Variation in Opportunity to Learn at Secondary Education: The Social Determinants of Between- and Within-School STEM Tracking in the US and Beyond

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This dissertation investigates the social determinants of STEM curriculum tracking and changes in the nature of STEM tracking in both US and cross-national settings over recent decades in five NCES High School longitudinal datasets and in seven TIMSS studies. Methodologically, this dissertation contributes to the field by developing a consistent and comprehensive transcript-based and instructional content-based measurement scheme of the most important organizational dimensions of tracking. This research also advances the current state of knowledge in the field of STEM curriculum and education inequality by adding rich description of the organizational dimensions of tracking both in the US and globally and drawing attention to the ways in which STEM curriculum tracking departs from its functional ideal. Although tracking systems are intended to benefit all students, too often they result in widening educational inequality. Using rich data on student course taking over the course of secondary education, I produce new measures at both the school-level and country-level capturing inequality in STEM opportunity to learn, both of which are essential to the STEM pipeline. At the same time, as with prior policy-focused studies, this research project draws attention to tracking policies and practices themselves in hopes of generating organizational awareness of, and introspection by administrators towards tracking. In an era of curriculum intensification, this work helps researchers and policymakers understand how schools with different compositional characteristics expose students to differently tracked learning environments. Moreover, this dissertation study also advocates a systematic understanding of

tracing the fundamental sources of inequality in opportunity to learn. Overall, while it may be difficult to describe a given determinant of tracking in the context of the secondary data analyses in this dissertation as unequivocally dysfunctional, this research may nevertheless encourage scrutiny of curricular policy and practice that too often go unexamined.

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Preface

I feel immense gratitude for all the help that I have received in my academic journey from my advisor, committee members, professors, peer graduate students and friends, and my loving family. I extend my great appreciation to my advisor, Dr. Sean Kelly, for his continuing support, guidance, and encouragement over the past eight years, even since I was a MEd student. I still remember the days when I just entered the program with little knowledge of the field and limited language ability. Dr. Kelly shows me the door of the entire field of education, leads me into the world of social science research, and brings me to an early academic career. I always feel great fortunate to be able to extend his early theoretical work and bring more systematic empirical evidence in my dissertation projects. I also wish to thank my other dissertation committee members, Dr. Najeeb Shafiq, Dr. Rip Correnti, and Dr. Eric Grodsky for their invaluable feedback and constructive criticism during my dissertation work.

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1.0 Introduction

Existing research on tracking has primarily focused on two main aspects that contribute to educational inequality: the process of track placement and the effects of tracking. Track placement refers to the process that, in theory, primarily groups students based on their achievement levels. Official organizational logic views tracking as a rational approach to tailoring instruction to better match students' learning needs in different, relatively skill-homogeneous classrooms (Rosenbaum, 1976). However, in addition to the assignment process ostensibly based on achievement, track placements can also be influenced by social factors including gender, SES, race/ethnicity. Family SES, for example, is found to influence track placements as high-SES parents become involved in track selection (Useem, 1992) and generate higher educational expectations for kids (Kelly, 2004; Parker et al., 2016). Research on the effects of tracking considers the role of track placements in magnifying initial achievement discrepancies and producing educational inequality. In theory, tracking benefits all students, by providing instruction in their zone of proximal development (Hanushek, & Wößmann, 2006; Oakes, 1985; Van Houtte, & Stevens, 2009). However, in practice, track placements determine the extent of learning opportunities offered to students, including instructional content, pace, and learning environment (Hallinan, 1987). On average, lower-track students experience more constrained learning opportunities compared to their high-track counterparts. As students progress through schooling, and depending on both placement processes and the effects of tracking, initial variation in student engagement and achievement is magnified (Kelly, & Covay, 2008).

Although not the focus of the present study, it should be noted that in the US, students first experience curriculum differentiation upon entry to primary education, in the form of ability grouping within classrooms (Curran et al., 2020). In particular, students of different reading and literacy abilities, are assigned into different ability groups for various forms of literacy instruction (Entwisle, & Alexander, 1993; Slavin, 1987). Later in secondary education, tracking takes place between classrooms. Considering both the accumulated effect of differentiated learning opportunities and the role of social inequality in track and ability-group placement, tracking at secondary education is theoretically less responsive to achievement distributions than primary education, where we might expect variation in achievement to more closely determine track placements (Kelly, & Covay, 2008).

