 2000, 1994; No Child Left Behind, 2002; Recovery Act, 2009). As displayed in Figure *1*, STEM disciplines are associated with higher earnings than non-STEM disciplines, a trend that holds for individuals with and without post-secondary degrees (Carnevale et al., 2015). Moreover, discrepant participation in STEM by ethnicity is evident as early as high school, particularly in the physical sciences (National Center for Education Statistics, 2019; Rothwell, 2013).

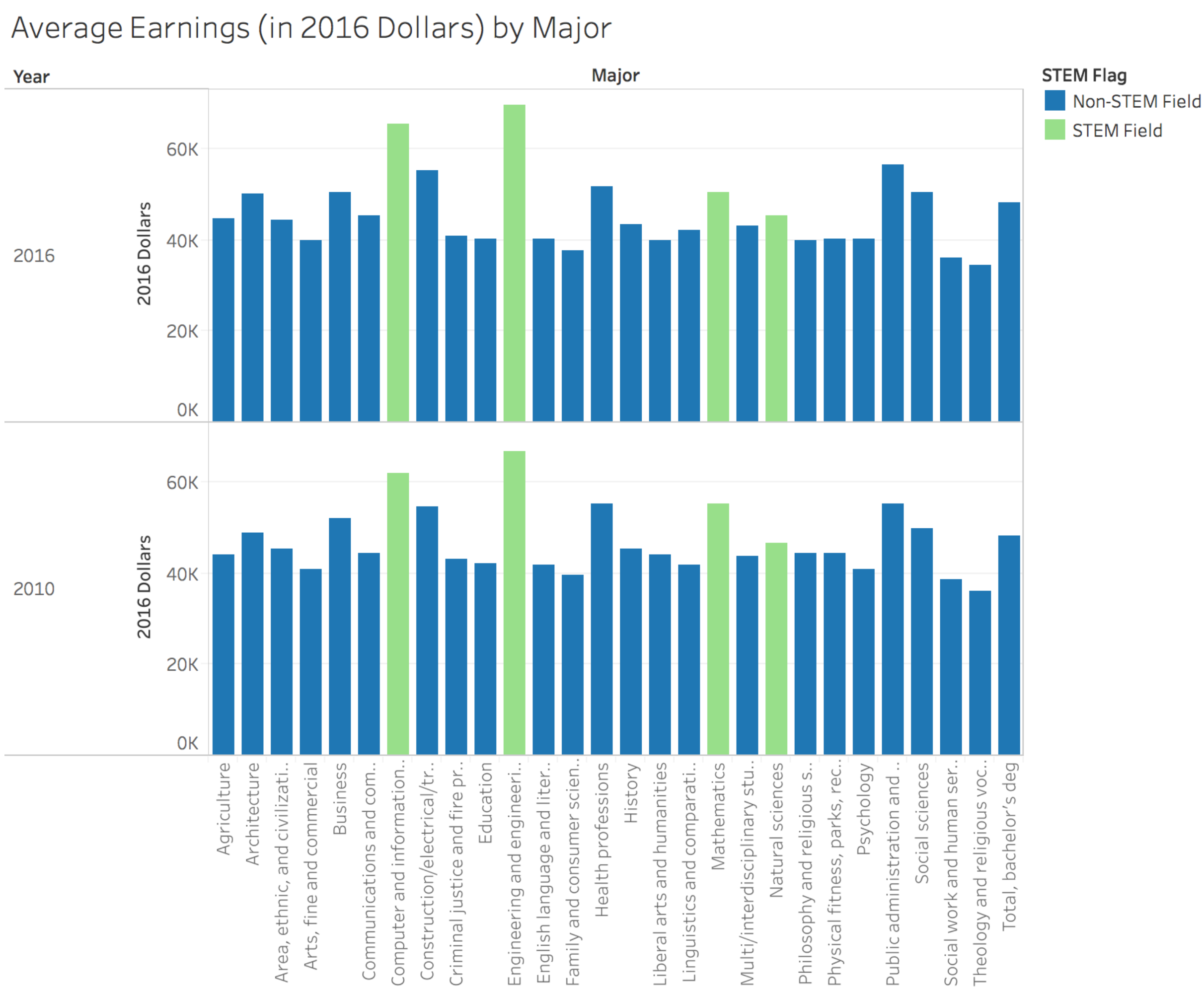

Figure 1. Average earnings in 2016 dollars for bachelor's degree holders by major.
Note: Data obtained from the 2017 Digest of Educational Statistics Table 505.10 (National Center for Education Statistics, 2019).

Figure 2 shows the average number of high school credits students in the United States earn in Biology, Chemistry (Chem), Physics, and Mathematics by race for selected years between 1980 and 2010. As can be seen, Asian and White students are more likely than students from other racial groups to take chemistry and physics. Given the economic advantages of pursuing STEM careers and the fact that charter schools are positioned as a means to promote social mobility, it is important to examine how charter schools either promote or constrain student access to STEM, as preparation in STEM disciplines is a plausible way for students to achieve social mobility.

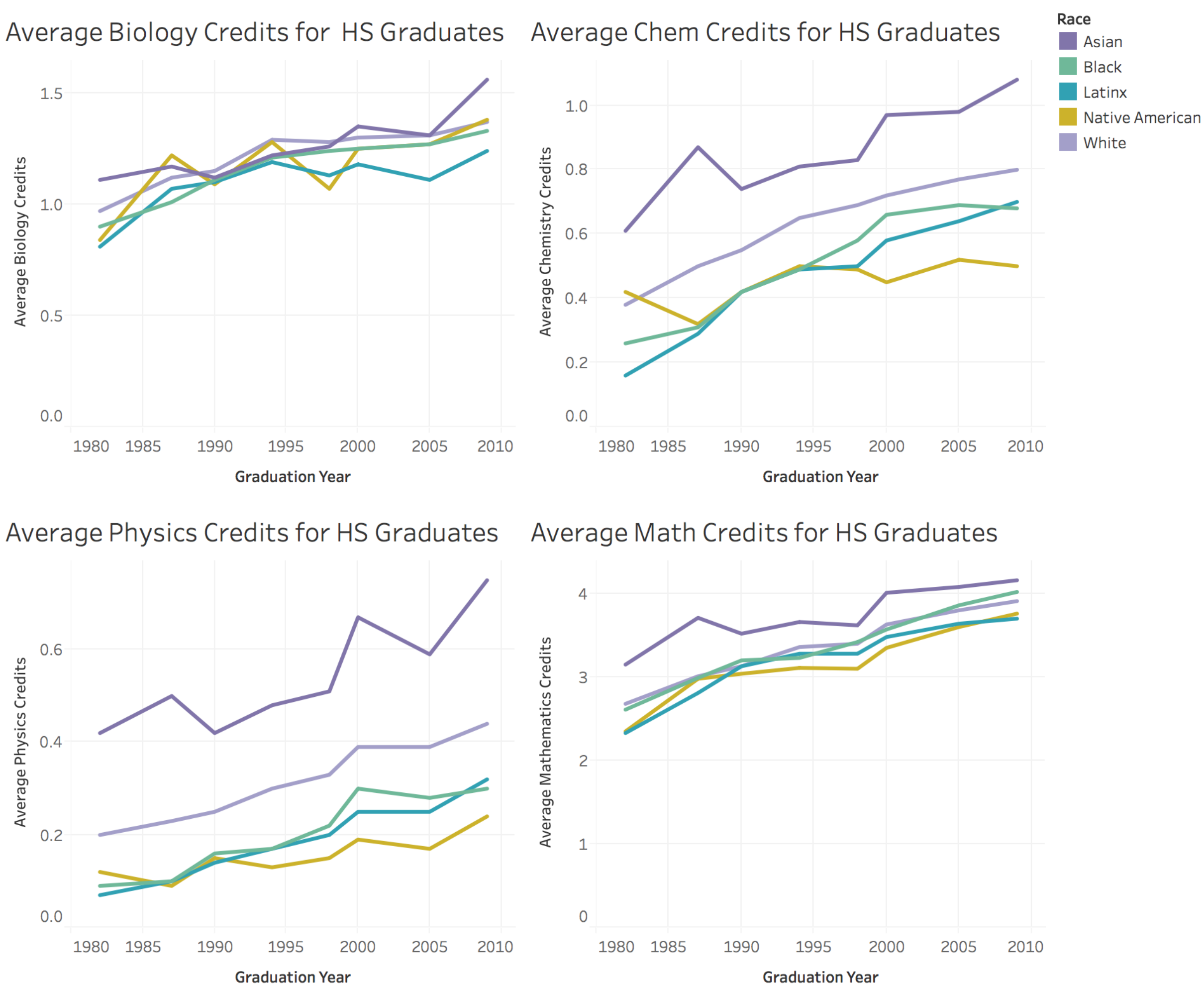

Figure 2. Average science and math credits (in Carnegie Units) for high school graduates from select years between 1980 and 2010. Data obtained from the 2017 Digest of Educational Statistics Table 225.10 (National Center for Education Statistics, 2019)

We analyze statewide student level educational data by constructing one-mode networks of STEM courses, schools, and students and employ community detection, the process of parsing nodes in a network into smaller groups based upon their similarity, within these networks to identify groups of nodes that are closely related to one another. Nodes in one-mode networks are all of the same type (e.g., all nodes represent students or schools) as opposed to bipartite networks, in which nodes represent two different units (e.g., some nodes represent students and others represent schools). Outcomes from one-mode network analysis and community detection are then used within hierarchical and multinomial logistic regression to address the research questions articulated above.

Given the size and diversity of the student population in Texas, Texas is an ideal setting in which to explore course-taking patterns in charter and non-charter schools. With a large and varied student population, findings from educational studies conducted in Texas can be generalized to and inform policy in other parts of the United States (the demographic characteristics of the students and schools included in this study are provided in
Table **1**).

Social network analysis (SNA) is well-suited to explore school level course-offerings and student level course-taking patterns because SNA allows researchers to quantify and investigate the characteristics of agents within a network (such as students enrolled in the same courses within a school) based upon their mutual participation in or association with an organization and/or event (Borgatti & Ofem, 2010; González Canché & Rios-Aguilar, 2015). At the school level, the programmatic similarities between Texas charter and non-charter public schools can be investigated by looking specifically at how many STEM courses are mutually offered in a given set of schools. Similarly, at the student level, students' mutual membership in STEM courses makes it possible to explore ability grouping in charter and non-charter schools with greater nuance than would be possible using only descriptive statistics. Whereas descriptive statistics show the numbers of students enrolled in various STEM courses in charter and non-charter schools, SNA allows us to identify which STEM courses are associated with one another based upon student enrollment. Through community detection, it is possible to identify course-taking patterns in the STEM disciplines by grouping students who mutually enroll in the same sets of STEM courses.