At least since Rosenbaum's (1976) case study of Grayton high, sociologists have sought to ascertain just how functional secondary school tracking systems really are. The term "functional" works in at least three ways (Davis & Moore, 1945; Kelly, 2009). First, according to functionalists' view of education, education is a rational and efficient system that sorts students who exhibit different levels of ability and effort into different occupational positions. Second, track assignment is functional at the individual student level, as the achievement distribution is closely related to track placement and appropriate content and pace of learning. Third, from the teachers' perspective, tracking offers functional, or perhaps, "technical" benefits, allowing them to more easily tailor instruction to students' level of readiness. Critical to my dissertation, this investigation goes beyond simply determining whether high track students learn at a faster rate, or whether students from different social backgrounds are placed in different tracks, although both of those questions speak to functionalism. At the system/policy level, several organizational dimensions of tracking are relevant to evaluating the functional logic of tracking. To preview these dimensions that I consider in more detail subsequently, consider the following examples. First, to what extent does a school consider student achievement during enrollment? Schools may tailor their enrollment process to be explicitly sensitive to achievement (later I refer to this as high selectivity) to create skill homogeneous instructional environments and better fit the achievement distribution of the student body (e.g., Eccles, & Roeser, 2011). Relatedly, in addition to considering students' "subject-specific" needs, schools may also promote corequisites, a form of "cross-subject" tracking (later I use the term scope), based on students' achievement on both subjects. Moreover, a school's ability to flexibly reconsider students' instructional needs by allowing for mobility across tracks may also be considered as functional, as effectively matching students' ability/capacity with instruction may boost students' achievement (Domina et al., 2019). However, as many have argued (e.g., Lucas, & Good, 2001; Domina et al., 2019), tracking systems that follow a "tournament style" (i.e., where students only move down, and rarely or never upward; see Rosenbaum, 1976 for the origin of this term) may depress the positive effect of having high flexibility. Therefore, the flexibility to move students upward may be the more relevant form of mobility under the functional logic of tracking.

Scholars of tracking have also directly considered less functional (or even conflict) determinants of tracking, including policies and practices that affect track placement based on various social determinants (e.g., race and SES). For example, prior sociology research on tracking finds that high-SES families have an advantage in accessing high-track courses (Kelly, 2004; Lareau, 2011; Hanselman et al., 2022) and are able to maintain their advantages (Domina et al., 2016; Gamoran, 2004). These studies suggest non-functional aspects of tracking; that is, when achievement is clearly not the sole determinant of track placements, and when inequality in track placements go beyond functional explanations and occur across several socio-demographic dimensions (e.g., Kelly, 2009), and further exacerbate the existing racial-ethnic or gender inequality in achievement (e.g., Riegle-Crumb, 2006; Riegle-Crumb, & Grodsky, 2010).

This dissertation builds on the conceptual framework proposed by Kelly and Price (2011) and measures developed in Xu and Kelly (2020, see also Kelly, 2004, 2009; Riegle-Crumb, & Grodsky, 2010; Schneider, Swanson, & Riegle-Crumb, 1997; Stevenson, Schiller, & Schneider, 1994) to explore the social determinants of STEM curriculum tracking in both US and international settings. In Kelly and Price's (2011) empirical work on examining the relationship between school compositional characteristics and school-to-school differences in school tracking policies, they innovatively applied theories of social stratification, including technical-functional theory, opportunity hoarding, and status competition, to explain the observed school-to-school variations in tracking policies themselves. This study extends this framework by examining how both functionalism and social forces are related to curriculum differentiation, utilizing actual measures of course-taking experiences, in both US and cross-national research settings. In the US analysis, overall, I examine the relationship between school composition and the organizational dimensions of tracking. This analysis includes a longitudinal investigation of how and why the US school tracking system changed over the period of roughly 1980-2010. In particular, I pose two research questions. First, are observed school-to-school differences in math and science tracking practice more obviously related to easy-to-document functional motivations for tracking or to potentially dysfunctional social forces of tracking? Second, how have US schools' math and science within-school tracking structures changed over past decades, and are these changes explained primarily by functional or dysfunctional mechanisms. Procedurally, and in Chapter organization, I begin in Chapter 2 by providing a descriptive portrait of the levels, variation, and changes in the organizational dimensions of tracking across cohorts, which helps ease readers into working with these measures, and the inferential analysis in Chapter 3 proceeds according to the research questions above.