Results from community detection are used as outcome variables in hierarchical linear models and multinomial logistic regression models to ascertain the degree to which STEM course-offerings and student course-taking patterns differ by sector. Statistical analyses are conducted at the school and student levels. At the school level, we find that STEM course-offerings at charter schools are more likely than those in non-charter schools to include either exit from the school system (i.e., dropping out) or transfer to and from that school. At the student level, we identify six STEM course-taking patterns in Texas charter and non-charter schools through community detection. Relative to a "college preparatory" course set, characterized by a mix of core STEM courses and some advanced or elective STEM courses, students in charter schools are more likely to enroll in course sets that are either more advanced than the "college preparatory" set or more basic than the "college preparatory" set. In addition, students in charter schools are more likely than students in non-charter schools to enroll in course sets associated with either exit from the school system or transfer.

The methods employed within this work in addition to our findings can enhance research into education policy networks. Au and Ferrare (2014) employed SNA to illustrate how wealthy individuals used philanthropic organizations to shift discourse about charter schools in Washington state and ultimately garner support for charter school legislation. Au and Ferrare (2014) express "serious concerns regarding the disproportionate power of super wealthy individuals and their related philanthropic organizations relative to public education policy and the democratic decision-making process of individual voters" (p. 19). They draw upon Brandt's (1998) conception of policy sponsorship, in which sponsors' support is motivated by the prospect of gaining either material or ideological advantage. This work uses methods within SNA to characterize the academic programming in charter and non-charter schools in Texas and can be used in conjunction with policy network research to investigate the degree to which sponsors of charter schools use their influence to direct the curricula offered within charter schools. This application of our methods and results is discussed in greater detail in the concluding section.

Literature Review

As Lubienski (2003) describes, critics of the public education system argue that public education is a monopoly that stifles the abilities of individual schools to innovate. Charter schools are offered as a means to circumvent this limitation. Proponents of charter schools contend that removing bureaucratic regulations afford charter schools greater autonomy with which to innovate and create novel instructional paradigms that will meet students' needs with greater quality and efficiency (Berends et al., 2010; Bierlein & Mulholland, 1994; Friedman, 2002; Henig, 1995; Lubienski, 2003). In addition, charter school advocates argue that increasing choice in the educational marketplace allows families to enroll their students in schools that best serve their children's needs and that market pressures will force schools that are unable to innovate or meet the needs of students to close.

Skeptics contend, however, that because public education is a public good it may not respond to market pressures in the way some economists suggest. Henig (1995) notes that education benefits the broader community by creating a better trained work force and a populace that is both prepared for civic engagement and able to lead fulfilling lives. These public benefits are not necessarily considered when families are left to invest in education as they see fit, and as a result, families may underinvest in their children's education resulting in decreased efficiency in public education. In addition, Lubienski (2003) notes that research on charter schools indicates that the innovation expected due to market pressures is often limited to schools' organizational structure, but is not evident in novel curricula or instruction. Lubienski (2003) argues that "curricular conformity and instructional standardization may in fact be caused by the very market mechanisms that were unleashed to address those ills" (p. 397).

That charter schools revert to established curricular and instructional norms is predicted by institutional theory, in which an organization's "legitimacy is derived from conformity to the normatively held rules and scripts of the institutional environment, rather than instructional effectiveness" (Huerta & Zuckerman, 2009, p. 414). According to institutional theory, competition and innovation introduced to the public education system through market pressures are not as powerful as charter school advocates suggest. The bureaucracy of the public education system has long established normative schooling, and schools, regardless of sector, adhere to practices that serve to legitimize these organizations as educational entities (Berends & Donaldson, 2016; Huerta & Zuckerman, 2009). While charter schools have greater autonomy with which they have the potential to innovate, established norms and state regulations within education may prove insurmountable. Thus, while it is important for research to investigate the effects of charter schools upon student outcomes, it is also important for charter school researchers to attend to the conditions within charter schools that may explain why they either are or are not improving student outcomes.

Charter School Outcomes

Extant literature investigating the impacts of charter schools upon student outcomes on standardized exams suggests that charter school impacts are contextual at best. In a multi-state study, Zimmer et al. (2012) found little or no difference in student outcomes by sector: charter schools in some states increased students' test scores in math and reading, while charter schools in other states decreased students' standardized test scores. Similarly, Gleason et al. (2010) and Clark et al. (2015) found no average differences in student achievement in math or reading between charter and non-charter public schools; however, differences in student achievement were identified when disaggregating schools by student populations. Specifically, Gleason et al. (2010) reported that charter schools serving low-income students yielded positive student outcomes in mathematics, whereas charter schools serving high-income students yielded negative student outcomes in mathematics and reading. In their work, Clark et al. (2015) reported that charter schools in urban settings improved student mathematics scores while those in non-urban settings did not.

Research into the effects of charter schools upon student outcomes is important, as this can help policymakers assess the degree to which charter schools have realized the educational improvements reformers predicted. However, given the contextual nature of sector differences in student achievement (Clark et al., 2015; Gleason et al., 2010; Tuttle et al., 2012; Zimmer et al., 2012), it is important for research to also examine the underlying mechanisms driving context-dependent sector differences in student outcomes. In this vein, Dobbie and Fryer (2016) examined a variety of outcomes—student test score gains, college enrollment, and early market labor outcomes—of charter school graduates. They found "no excuses" charter schools—schools with longer school days, rigorous test preparation, and high behavioral standards—increased student test score gains and college enrollment but had little noticeable impact upon graduates' future earnings. Additional evidence for the importance of a charter school's educational model on student achievement comes from Curto and Fryer (2014) who studied student math and reading achievement at SEED, a college-preparatory boarding charter school in Washington, D.C. When comparing students randomly selected for attendance through lottery to students not selected for attendance, Curto and Fryer (2014) report students attending SEED increased both their mathematics and their reading scores.

Although not specific to STEM disciplines, other lines of research have identified practices used by and employed within charter schools that may explain why some charter schools are more effective than others at promoting student outcomes on standardized exams. Some evidence suggests that charter schools may be engaging in "cream-skimming," a practice in which schools target their recruiting efforts toward high-achieving students from low-income backgrounds (Jabbar, 2015, 2016; Lacireno-Paquet et al., 2002). Of concern, cream-skimming serves to exacerbate inequities in access to education and also raises concerns regarding the true nature of charter school impacts on student outcomes. In addition to cream-skimming, some scholars argue that charter schools may achieve increases in student test scores by teaching to the test rather than implementing novel instructional practices (Finn et al., 2014; West et al., 2014). Yet another line of research has found evidence that "effective" charter schools are able to increase college enrollment through "new paternalistic" approaches to education in which low-income students of color are taught how to exhibit middle-class values through intensive character education that supplements academic programming (Curto & Fryer, 2014; McDermott & Nygreen, 2013). Similarly, Modica (2015) observed that instructional conditions in a diverse charter school pressured students of color to act "White" in order to be perceived as academically capable.

Although research into the characteristics of (e.g., "no excuses" paradigms) and practices employed by (e.g., "skim-creamming" and "new-paternalism") charter schools do not focus specifically on STEM disciplines, this research can help scholars and policymakers understand some of the general conditions in charter schools that may make some more effective at influencing student achievement than others. However, it is also important to explicitly look at the instructional conditions within charter schools that may explain context-dependent sector differences in student outcomes. Toward this end, Berends and Donaldson (2016) explore how differences in ability grouping between charter and non-charter public schools explain differences in student achievement. With respect to differences in ability grouping between charter and non-charter public schools, Berends and Donaldson (2016) find that students in charter schools are more likely than students in non-charter public schools to be in a high ability group and less likely to be in an average ability group. While there are differences between mathematics achievement gains between students in high and low ability groups, this relationship does not differ between charter and non-charter public schools, suggesting that ability grouping practices between the two sectors are more alike than they are different, despite the different proportion of students enrolled in ability groups by sector (Berends & Donaldson, 2016). This leads to questions about the programmatic differences between charter and non-charter schools; while instructional norms may be more similar by sector than they are different, it is also important to investigate whether general academic programming differs by sector. We aim to expand upon research investigating the instructional conditions in charter and non-charter schools by identifying sector differences in academic course offerings.

Tracking and Ability Grouping

Although formal tracking programs in United States secondary schools were largely dismantled by the 1980's, Lucas (1999) found evidence of more differentiated academic sorting at the secondary level. Rather than being organized into cohesive tracks (e.g., college-preparatory or vocational) in which students enroll in comparably rigorous courses across discipline, Lucas (1999) constructed statistical models that suggested students were more likely to enroll in discrepant courses across academic disciplines (e.g., college-preparatory mathematics and regular English). Despite the increased likelihood of students enrolling in discrepant courses across discipline, Lucas found patterns among the discrepant course enrollment, suggesting that tracking did not go away completely but instead became more nuanced and complex after formal programs diminished. Given such nuance in academic sorting, Berends and Donaldson (2016) differentiate between tracking—the practice of sorting students into entire course sequences based upon their perceived academic aptitudes or prior achievement—and ability grouping, which refers to the practice of enrolling "students into classes on a subject-by-subject basis" based on their perceived ability (p. 7). The explicit practice of tracking has diminished in the United States; however, the vertical sequence of courses at the high school level has allowed ability grouping to continue (Heck et al., 2004). Specifically, students who are deemed prepared may be able to enroll in more advanced coursework, while other students are forced to enroll in lower-level coursework.

Heck et al. (2004) followed a cohort of 274 students throughout their high school careers and linked students to the courses they took each semester. In doing so, Heck et al. (2004) identified emergent course-taking patterns and found that enrollment in these pathways is both predicted by socioeconomic status and predictive of post-secondary plans. Specifically, advantaged students with high prior achievement are more likely to be enrolled in advanced course sequences, to have high college admissions exam scores, and to plan on attending colleges after graduating from high school.

McFarland (2006) identified curricular pathways in two high schools and explored mobility between these academic tracks. Notably, McFarland (2006) reported that the types of curricular trajectories can vary widely between schools as a function of what course offerings are available at that school. Moreover, the structures of course sequences play an important role in determining whether or not students are able to move between and among different tracks within a school. For example, students in a school with increased differentiation in higher-level courses have greater opportunities to move to advanced tracks, whereas students in schools with limited higher-level courses must compete for spots in these courses.

Differential enrollment in advanced courses in the public-school system can easily be seen using publicly available educational data. Plots generated using data from Texas show clear ethnic differences in the rates at which students are enrolled in advanced coursework, corroborating research that suggests advantaged students with high socioeconomic status are more likely to enroll in advanced coursework (Friedkin & Thomas, 1997; Heck et al., 2004).