Moving to the international setting, there is a foundational difference with the US: between-school tracking in some countries is much more extensive than in the US. For example, it is expected that some countries implement strict between-school tracking to better fit their developmental goals (e.g., Germany's "tripartite" secondary education tracking system enables vocational students to receive early on-site vocational training). Yet, studies of cross-national inequality in education often fail to trace the sources of inequality in opportunity to learn in as systematic way. In Chapter 4, I propose a theoretical framework, encompassing internal-development processes, basic social inequality, the distribution of achievement across schools, and national educational policies, to explore the fundamental origins of inequality in opportunity to learn. This conceptual framework first draws attention to the theoretical link between education inequality and basic social inequality as a country develops; thereafter, school-to-school differences in opportunity to learn may be further attributed to both functional and conflict forces of tracking.

While it may be difficult to describe a given determinant of tracking in the context of the secondary data analyses in this dissertation as unequivocally dysfunctional, this research may nevertheless encourage scrutiny of curricular policy and practice that too often go unexamined. To summarize, Chapter 2 and 3 of this integrated dissertation contain analyses of within-school tracking in the US, while Chapter 4 contains cross-national analyses of between-school tracking.

2.0 Organizational Dimensions of Tracking, a Descriptive Analysis

2.1 Introduction

In the sociology of education and other social science research on curriculum tracking, scholars have focused on two factors that collectively have consequences in producing and re-producing educational inequality: the placement process of curriculum tracking and the effect of curriculum tracking on learning. As a major component of opportunity to learn, systematic differences in school curricular organization can induce inequality in learning opportunities and may ultimately produce inequality in learning outcomes when students experience different degrees of exposure to curricular content. Yet, despite the fact that scholars know much about: (1) the unequal process of track assignments, and (2) the effect of track placement on educational inequality, such studies often neglect the social forces that motivate the origin of, and explain changes in, tracking practices. In Kelly and Price's (2011) empirical work on examining the relationship between school compositional characteristics and school-to-school differences in school tracking policies, they innovatively applied theories of social stratification, including technical-functional theory, opportunity hoarding, and status competition, to explain the observed school-to-school variation in tracking policies. Building on Lucas and Berends' (2002) conceptualization of linking the school-level curriculum tracking system with schools' student body compositions (i.e., where the tracking system is responsive to the composition of student populations), Kelly and Price (2011) identified various functional factors at the school level (e.g., school size and achievement heterogeneity) and conflict factors, such as racial-ethnic heterogeneity, that were associated with the schools' overall elaboration of tracking policies. At the same time, as in prior work with similar policy data (Kelly, 2007), they draw attention to tracking policies and practices themselves, rather than patterns of outcomes.