The plots in Figure 3 compare the percentages of ethnic minority students (Asian, Black, and Latinx, from top to bottom) to the percentage of White students enrolled in advanced courses

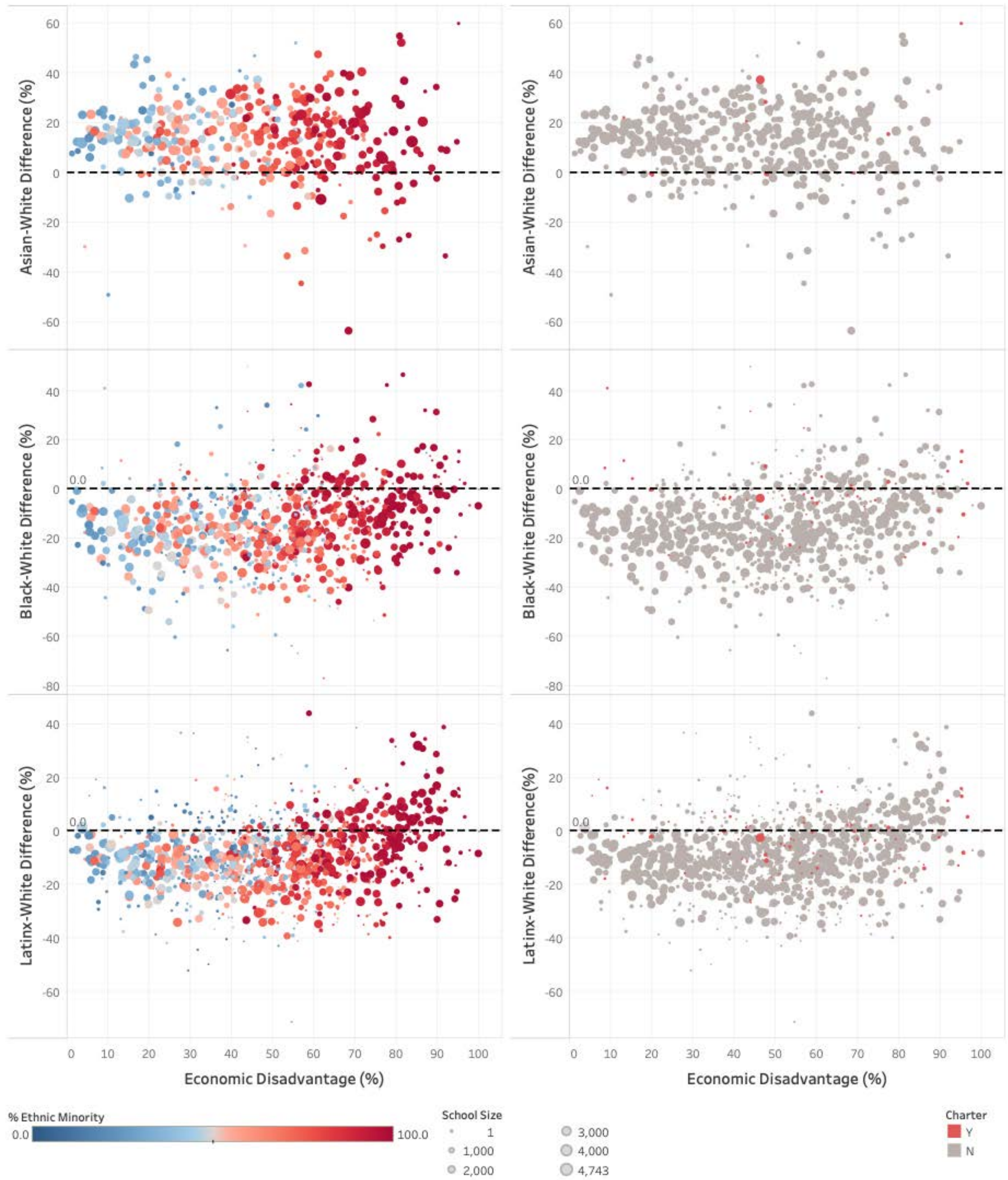

Figure 3. Percent difference in advanced course-taking between students from select ethnic groups and White students in charter and non-charter schools in Texas by the concentration of economic disadvantage in these schools. The left panel is colored by the percentage of ethnic minority students in each school, the right panel is colored by school sector, and bubbles are proportional to school size.

coursework as a reference, it is easier to see that Asian students are more likely than White students to enroll in advanced coursework a trend that does not vary by the concentration of economic disadvantage. Generally, lower percentages of Black and Latinx students enroll in advanced coursework than White students. In schools with higher concentrations economic disadvantage, however, the percentages of Black and Latinx students taking advanced coursework is greater than the percentage of White students taking advanced courses. Coloring these plots by sector (the right panel) provides insight into whether or not charter schools serve to disrupt such discrepant in each school, the right panel is colored by school sector, and bubbles are proportional to school size. participation in advanced STEM by ethnicity. By visual inspection, it appears there are minimal differences in advanced course-taking by sector, but further analysis is needed to explore this in greater depth.

Data & Sample

To explore course offerings and student course-taking patterns in Texas charter and non-charter public schools, this study analyzes administrative educational data available through the Texas Education Research Center (ERC). The Texas ERC collects and maintains public education data dating back to 1993, including: teacher certification data from the State Board for Educator Certification (SBEC); K-12 student level demographic, enrollment, performance, and assessment data from the Texas Education Agency (TEA); campus and district level administrative data from the TEA; and post-secondary student level demographic, enrollment, and performance data from the Texas Higher Education Coordinating Board (THECB).

In order to address our two research questions, we construct a cohort of students in Texas charter and non-charter public schools beginning in the ninth grade in the 2011-2012 school year, and we follow these students for four academic years through the 2014-2015 school year. Students are followed over four years because this is a typical timespan during which students complete high school. We use the following data elements available from the Texas ERC: student demographic data (e.g., race, gender, and designation as economically disadvantaged, limited English proficiency (LEP), special education (SPED), and gifted); student secondary coursework in STEM; school sector (charter or non-charter public school); and school level demographic data (which are obtained by aggregating student level demographic data at the campus level). To create a data set for this analysis, students are matched to STEM courses for each school in Texas by year. Our final data file includes a student identification, a school identification, a unique course identification by year (e.g., adv_physics_2012 to denote that a student took advanced physics during the 2011-2012 school year), and student demographic data. The average number of unique STEM course-year combinations in the set of schools included in our sample is 45.45 (with a standard deviation of 20.03), and the number of unique STEM subjects offered in these schools over the four years of the study is 21.10 (with a standard deviation of 7.58).

Only schools that are open during all four years for a given cohort are included in the data set. Including schools that are only open for a fraction of a cohort's four years may serve to bias the results, as these schools do not offer four full years of STEM coursework to students. Moreover, schools classified as Disciplinary Alternative Education Programs (DAEP) or Juvenile Justice Alternative Education Programs (JJAEP), which serve students who have been removed from schools due to felonious activity, are not included in the present study. The course offerings in these schools are limited and the number of students completing four years in DAEP and JJAEP schools is minimal. In addition, the academic programs offered in these schools do not reflect sector differences but are instead established to meet the needs of students who have faced severe disciplinary action within the public education system. These schools are characteristically not emblematic of school choice. Given these decisions, a total of 1630 charter and non-charter secondary schools are included in the present study. The average demographic characteristics of charter and non-charter schools included in this study are provided in Table **1**.

Table 1
Average demographic characteristics of Texas charter and non-charter secondary schools

	Charter	Non-charter
# of Schools	178	1452
Cohort Size	51	208
% FRL	67.0	52.6
% LEP	7.9	4.1
% SPED	11.4	10.8
% Gifted	3.1	9.2
% Female	52.1	48.4
% Asian	2.1	1.8
% Black	15.5	10.3
% Latinx	58.2	42.0
% White	22.3	43.6
% 8th Advanced Math	19.7	19.2

In addition to removing schools that are not open for all four cohort years and DAEP/JJAEP schools, students who leave a school for reasons other than dropping out or transferring to another school are removed. Students who exit a school, but neither drop out of high school entirely nor transfer to another school, exit for reasons that do not necessarily reflect their academic trajectory (e.g., returning to a students' home country, death, homeschooling, or moving out-of-state). Moreover, these exit reasons do not necessarily preclude students from continuing or discontinuing a certain curricular path (i.e., students' out-of-state course-taking is unavailable in Texas ERC data).

To track students who either drop out of the public-school system entirely or transfer to another school, dummy "course" variables are created in order to indicate the year and manner in which a student leaves a school (e.g., transfer_out_2012 indicates that a student transferred from a school in 2012). Student exit (either drop-out or transfer) in addition to student STEM course enrollment comprise a student's secondary course memberships from which a network is created.

In order to account for students enrolled in more than one campus in a given academic year or who transfer to another campus in a subsequent academic year, a student's membership in the data set is weighted by 0.25 for each year in which that student is present. This weight is then divided by the number of schools attended by a given student in that year. Because students are followed across the four years after which they begin high school, these weights are used to compute cohort-level demographics in schools. A school cohort is defined as the total group of students who attended that school for either the entirety of their high school careers or a fraction thereof. In addition to using these weights to compute cohort demographics, student weights are used in student level statistical models.

Methods

This study analyzes course-offerings and course-taking in Texas charter and non-charter school at three different levels. A state-wide analysis is first conducted to provide an overview of STEM course-taking in Texas in an effort to contextualize subsequent analyses. Then school level analyses are conducted in which STEM course-offerings in charter and non-charter schools are compared. Finally, student level analyses are conducted to characterize prominent STEM course-taking patterns among students in Texas charter and non-charter secondary schools. In discussing these analytical methods and results, we use the term *course offerings* to refer to the sets of STEM courses common to various groups of schools, and the terms *course-taking patterns* or *course sets* to refer to the STEM courses common to various groups of students within schools. Herein, a *community* refers to a group within a network, and the type of network being analyzed determines whether or not the identified communities correspond to *course offerings* or *course-taking patterns*.

Identifying Course-offerings and Course-taking

Social network analysis is employed to identify courses associated with charter and non-charter schools in Texas and to identify courses associated with groups of students in these schools. In contrast to inferential statistics, which focuses upon attributes of individuals within a group (e.g., race and gender) to explore trends between these attributes and an outcome of interest, social network analysis uses relationships between actors within a group to construct a network and explore how network characteristics explain the behavior of either the system or individuals and subgroups within the system (Borgatti & Ofem, 2010; Carolan, 2014). The network perspective reflects a shift to using relationships between actors to contextualize actors' behaviors rather than quantifying the similarity between actors based on their communal attributes as is typical in traditional social sciences. Using networks to evaluate actors' behaviors in relation to one another offers researchers a novel technique for understanding how school choice policy is experienced by students in schools.

A sociogram is a visualization technique used to show how actors within a network are related to one another. Nodes (or vertices) within sociograms represent individual agents, and ties (or edges) between nodes indicate that a relationship exists between two actors. Edges can be either directed, indicating that one node interacts with another but not reciprocally (such as a student speaking to another student without that student responding) or undirected, indicating that the edge represents a mutual interaction, such as two students enrolled in the same class. In addition, edges can be weighted according to the strength of the interaction between two nodes (Barrat et al., 2004; Lancichinetti & Fortunato, 2009). The analysis of sociograms with community detection algorithms—discussed in detail later—is particularly apt for our research questions, as we are able to group students and schools according the number of STEM courses common to them and therefore analyze differences in course offering and course enrollment by school sector.

To create a sociogram, an m by n matrix, **A**, is constructed in which matrix element $A_{vw} \in \{0, 1\}$ indicates whether or not node v is associated with event w. In this work, v represents an individual student or school and w indicates either that student v was enrolled in course w or that school v offered course w. An example of such a matrix is given by Equation 1:

$$\mathbf{A} = \begin{bmatrix} A_{11} & \cdots & A_{1w} \\ \vdots & \ddots & \vdots \\ A_{v1} & \cdots & A_{vw} \end{bmatrix} \tag{1}$$

Multiplying **A** by its transpose $\mathbf{A}^{\mathrm{T}}$ produces a weighted adjacency matrix in which each element gives the edge weight, or the strength of the connection, between two nodes. The weighted adjacency matrix then produces a one-mode network in which edges are weighted by the strength of the connection between two nodes (i.e., the number of STEM courses that either two students share or the number of STEM courses common between two schools). In our study, we construct three different levels of networks in this fashion. First, we construct networks in which nodes represent STEM courses and edges between them represent the number of schools offering both sets of courses. Next, we construct networks in which nodes represent Texas charter and non-charter schools with weighted edges representing the number of courses common to both schools. Finally, we construct student level networks for each campus, in which nodes represent students and edges between nodes are weighted by the number of courses in which both students enrolled.

Communities within networks are defined as groups of nodes that are highly connected to other nodes within the community, but loosely connected to nodes outside of the community (Fortunato, 2010; Girvan & Newman, 2002; Reichardt & Bornholdt, 2006). Communities in network analysis are similar to cliques, in so far as they both identify groups of closely related nodes within a network; however, cliques are defined as maximally connected subsets of nodes within a network (Carolan, 2014), making cliques more restrictive than communities. Given the highly interconnected nature of the networks examined in our study (e.g., nearly all students take Biology during high school and all Texas high schools offer this course, as it is a graduation requirement), use of community detection algorithms makes more analytical sense.

Community detection is operationalized in many algorithms by maximizing a network's modularity (Blondel et al., 2008; Clauset et al., 2004; Fortunato, 2010; Girvan & Newman, 2002; Newman, 2004, 2006). In this work, a community represents a set of students or schools that are similar to one another given the number of courses they have in common. Modularity, given by Equation 2, compares the density of edges within and between communities in a network.

$$Q = \frac{1}{2m}\sum_{vw}\left[A_{vw} - \frac{k_v k_w}{2m}\right]\delta(c_v, c_w) \tag{2}$$

For weighted networks, A_{vw} gives the edge weight between nodes v and w (as calculated by multiplying **A**, from Equation 1, by its transpose), k_v is the sum of the weights of edges connected to node v, c_v is the community to which node v belongs, $\delta(c_v, c_w)$ equals 1 when $c_v = c_w$ and 0 when $c_v \neq c_w$, and $m = \frac{1}{2}\sum_{vw} A_{vw}$. Conceptually, modularity is the difference between the number of weighted edges within communities and the expected number of weighted edges within communities had the same number of edges been randomly distributed in the network. Therefore, a high, positive value of modularity indicates that a network has a strong underlying community structure.

In this work, we employ the multi-level algorithm (Blondel et al., 2008) using the igraph package in R (Csardi, 2015). In this algorithm, nodes are initially placed into arbitrary communities and subsequently moved from their initial communities into adjacent communities. Since increased modularity in the network indicates stronger community structure, nodes are only moved into adjacent communities when the move serves to increase the modularity of the network. For each move, the resulting change in modularity is given by Equation 3:

$$\Delta Q = \left[\frac{\sum_i (w_i^{in} + 2k_i^{in})}{2m} - \left(\frac{\sum_i (w_i^t + k_i^t)}{2m}\right)^2\right] - \left[\frac{\sum_i w_i^{in}}{2m} - \left(\frac{\sum_i w_i^t}{2m}\right)^2 - \left(\frac{\sum_i k_i^t}{2m}\right)^2\right] \tag{3}$$

In Equation 3, w_i are the weights of edges connected to a node i, k_i gives the degree of node i, and these are summed over the total network (t) or community (in) to which a node belongs. If there is a positive change in modularity (e.g, $\Delta Q > 0$), the node is then moved into that community, and node weights are recalculated. This process is repeated until modularity is maximized (i.e., modularity cannot be increased any more).

Yang et al. (2016) explore community detection algorithms for networks with various parameters. They report that the multilevel algorithm from Blondel et al. (2008) is effective for networks with between 0 and 6,000 nodes in addition to other network characteristics that typify the networks analyzed in this study. Given the versatility of the multilevel community detection algorithm and the characteristics of the networks explored in the present study, the multilevel algorithm is used in this analysis.

Course-offerings and Course-taking in Charter and Non-charter Public Schools

Our analysis begins by constructing state-wide networks of STEM courses in which we build two sociograms—one for charter schools and a second for non-charter public schools. The goal of this analysis is to get a general sense of whether or not curricular offerings in charter and non-charter schools differ. In these networks, nodes represent STEM courses and edges connecting nodes represent the number of schools (either charter or non-charter) in which both courses are offered. Networks (for all analyses) are plotted using the Fruchterman-Reingold algorithm, a force-directed graphing technique in which nodes are given an electrostatic charge such that all nodes experience repulsive forces between one another and edges between nodes act as springs that exert an attractive force between pairs of nodes (1990). Communities in these sociograms identify groups of STEM courses that are closely related to one another based upon the number of schools in which each pair of courses are mutually offered. Course identifiers used in the present study include the year in which a given STEM course was offered, so the statewide analysis provides an overview of the sequence and content of courses that are associated with one another in Texas by school sector. From the analysis of the networks displayed in these sociograms, it is possible to characterize curricular offerings in charter and non-charter schools at a general level. For example, if more communities are identified in the STEM course network using charter schools as edges than when using non-charter schools as edges, this may suggest that curricular offerings in charter schools cater to niche interests, consistent with what market theory predicts.

At the school level, sociograms are constructed in which nodes represent Texas public schools (both charter and non-charter) and edges between nodes are weighted by the number of STEM courses mutually offered between those schools. The multilevel algorithm is used to identify communities within this network. Communities in this network signify that schools are similar to one another based upon the number of STEM courses they mutually offer, and we describe communities identified in the school level network analysis as the *STEM course offerings* in Texas public schools. We analyze the STEM courses most commonly offered in each community to characterize *STEM course offerings*. The goal of the school level analysis is to investigate whether or not curricular offerings in STEM disciplines differ by sector. Therefore, the results from the school level network analysis are used as outcome variables in a multinomial logistic regression model (Equation 4). This model predicts the odds of a school having a set of STEM courses α relative to a reference set of courses as a function of school level predictor variables:

$$log\left(\frac{\theta_i^{\alpha}}{\theta_{ref}}\right) = \beta_C C_i + \beta_S S_i + \beta_M M_i + \sum_i \beta_X X_i \tag{4}$$

Here, $\frac{\theta_i^\alpha}{\theta_{ref}}$ gives the odds ratio of campus *i* offering STEM courses α relative to a reference set of courses, C_i indicates whether or not a school is a charter school, S_i gives a school's size as determined by its cohort population, M_i gives the proportion of students at school *i* who enrolled in a high-school level math course (at least algebra 1) in 8^{th} grade, and X_i are school level demographic variables for the percentages of students labelled as economically disadvantaged, special education (SPED), underrepresented minority, gifted, and limited English proficient (LEP). These labels are consistent with the language used by the Texas Education Agency. The variable of interest in the model specified by Equation 4 is β_C, which quantifies how school sector is related to the odds of that school offering STEM courses α relative to the reference category.

At the student level, a network is constructed in which each node represents an individual student and edges between students are weighted by the number of STEM courses common to each pair of students. These networks are constructed independently for each school included in the present study. For each school network, the multilevel community detection algorithm is used to identify communities of students associated by their mutual enrollment in STEM coursework. The communities at the student level are used to identify and characterize prominent *STEM course-taking patterns* or *course sets*, as students are grouped by their mutual enrollment in STEM coursework. The average number of communities identified in Texas charter and non-charter secondary schools is about 3.4. Given that this study includes a total of 1630 schools, categorizing the communities of students based upon their shared courses requires analyzing course-taking in over 4,800 communities. k-means clustering is a method of partitioning data into groups in which the data points in each group have similar means across a vector of attributes (Guthrie, 2018; MacQueen, 1967). The k-means clustering algorithm takes a set of *N* data points, each with a vector of attributes $\overrightarrow{x_\iota^{(J)}}$, and partitions these data points into *k* groups: $S = (S_1, S_2, \ldots, S_k)$. Each group S_i is constructed such that the within-group sum of squares is minimized, as given by Equation 5:

$$S_j = arg\min_{S_j} \sum_{j=1}^{k} \sum_{i=1}^{n} \left| \overrightarrow{x_\iota^{(J)}} - \vec{c_j} \right|^2 \tag{5}$$

In the present study, *k* is set to 6, thus identifying six distinct course-taking patterns in Texas charter and non-charter schools. To find an appropriate value for *k*, we plotted the within group sum of squares for varying values of *k* (a Scree plot) and identified the value at which the plot begins to flatten, indicating that additional values of *k* no longer reduce the within group sum of squares to an appreciable degree.

The course-taking patterns identified within student level networks are used as the outcome variables in two school level models and one student level model. The first school level model, given by Equation 6, seeks to determine whether the number of course-taking pathways in Texas public schools differs between charter and non-charter schools:

$$P_i = \beta_C C_i + \beta_S S_i + \beta_M M_i + Dist_{j[i]} + \sum_i \beta_X X_i \tag{6}$$

In Equation 6, P_i gives the number of pathways identified within school *i*, and the predictor variables are the same as those used in Equation 4, except that a random effects variable for district *j* to which school *i* belongs is also included.

The second school level model is a multinomial logistic regression model similar to the model specified by Equation 4; however, this model also controls for the number of pathways P_i identified in school i:

$$log\left(\frac{\theta_i^{\alpha}}{\theta_{ref}}\right) = \beta_C C_i + \beta_S S_i + \beta_M M_i + \beta_P P_i + \sum_i \beta_X X_i \tag{7}$$

At the student level, the probability of a student belonging to a community characterized by one of the six course-taking patterns identified through k-means clustering is assessed through the multilevel logistic regression model specified by Equation 8:

$$log\left(\frac{\theta_i^{\alpha}}{\theta_{ref}}\right) = \beta_c C_i + \beta_M M_i + School_{j[i]} + \sum_X \beta_X X_i \tag{8}$$

In Equation 8, θ_i^{α} represents the odds that student i enrolls in course-sequence α, θ_{ref} represents the odds of enrolling in a reference course-sequence, C_i denotes whether or not student i attends a charter school, M_i is a flag indicating whether or not a student i took an advanced math course in middle school, and X_i are student level demographic variables for gender, ethnicity and designation as SPED, LEP, economically disadvantaged, and gifted. In addition to these fixed effects, random effects coefficients for school j in which student i is enrolled are included in order to account for the fact that students in a school are not independent of one another. The outcome variable is the log odds ratio giving the likelihood of a student enrolling in a given course-sequence within a school as compared to a reference course-sequence.

Mixed-effects multinomial logistic regression models cannot be run in R; however, individual mixed-effects logistic regression models can be run using the package lme4. Begg and Gray (1984) show that it is possible to estimate a mixed effects multinomial regression model by running individual mixed-effects logistic regression models comparing each category of the outcome variable. This approximation is more conservative than a single multinomial regression model and works best when the reference category is the most common category of the outcome variable. Therefore, this work employs the Begg and Gray (1984) approximation and specifies individual logistic regression models comparing each category of our outcome variable, the course-taking communities identified in the student level network. An overview of the analytic methods employed in this work is provided in Table 2.

Table 2

Overview of the methods employed to analyze STEM course-offerings and course-taking patterns in Texas charter and non-charter public schools

Analytic Level	Social Network	Community Interpretation	Statistical Analysis
State-wide	*Nodes*: STEM Courses *Edges*: Schools	Sector-level STEM course differences	None
School	*Nodes*: Schools *Edges*: STEM Courses	School-level course offerings	Multinomial Logistic Regression & HLM
Student	*Nodes*: Students *Edges*: STEM Courses	Student-level course-taking patterns	Multinomial Logistic Regression

Results

The results of this study are organized by the analytic levels described in *Methods*. First, statewide analysis is presented, followed by results from school and student level analyses.

Texas Statewide STEM Course-Taking

Two sets of sociograms (one for charter schools and the other for non-charter public schools) displaying STEM courses connected by the number of Texas schools offering each pair of courses are generated. Nodes in these sociograms represent individual STEM courses and edges connecting nodes are weighted by the number of schools (either charter or non-charter public schools) in which both courses are offered. The sociograms in Figure 4 and Figure 6 are colored by course category (advanced or regular mathematics and science courses or dummy "courses" indicating exit/transfer) for charter and non-charter schools, respectively. The sociograms in Figure 5 and Figure 7 are colored by the communities identified by the multilevel algorithm in charter and non-charter schools, respectively.

Four communities were detected in the network using charter schools to connect STEM courses and three communities were detected in the network using non-charter schools to connect STEM courses. As described in the methods section, the communities in these networks describe the sequence and content of STEM courses associated with one another in Texas charter and non-charter public schools. In both sets of sociograms, nodes that are located in the central, more densely concentrated region are STEM courses that are offered in more schools than the nodes located at the periphery of the sociograms. In this analysis, the STEM courses located on the periphery of the sociograms differentiate the course offerings in charter and non-charter public schools. As such, by analyzing the sets of courses identified through community detection, it is possible to define the types of STEM courses available to students in different charter and non-charter schools.

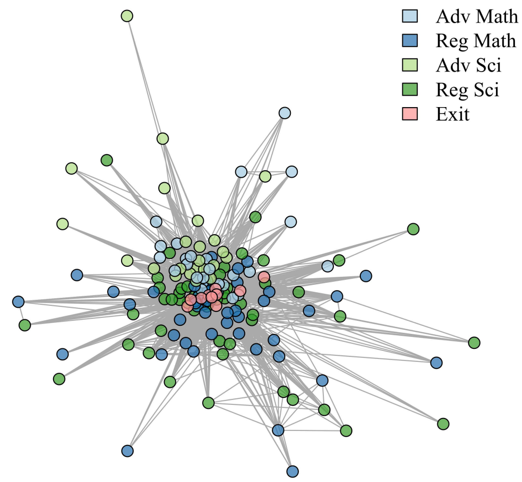

Figure 4. Sociogram depicting STEM courses connected by Texas charter schools. Color represents course type.

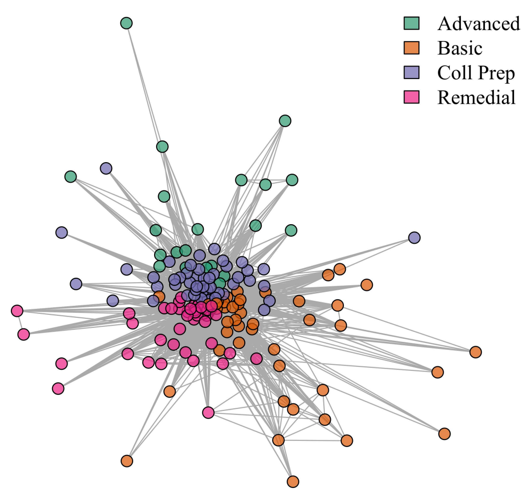

Figure 5. Sociogram depicting STEM courses connected by Texas charter schools. Color represents community identified through the multilevel algorithm.

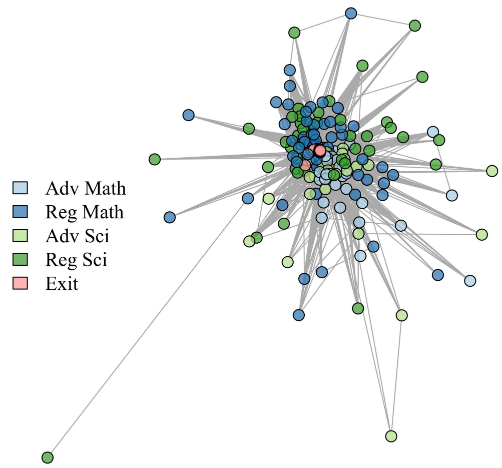

Figure 6. Sociogram depicting STEM courses connected by Texas non-charter public schools. Color represents course type.

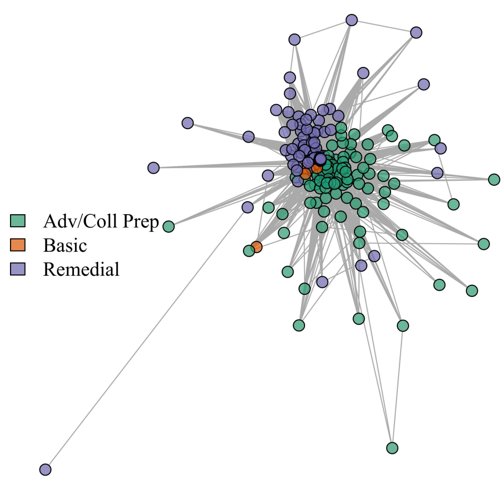

Figure 7. Sociogram depicting STEM courses connected by Texas non-charter public schools. Color represents community identified through the multilevel algorithm.

The four sets of courses in the charter school network can be characterized as advanced, college preparatory, basic, and remedial. The college preparatory set of STEM courses include "staple" courses (e.g., algebra 1, algebra 2, biology, chemistry, etc.) that students take early on during the four-year high school period with AP and IB courses that students take during their final two years. The advanced set of STEM courses is an accelerated version of the college preparatory set. In the advanced set of courses, students are more likely to take AP and IB STEM courses at an earlier stage in their high-school careers. The basic set also includes the "staple" STEM courses; however, after taking the STEM staples, students enroll in non-AP elective courses, such as aquatic science, in their final high school years. Finally, the remedial set consists of STEM courses geared toward students identified as SPED in addition to core courses offered during the latter half of students' high school careers.

The sets of STEM courses identified in the non-charter public school network are characterized as advanced college preparatory, basic, and remedial. The basic and remedial sets of STEM courses in the non-charter public school network are similar to the sets identified in the charter school network, and the advanced college preparatory is a hybrid of the advanced and college preparatory sets of courses identified in the charter school network. In the advanced college preparatory hybrid set of STEM courses, students enroll in both cores and advanced (AP and IB) STEM courses at various points throughout the course of their four years of high school.

Although the findings of the statewide analysis do not conclusively point to differences in the academic programming between charter and non-charter schools in Texas, that four sets of STEM courses are found in the charter school network as opposed to the three found in the non-charter public school network is suggestive of some general sector differences. Charter schools may be organized such that their curricular offerings cater to niche interests to a greater degree than non-charter public schools. There is a distinction in the charter network between advanced and college preparatory STEM course offerings, while these two sets of STEM courses exist as a hybrid in non-charter schools. Hence, students may have more choice in the charter sector when selecting between schools; however, students enrolled in non-charter public schools may have access to more diverse curricular offerings.

STEM Course-offerings in Charter and Non-charter Public Schools

In our next analysis, we do not construct sociograms for charter and non-charter separately, but instead construct a sociograms in which nodes represent Texas public schools and edges are weighted by the number of STEM courses shared between pairs of schools. Communities in this analysis consist of schools that are closely associated with one another due to the number of STEM courses common to that subset of schools. Sociograms of this network are provided in Figure 8 and Figure 9. The nodes in Figure 8 are colored by school sector, and the nodes in Figure 9 are colored by the communities detected through the multilevel community detection algorithm. These networks are densely connected because some STEM courses are offered in all public schools. Inspection of Figure 9 shows that community structure seems to be related to schools' radial distance from the center of the sociogram.

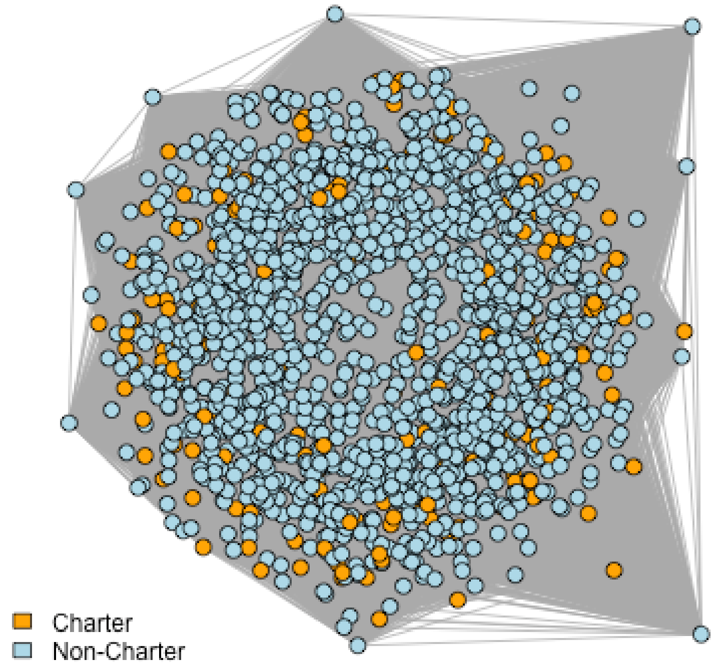

Figure 8. School level sociogram in which edges are weighted by the number of courses shared by pairs of schools. The sociogram is colored by school sector.

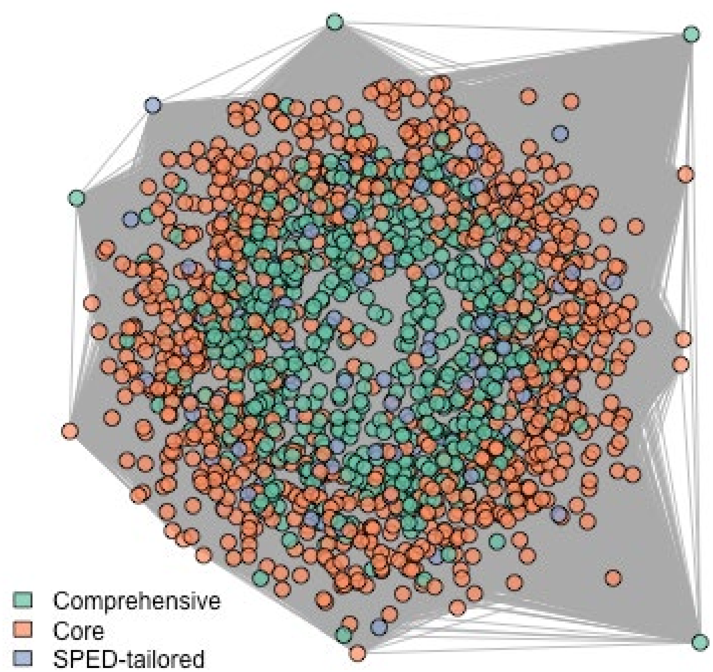

Figure 9. School level sociogram in which edges are weighted by the number of courses shared by pairs of schools. The sociogram is colored by community.

At the school level, three sets of schools, each with different STEM characteristic course-offerings, are found through the multi-level community detection algorithm: schools with *comprehensive* STEM courses; *core* STEM offerings; and STEM offerings tailored for students labeled as *SPED*. There are 641 schools that offer a *comprehensive* set of STEM courses, 879 schools that offer *core* STEM coursework, and 110 schools that offer a *SPED*-tailored STEM curriculum. The specific courses associated with each set are provided in Table 3 along with the percentage of schools within each respective community offering those courses.

Table 3

STEM courses in Texas public schools by community (as identified in the school-level network) and percentage of schools in each community offering those courses

% Schools	*Comprehensive* 641 Schools	*Core* 879 Schools	*SPED* 110 Schools
75-100	Algebra 1 (SPED) Algebra 1 Algebra 2 AP Biology AP Calculus AB AP Chemistry Biology (SPED) Biology Chemistry Geometry (SPED) Geometry Integrated Phys/Chem Mathematical Models Physics Precalculus Dropout Transfer In Transfer Out	Algebra 1 Algebra 2 Biology Chemistry Geometry Integrated Phys/Chem Mathematical Models Physics Precalculus Transfer In Transfer Out	Algebra 1 (SPED) Algebra 1 Algebra 2 (SPED) Biology (SPED) Biology Chemistry Geometry (SPED) Geometry Integrated Phys/Chem Mathematical Models Physics Precalculus Transfer In Transfer Out
50-75	Advanced Quant Reasoning AP Calculus BC AP Environmental Science AP Physics 1 AP Statistics Environmental Science Independent Study, Math	Algebra 1 (SPED) Dropout Geometry (SPED)	Dropout Environmental Systems Independent Study, Math
25-50	Algebra 2 (SPED) AP Physics B AP Physics C Aquatic Science Astronomy Chemistry (SPED) Earth & Space Science	AP Calculus AB Biology (SPED) Environmental Systems Independent Study, Math	AP Calculus AB Earth & Space Science

Coefficients from the multinomial logistic regression model specified in Equation 4 are given in Table 4. For this model, the probability of a school offering a comprehensive set of courses serves as the reference category to which the probabilities of a school offering either a core or SPED-tailored STEM coursework are compared. Exponentiating the coefficients in Table 4 indicates how much a predictor variable increases or decreases the odds of a school offering a set of STEM courses (in our case, core or SPED-tailored) relative to the reference (comprehensive course offerings).

With the exception of school size, which is in units of individual students, predictor variables in Table 4 represent the proportion of students classified as belonging to a given demographic category at each school. Controlling for school level demographics and school size, a charter school is no more or less likely than a non-charter public school to only offer core STEM courses relative to a comprehensive set of courses. Charter schools are, however, 93% less likely to offer SPED-tailored STEM coursework relative to comprehensive coursework. In addition, schools with greater student populations and greater percentages of students who enrolled in a high-school level math course in eighth grade are less likely to offer only core and SPED-tailored STEM courses relative to comprehensive courses.

Table 4

Results for a multinomial regression model (Equation 4) comparing the odds of a school offering core or SPED courses relative to a comprehensive set of STEM courses

Model	**Core to Comp.**			**SPED to Comp.**		
	Est.	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*
Charter	0.44	0.36		-2.70	1.11	*
Econ. Dis.	1.32	0.79	.	1.13	0.96	
SPED	-5.12	0.86	***	-1.39	0.90	
Gifted	-0.77	1.11		-1.52	1.81	
LEP	0.79	1.93		-3.98	3.17	
MS Math	-2.27	0.60	***	-3.40	0.99	***
Asian	1.01	2.07		9.88	2.20	***
Black	4.46	0.92	***	4.45	1.05	***
Latinx	5.28	0.78	***	5.15	0.81	***
Multi-racial	9.49	2.03	***	13.13	1.73	***
Nat. Am.	0.53	2.80		3.83	2.40	
Pac. Is.	-28.85	0.05	***	-48.12	0.02	***
White	6.66	0.77	***	7.02	0.76	***
School Size	-0.03	0.002	***	-0.01	0.001	***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Coefficients from the regression model predicting the number of course-taking pathways associated with school level predictors and charter school status (Equation 6) are provided in Table 5. Two variants of this model were run—one including random effects coefficients for district and another without. The statistical significance of the predictor variables is the same for both models as are the directions of the effects. The estimates from the model including district-level random are slightly smaller, so we report these more conservative estimates in Table 5. The scales of the predictor variables in this model are the same as the scale of the predictor variables in the multinomial model just discussed. In the model specified by Equation 6, there is no statistically significant effect of school sector on the number of course pathways identified in Texas public schools. Increasing school size and the percentages of Asian, Black, Latinx, Multi-racial, Native American, and White students in a school are associated with statistically significant increases in the number of course pathways identified in that school. The percentage of students identifying as

Pacific Islander is not statistically significant; however, this is likely due to the fact that there are very few students identifying as Pacific Islander in the present study. That increasing the percentages of all racial groups in a school yields an increase in the number of course-taking pathways in that school is somewhat counterintuitive; however, a students' membership in a given racial group is mutually exclusive with his or her membership in another racial group. Thus, for example, a school with a student population identifying exclusively as Asian is estimated to have 2.89 STEM course-taking patterns, whereas a school serving students identifying exclusively as Black is estimated to offer 3.92 distinct STEM course-taking patterns. The estimated number of STEM course-taking patterns for schools with diverse student populations can be computed by multiplying the coefficient for each racial group by the proportion of the student body that identifies as members of that group and summing across all groups. A final note of interest, increases in the percentages of gifted students and students who enrolled in a high school math course during eighth grade are associated with decreases in the number of course pathways identified in a given school.

Table 5
Regression coefficients predicting the associated change in the number of course-patterns identified in schools due to school level demographic characteristics (Equation 6)

	Est.	*SE*	*Sig.*
Charter	-0.10	0.07	
Econ. Dis.	0.10	0.15	
SPED	-0.04	0.21	
Gifted	-1.14	0.29	***
LEP	0.69	0.35	
MS Math	-0.42	0.15	**
Asian	2.89	0.50	***
Black	3.92	0.20	***
Latinx	3.30	0.15	***
Mutli-racial	3.09	0.98	**
Nat. Am.	7.00	1.69	***
Pac. Is.	7.11	4.38	
White	3.07	0.08	***
School Size	0.001	0.0001	***

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.10$

Student STEM Course-taking in Charter and Non-charter Public Schools

In order to categorize the 4800 communities identified within the student level network, k-means clustering (Equation 5) partitioned these communities into clusters based upon community level attributes. These attributes are: students' average STEM, AP and IB, SPED, "staple," non-AP/IB advanced, and total STEM course enrollment; the average percentage of students with STEM credits to graduate under a "distinguished academic program" and under a "foundational" program; and the average percentage of students who dropped out, transferred into a school, transferred out of a school, and enrolled in at least one AP or IB STEM course, advanced STEM course, and SPED STEM course. Six distinct course-patterns were identified: an *advanced* set (Adv); a *basic* set (Basic); a *college preparatory* set (Cprep); a *transitional* set (Trans); a *SPED* set (SPED); and an *exit* set (Exit). The average values of the attributes used to identify clusters of communities using the k-means algorithm are given in Table 6.

In the *advanced* set, students take the highest number of STEM courses (7.6) with 90.3% of students also taking at least one advanced course and 68.6% of students enrolling in at least one AP/IB STEM course. Students grouped in the *basic* STEM course set take an average of 5.4 STEM courses, with 22.2% of students enrolling in at least one advanced course and 4.4% enrolling in at least one AP/IB course. In the *college preparatory* set, students take an average of 6.8 STEM courses with 62.6% of these students taking at least one advanced course and 13.9% of these students taking at least one AP/IB course. The *college preparatory* set is more rigorous than the *basic* set and less rigorous than the *advanced* set. The *transition* set is characterized by a high percentage of students either transitioning into (42.9%) or out of (51.4%) a school. In this course pattern, 7.6% of students drop out of school. The *exit* set differs from the transition set in that students take fewer STEM courses on average (2.0 as opposed to 3.8), and a higher percentage of students in the exit set drop out (10.6%). Finally, students in the *SPED* set take an average of 4.4 STEM courses, and 96.6% of these students enroll in at least one STEM course geared specifically for SPED students.

Table 6
Average number of courses and average percentage of student enrollment in STEM courses by type and by cluster identified using the k-means algorithm

		Adv	Basic	CPrep	Trans	SPED	Exit
Number of Courses	STEM	7.6	5.4	6.8	3.8	4.4	2.0
	Science	3.8	2.5	3.5	1.4	2.4	0.7
	Math	3.7	2.3	3.1	1.4	1.8	0.5
	AP/IB	1.4	0.1	0.2	<0.1	<0.1	<0.1
	Advanced	2.3	0.3	0.9	0.1	<0.1	<0.1
	Core	5.6	3.9	5.7	2.3	0.3	0.5
	SPED	0.2	0.2	0.1	0.2	3.6	0.4
Percent of Students Enrolling	DAP	48.8	9.6	29.5	<0.1	1.4	<0.1
	Foundations	15.5	13.2	15.7	<0.1	5.8	<0.1
	Drop Out	0.4	4.3	1.5	7.6	3.7	10.6
	Transfer In	9.1	30.9	14.5	42.9	10.2	52.3
	Transfer Out	8.1	28.9	10.1	51.4	11.2	14.2
	AP/IB	68.6	4.4	13.9	0.6	0.1	1.4
	Advanced	90.3	22.2	62.6	6.0	2.6	6.2
	SPED	1.3	8.5	2.6	8.0	96.6	22.2

Definitions: AP/IB – Advanced Placement/International Baccalaureate courses; DAP – Qualified for Distinguished Achievement Program; Foundation – Foundation High School Program SPED – Special Education; STEM – Courses in science, technology, engineering, and mathematics

Table 7 gives the average percentage of students in charter (C) and non-charter (NC) public schools in Texas enrolled in each type of course-taking pattern identified through the k-means clustering by demographic category. Statistically significant differences between sector at the $p< 0.05$ level as determined by t-tests are highlighted in gray. For example, of the students enrolled in advanced course-taking patterns in charter schools, 70.3% are identified as economically disadvantaged, as opposed to 31.7% of the students enrolled in advanced course-taking patterns in non-charter schools. This table provides an overview of how course-taking patterns differ between sector for student demographic groups.

The clusters identified through the k-means algorithm are used as the outcome variable in a school level multinomial logistic regression model (Equation 7) and a series of student level hierarchical logistic regression models (Equation 8). The cluster with the largest number of students is the college preparatory group and is therefore set as the reference category in both models. Average demographic characteristics of students in each of identified clusters of communities for charter, non-charter, and all Texas public schools are provided in Table 7. The coefficients from the school level multinomial logistic regression model are provided in Table 8, and the coefficients from the 15 student level hierarchical logistic regression models are provided in Table 9.

Table 7

Average demographic characteristics of students associated with clusters of communities identified through k-means clustering in charter (C) and non-charter (NC) public schools. Statistically significant sector differences at the p < 0.05 level determined through t-tests are highlighted in gray

	Adv		CPrep		Basic		Trans		SPED		Exit	
	NC	C	NC	C	NC	C	NC	C	NC	C	NC	C
Econ. Dis.	31.7	5.8	54.8	70.4	60.1	69.1	70.0	62.8	73.1	81.2	64.5	59.0
LEP	1.3	2.6	5.7	6.8	7.7	10.9	10.3	8.6	7.9	7.6	4.7	6.3
SPED	0.9	10.5	5.2	5.9	15.7	9.9	18.9	11.5	91.3	93.1	21.1	12.6
Gifted	28.5	55.5	7.2	6.3	3.9	2.0	3.2	1.2	0.5	0.0	1.7	0.9
Fem.	51.4	8.2	50.3	52.8	46.1	52.9	46.2	50.5	37.4	39.1	45.2	43.8
Asian	10.5	0.1	2.3	2.7	2.3	1.3	1.5	1.3	1.0	4.3	0.9	0.8
Nat. Am.	0.4	9.2	0.4	0.3	0.5	0.6	0.5	0.4	0.5	0.0	0.5	0.7
Black	8.0	0.0	12.5	13.6	17.0	17.9	19.4	18.4	19.4	8.7	17.0	16.2
Pac. Isl.	0.2	73.7	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.0	0.3	0.4
Latinx	35.6	0.6	52.0	69.7	47.7	60.4	53.8	50.3	52.5	56.5	48.3	47.3
Multi-racial	2.4	8.1	1.5	0.8	1.8	1.1	1.4	1.9	1.2	0.0	2.1	1.5
White	42.9	5.8	31.1	12.9	30.5	18.7	23.3	27.5	25.3	30.4	30.8	33.2

Table 8

Coefficients predicting the associated change in the log-odds of a school offering advanced (Adv.), basic, transitional (Trans.), SPED, or Exit course-sets relative to a college preparatory course set (Equation 7)

	Adv.	Basic	Trans.	SPED	Exit
	Est (SE) Sig	Est (SE) Sig	Est (SE) Sig	Est (SE) Sig	Est (SE) Sig
Charter	0.64 (0.21) **	0.71 (0.15) ***	1.20 (0.14) ***	-0.76 (0.41) .	0.98 (0.17) ***
Econ. Dis.	-1.31 (0.37) ***	-0.07 (0.26)	-0.10 (0.26)	0.80 (0.35) *	-0.04 (0.34)
SPED	-4.20 (0.12) ***	1.41 (0.40) ***	3.40 (0.28) ***	7.49 (0.33) ***	3.62 (0.34) ***
Gifted	1.29 (0.53) *	-2.22 (0.59) ***	-1.64 (0.63) **	0.03 (0.20)	-5.71 (0.17) ***
LEP	1.66 (0.57) **	1.57 (0.50) **	1.86 (0.43) ***	-0.80 (0.12) ***	1.62 (0.56) ***
MSMath	2.02 (0.32) ***	-0.53 (0.27) .	-1.63 (0.30) ***	1.65 (0.45) ***	-2.20 (0.46) ***
Asian	1.31 (0.64) *	1.60 (0.63) *	1.61 (0.69) *	-2.82 (0.15) ***	1.23 (0.17) ***
Black	-0.56 (0.49)	0.27 (0.37)	-0.81 (0.35) *	-7.36 (0.40) ***	-3.97 (0.46) ***
Latinx	-1.17 (0.39) **	-0.55 (0.28) .	-1.69 (0.28) ***	-7.17 (0.32) ***	-4.42 (0.37) ***
Mutli	3.42 (0.03) ***	0.90 (0.03) ***	1.68 (0.03) ***	-3.40 (0.01) ***	2.64 (0.01) ***
Nat. Am.	3.12 (0.01) ***	-0.69 (0.01) ***	-1.42 (0.01) ***	-0.44 (0.01) ***	-6.42 (0.01) ***
Pac. Is.	1.24 (0.01) ***	2.00 (0.01) ***	7.69 (0.01) ***	-10.2 (0.01) ***	3.54 (0.01) ***
White	-2.34 (0.26) ***	-0.07 (0.20)	-1.97 (0.21) ***	-6.66 (0.29) ***	-3.92 (0.28) ***
Schl. Size	.0007 (.0002) **	-.0003 (.0002)	-.002 (.0003) ***	.0005 (.0003)	-.002 (.0003) ***
Comm	0.05 (0.06)	-0.05 (0.05)	0.36 (0.05) ***	0.84 (0.07) ***	0.85 (0.06) ***

*** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1

Table 9

Coefficients for student level hierarchical logistic regression models specified by Equation 8

Log-Odds	Adv. to CPrep			Basic to CPrep			Exit to CPrep			Trans. to CPrep			SPED to CPrep		
	Est.	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*
Intercept	-12.1	0.45	***	-3.3	0.2	***	-8.64	0.63	***	-4.67	0.25	***	-13.8	0.86	***
Charter	3.41	0.94	***	2.8	0.5	***	4.9	0.78	***	6.01	0.41	***	-0.25	0.81	
Econ. Dis.	-0.57	0.04	***	0.51	0.02	***	0.33	0.18	.	0.61	0.05	***	0.43	0.15	**
Gifted	1.13	0.04	***	-0.47	0.04	***	-2.49	0.67	***	-0.88	0.12	***	-1.59	1.26	
LEP	-0.75	0.08	***	0.71	0.03	***	-0.55	0.43		0.52	0.05	***	-0.02	0.2	
SPED	-0.74	0.09	***	2.14	0.03	***	2.85	0.17	***	2.27	0.03	***	8.74	0.38	***
Female	0.08	0.03	***	-0.25	0.01	***	-0.23	0.15		-0.27	0.03	***	0.16	0.1	.
MS Math	5.71	0.03	***	-0.94	0.03	***	-1.5	0.35	***	-1.3	0.1	***	-11.1	4.99	*
Asian	1.5	0.21	***	-0.75	0.13	***	-3.41	0.8	***	-0.91	0.26	***	-3.66	1.05	***
Black	-0.27	0.21		0.14	0.12		-2.9	0.55	***	-0.25	0.21		-1.62	0.66	*
Pac. Isl.	0.49	0.38		-0.91	0.29	**	-5.77	1.84	**	-0.4	0.47		-0.84	3.49	
Latinx	-0.19	0.21		0.09	0.12		-2.8	0.53	***	-0.45	0.21	*	-1.72	0.65	**
Multi-racial	0.29	0.23		-0.11	0.13		-2.58	0.75	***	-0.37	0.25		-1.48	0.76	.
White	0.08	0.21		-0.13	0.12		-2.28	0.52	***	-0.44	0.21	*	-1.77	0.65	**
Log-Odds	Adv. to Basic			Exit to Basic			Trans. to Basic			SPED to Basic			Adv. to Trans.		
Intercept	-11.4	0.57	***	-8.24	1.45	***	-2.82	0.54	***	-16.9	1.11	***	-3.72	1.01	***
Charter	-1.46	1.65		3.79	0.61	***	8.21	1.03	***	1.14	0.73		-5.33	0.75	***
Econ. Dis.	-1.19	0.06	***	0.03	0.29		0.33	0.08	***	-0.16	0.19		-1.19	0.1	***
Gifted	1.66	0.09	***	0.19	0.72		-0.71	0.19	***	-12.7	8.5		1.62	0.17	***
LEP	-1.22	0.11	***	-0.72	0.56		-0.04	0.11		-0.39	0.31		-1.04	0.14	***
SPED	-1.87	0.1	***	0.87	0.25	***	0.94	0.07	***	7.42	0.43	***	-2.61	0.13	***
Female	0.28	0.04	***	0.1	0.21		-0.12	0.06	*	-0.12	0.14		0.09	0.07	
MS Math	6.15	0.06	***	-0.85	0.57		-1.7	0.15	***	-3.61	1.35	**	5.33	0.13	***
Asian	2.54	0.32	***	0.32	1.56		-1.17	0.52	*	2.08	1.23	.	-1.00	0.72	
Black	0.02	0.32		-0.17	1.42		-0.37	0.41		1.66	0.92	.	-3.15	0.69	***
Pac. Isl.	0.82	0.66		1.47	2.15		-1.3	2.15		-9.13	11.5		-2.31	0.95	*
Latinx	0.23	0.31		-0.22	1.4		-0.55	0.41		2.41	0.92	**	-2.81	0.69	***
Multi-racial	0.56	0.34	.	-0.67	1.72		-0.28	0.46		3.06	1.06	**	-2.56	0.75	***
White	0.66	0.31	*	-0.03	1.41		-0.48	0.41		2.00	0.91	*	-2.66	0.69	***

Table 9 (continued)

Coefficients for student level hierarchical logistic regression models specified by Equation 8

Log-Odds	Exit to Trans.			SPED to Trans.			Exit to Adv.			SPED to Adv.			SPED To Exit.		
	Est.	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*	*Est.*	*SE*	*Sig.*
Intercept	-7.61	4.8		-17.2	<0.01	***	-6.3	2.13	**	-6.22	<0.01	***	-0.13	0.88	
Charter	0.75	0.7		-3.14	<0.01	***	6.71	1.27	***	-7.03	<0.01	***	-0.85	0.17	***
Econ. Dis.	0.15	0.46		0.21	<0.01	***	0.95	0.33	**	1.52	<0.01	***	-0.59	0.17	***
Gifted	-0.52	2.53		-3.25	<0.01	***	-2.61	1.12	*	-1.95	<0.01	***	-1.11	0.69	
LEP	-0.28	0.78		-0.76	<0.01	***	-0.09	0.65		-0.09	<0.01	***	0.33	0.37	
SPED	2.07	0.51	***	8.01	<0.01	***	4.85	0.45	***	11.51	<0.01	***	2.96	0.21	***
Female	-0.22	0.39		0.22	<0.01	***	-0.21	0.26		-0.24	<0.01	***	0.59	0.16	***
MS Math	1.28	1.17		0.21	<0.01	***	-4.19	0.38	***	-9.66	<0.01	***	-3.72	0.45	***
Asian	3.35	4.84		3.59	<0.01	***	-2.02	2.28		-2.75	<0.01	***	-1.43	1.02	
Black	0.61	4.81		1.01	<0.01	***	0.06	2.09		-2.36	<0.01	***	1.93	0.89	*
Pac. Isl.	-17.7	512		-36.4	<0.01	***	0.2	3.2		-35.1	<0.01	***	-24.8	52267	
Latinx	0.75	4.79		0.86	<0.01	***	-0.41	2.07		-2.75	<0.01	***	1.85	0.87	*
Multi-racial	-0.5	5.78		0.92	<0.01	***	0.09	2.23		-2.89	<0.01	***	0.33	0.98	
White	1.67	4.79		0.84	<0.01	***	0.29	2.07		-2.09	<0.01	***	0.76	0.87	

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$

Controlling for school level demographics, school size, and the number of course-taking pathways identified within each Texas public school and relative to the odds of offering a "college preparatory" course pattern, charter schools are associated with an 86% increase in the likelihood of offering advanced course pattern, a 103% increase in the likelihood of offering a basic course pattern, a 232% increase in the likelihood of offering course patterns associated with transitions, and a 166% increase in the likelihood of offering course patterns associated with exit. These increases are all statistically significant. Charter schools are also associated with a 53% decrease in the likelihood of offering SPED tracks, but this is not statistically significant at the $p < 0.05$ level.

Student level analysis suggests enrollment in a charter school is associated with statistically significant increases in the likelihood that a student follows advanced, basic, transition, and exit course-patterns relative to the college preparatory course pattern. There is no statistically significant difference in the likelihood of a student enrolling in a SPED course pattern relative to a college preparatory pattern in charter schools. Relative to a basic course pattern, there is no statistically significant difference in the likelihood that a student enrolls in an advanced or SPED pattern; however, charter school students are statistically significantly more likely to enroll in exit and transition course patterns. The most likely course-patterns for charter school students are associated with exit and transition, while the least likely course-patterns for charter school students are the college preparatory and SPED course patterns.

Discussion

As articulated in the introduction, the goals of this study are twofold: 1) to characterize differences in STEM course-taking options between charter and non-charter schools; and 2) to examine differences in students' STEM course-taking patterns in charter and non-charter secondary schools. Differences in STEM course-offerings between charter and non-charter schools were investigated using school level analyses, while differences in students' STEM course-taking patterns in Texas charter and non-charter schools were investigated using student level analyses comparing the probabilities of students enrolling in different sets of STEM courses. A discussion of the primary findings related to the two research foci of this study are included in the two following subsections.

STEM Course-offerings in Charter and Non-charter Public Schools

Results from the school level statistical analysis herein suggests there are no sector differences in the number of course-sequences offered when controlling for school level demographics and the size of the cohort population (Equation 6 and Table 5). Although the number of individual STEM course-taking patterns was not found to differ between charter and non-charter schools in Texas, there are sector differences in the kinds of STEM courses offered. After constructing school level sociograms in which schools are connected by the number of STEM courses common to each pair of schools, three communities of schools are identified with their associated courses listed in Table 3. Relative to the community with the widest range of STEM courses offered (comprehensive), charter schools are less likely to offer a set of STEM courses tailored for SPED students. That charter schools are less likely to offer SPED course offerings is consistent with research indicating that charter schools typically serve fewer percentages of students qualifying for SPED services (Estes, 2003; Winters, 2015). There is no statistically significant difference in the likelihood of a charter school offering either a comprehensive set of STEM courses or courses that are limited to core STEM subjects.

In contrast to narratives that promote charter schools as educational institutions capable of offering novel instruction and curricula, results from the hierarchical model and analysis of the school level community detection show that charter schools and non-charter schools are more alike in course-offerings than they are different. Charter schools are not more or less likely than non-charter schools to offer STEM courses that are minimal, consisting of only staple courses with few electives, nor are they more or less likely to offer expansive course offerings, which include both advanced STEM courses and STEM courses tailored for SPED students. An important exception is that charter schools are less likely than non-charter schools to offer STEM courses that are heavily oriented toward SPED students.

Analyzing results from student level community detection, in which k-means clustering was used to group STEM course sets with common attributes, we find the course sets in which charter school students enroll are more likely to be "advanced" and "basic" when compared to "college preparatory" course-patterns. In addition, STEM course-taking patterns in charter schools are more often associated with mobility (transition and exit) than course-taking patterns in non-charter schools.

As studies exploring differences in student achievement have noted, the differences appear to be highly contextual. While the finding that charter schools are simultaneously more likely to offer "advanced" and "basic" course sequences relative to college preparatory course sequences may seem at first counterintuitive, it is possible that the charter schools offering "advanced" course sequences are contextually different than charter schools offering "basic" tracks. This is a speculation that warrants further consideration and may lend additional insight into the different kinds of academic programs offered in various charter schools. Specifically, it may be that charter schools target different populations: college preparatory charter schools may target populations who are pushed into advanced STEM coursework; whereas other schools—charter schools serving high populations of students deemed "at-risk" for dropping out of high school—may offer basic and minimal STEM coursework. By contrast, non-charter schools do not have the freedom to recruit specific subsets of students and thus do not tailor academic programming to meet the needs of a specific subset of students. As such, course-offerings in non-charter schools are broader than those in charter schools, as they cater to a more heterogenous student population.

The statewide analysis of STEM course networks connected by charter and non-charter schools help to contextualize this finding. Four sets of courses were identified when connected by charter schools, as opposed to three sets of schools when connected by non-charter public schools. This is not a robust difference, but it does provide some evidence of sector differences. In the statewide analysis, the advanced/college preparatory set of courses in the non-charter school network is a hybrid of the distinct advanced and college preparatory sets in the charter school network. That this difference is detected when charter and non-charter schools are analyzed separately may be due to the fact that there are far more non-charter public schools than charter schools in Texas. This finding also suggests students enrolling in charter schools may have more options to select between schools with more focused STEM curricula; however, their course-taking patterns may be limited after enrolling in these schools. By contrast, non-charter public schools have more expansive course-offerings, so there are more course-taking patterns available to students in these schools. This finding warrants additional attention and research moving forward.

STEM Course-taking Patterns in Charter and Non-charter Public Schools

STEM course-offering differences between charter and non-charter schools as identified during school level analyses align with differences in student level STEM course-taking pattern differences between charter and non-charter schools in Texas. This is a sensible finding, as course-offerings within a given school necessarily constrain student course-taking options. Results from hierarchical logistic regression models suggest that students in charter schools are more likely enrolled in course sequences characterized by high mobility (e.g., transfer and dropping out) than are students in non-charter schools, which makes sense given the premise of school choice. In addition, students in charter schools more often take course sequences that have a greater number of advanced STEM courses or that are characterized by minimal STEM coursework. Relative to these four sets of courses, students in charter schools are less likely to take "college preparatory" STEM course-sequences or STEM course-sequences that cater to SPED populations. Potential reasons for this are offered in the conclusion.

These results are consistent with other studies finding that students in charter schools are more likely than students in non-charter schools to be enrolled in advanced course sequences (Berends & Donaldson, 2016). It is likely that some of the differences observed may vary by each school, as different charter schools serve different populations and may very well have different course-offerings to meet the needs of these students.

As articulated in the preceding section, these seemingly contradictory findings may reflect school level differences within charter schools. The specific academic programs in some charter schools may be tailored such that students take more advanced courses, while the academic programs in other schools may serve to give students only basic preparation in STEM. In addition, charter school cohorts are smaller than cohorts in non-charter schools. Thus, while course-offerings may be more diversified *among* charter schools than among non-charter schools at the school level, which likely reflects the fact that charter schools cater to specific student groups, the course-taking patterns *within* charter schools appear to be more limited than course-taking patterns within non-charter schools. Considering that charter schools tend to serve student populations who have been historically underrepresented in STEM disciplines, that the STEM courses available to students in charter schools are more limited than the sets of courses available to students in non-charter schools, it is a matter of equity to explore how these differences serve to either promote or hinder students' engagement with stem at post-secondary levels. While charter schools are able to recruit students by catering to niche interests, it is important for research to investigate how these curricular differences relate to a variety of post-secondary patterns and to better understand whether or not the targeted STEM curricula in charter schools translates to positive outcomes for students, particularly considering charter schools are more likely to serve student populations who have been historically underrepresented in STEM.

Conclusion

Our results indicate that charter schools and non-charter schools offer similar STEM courses to students, except that charter schools are less likely to have course-offerings tailored for SPED students. Despite the similarity in STEM course-offerings in Texas charter and non-charter schools, there are sector differences in the students' course-taking. Of the six groups of course-sequences identified in this study, charter schools are most likely to offer course-sequences associated with mobility (transfer and dropping out), and least likely to offer course-sequences that have been defined herein as college preparatory (meaning students take several STEM courses, but not advanced electives) and course-sequences tailored for SPED students. Relative to the "college preparatory" course sequence, charter schools are more likely to offer tracks characterized by a high number of advanced coursework in STEM or characterized by minimal course-taking in STEM. A summary of these results is provided in Table 10.

Table 10
High probability STEM course-patterns by sector in Texas

STEM Course-Sequence	**Sector**	
	Charter	Non-Charter
Advanced	√	
Basic	√	
College Preparatory		√
SPED		√
Transfer	√	
Exit	√	

Our results suggest that while general course-offerings between charter and non-charter schools may not embody the "innovation" promised by school choice advocates, there are differences between charter and non-charter schools in student STEM course-taking patterns, namely that students in charter schools take either more advanced STEM courses or more basic STEM courses than students in non-charter schools. Investigating these differences more deeply is an important next step for research on charter schools. It seems that charter schools provide a mechanism by which they cater to certain groups of students rather than following a mandate to serve all students. Specifically, future work should explore how programmatic differences between charter and non-charter schools are related to differences in student outcomes, such as test score increases, college enrollment, or labor market outcomes. Moreover, that charter schools are less likely to offer STEM courses tailored for SPED students necessitates that research look into how this specific subpopulation of students experiences choice with respect to STEM course-taking.

In addition, the methods employed in this work offer researchers a way to systematically evaluate and characterize the conditions within charter and non-charter schools at a large scale. These methods and results can be used to inform other research, including how policy networks impact students' experiences in charter and non-charter schools. The growth of charter schools has given wealthy individuals a means by which to gain substantial influence within the public education system. Au and Ferrare (2014) document that wealthy individuals use philanthropic organizations to advance education policy, and Brandt (1998) argues that policy sponsors offer their support out of self-interest. In the current era of school choice, individuals have increased potential to exert substantial influence within the public education system, and it is therefore important for researchers to consider how this influence manifests for students and the programmatic elements of their schools. Are policy sponsors using their influence to promote equitable experiences for students or are they using their influence to limit students' academic programming in a way that aligns with individual policy sponsors' interest? For example, are individuals and companies in technology fields interested in establishing charter schools with increased an increased STEM focus?

In addition to informing research on policy networks, our results can inform administrators and teacher-leaders responsible for deciding course offerings at individual schools. With information about the ways in which course-offerings serve to either promote or hinder student participation in STEM, and by tying these results to students' post-secondary course-taking, school leaders can make better-informed decisions about which courses should be offered to best promote student success. The methods proposed in our work allow researchers to uncover a more nuanced view of student options in charter and non-charter schools, and linking this information to the individuals, funding, and policies related to certain charter schools has the potential to illuminate the ways in which policy networks affect students' experiences in charter schools.

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