In Chapter 2 and 3, I examine how school composition is related to tracking, and how and why the US school tracking system changed in recent decades. I begin (Chapter 2) by descriptively analyzing changes across decades/studies in the organizational dimensions of tracking, an analysis that will help introduce readers to the measurement of tracking without introducing complicated statistical models. How have US schools' tracking structures changed over past decades? Over the past 40 years, the US secondary school curriculum has experienced the standards-based reform movement, including national level policy change (e.g., NCLB), major waves of educational reform at the state and local level (e.g., standards-based reform), including state-level/regional policies about course taking in particular (e.g., algebra for all in CA). These policies introduced higher academic standards and graduation requirements, enforced high-stake tests and accountability, and, as a consequence, produced a concomitant rapid academic intensification (Austin, 2020; Domina, & Saldana, 2012). Domina and Saldana (2012) identified consistent trends of academic intensification of individual subjects using data from 1982 to 2004. They found that the proportion of high-schoolers who completed precalculus and calculus tripled, but inequality in calculus completion remained pronounced. Using a new measurement strategy with the consideration of both changes in individual subjects and changes in association among different subjects, Austin (2020) instead argued that the trends of curriculum intensification was prominent during the 1980s and 90s, but stable in the 2000s. What about scope and other dimensions of tracking? This project goes beyond the very basic measures of course taking in the existing literature by providing a way to consistently measure the multiple organizational dimensions of tracking systems at the aggregate level of the school, utilizing four NCES High School longitudinal studies. In Chapter 3, I turn to a more complex analysis of tracking that focuses on the association between school composition and tracking, both in pooled cross-section and in changes over-time. Are observed school-to-school differences in tracking practice and changes in tracking practices more obviously related to easy-to-document functional motivations for tracking, or instead, to dysfunctional social forces of tracking? For example, schools may promote curriculum tracking to increase efficiency by creating skill-homogeneous instructional environments, or schools with a high proportion of advantaged students may create especially elaborated tracking systems in response to opportunity hoarding or status competition processes.

This study is novel in several ways. First, while various research has examined the relationship between elaboration of tracking and school composition of student populations within single states (e.g., Domina et al., 2016; Kelly, & Price, 2011), we lack knowledge of how these findings can be generalized to the whole nation over the past 40 years. Second, it's also worthwhile to note that throughout the project I use multiple measures of the various organizational dimensions of tracking systems, instead of just a single ordinal measure of the overall elaboration of tracking. Sørenson's (1970) original theoretical work on organizational differentiation in school systems argued that school tracking systems varied along at least four organizational dimensions, including inclusiveness, selectivity, electively, and scope (see also, Domina et al., 2019; Gamoran, 1992; Kelly, 2007). Research on organizational dimensions of within-school curriculum tracking find that (1) different organizational dimensions may produce different educational outcomes; (2) a policy may have different effects on different organizational dimensions of tracking (e.g., Kelly, & Price, 2011) and, (3) organizational dimensions are noticeably unique/distinct, having limited correlation with each other (e.g., Domina et al., 2019). Thus, these empirical studies suggest that the full set of organizational dimensions of tracking is needed to conceptualize schools' practice of tracking, and, therefore, may capture greater variation across school-level tracking systems. Moreover, the observed changes in each organizational dimension of tracking may be motivated by different social mechanisms and thus examining the dimensions individually may be worthwhile. For parsimony, I will often refer to "tracking" as the overall topic of this dissertation, but I dedicate much effort to exploring specific dimensions of tracking, constructing rich measures from student transcript data. Third, to reiterate a key difference from Kelly's prior work, I focus on observed course taking patterns from transcript data, rather than schools' stated policies and practices in curriculum guides.

In these two chapters, I utilize four NCES High School longitudinal studies, HS&B, NELS: 88, ELS: 2002, and HSLS:09 to explore trends in school tracking systems over the period 1982-2013[1]. By addressing two main research questions with four datasets, I am able to extend the scope of the current studies by adding rich description of US schools' tracking structure and exploring changes in the determinants of tracking over time. Another unique contribution is that I examine the tracking system for both mathematics and science, whereas many prior studies have looked only at math. Considering a second discipline/content area not only increases the robustness of the results, it also addresses the on-going push to examine high school math and science education from the perspective of the STEM pipeline (e.g., Wang, 2013). Although the data collection time points do not necessarily align neatly with any specific policy changes, because we have 4 cohorts with on average 9 years in between data collection waves, I am able to capture trends in US tracking systems over the course of 40 years. This analysis is split into two chapters with Chapter

[1] The first NCES high school longitudinal study, NLS-72 didn't provide transcript data.

2 being the descriptive analysis of trends in US tracking systems over the past 40 years and Chapter 3 being multivariate models of the correlates of tracking system over time.

Because Chapter 2 and 3 draw on multiple longitudinal studies, finding a way to consistently measure tracking elaboration and multiple organizational dimensions of tracking from several databases is a substantial part of this work. The measurement of tracking consists of two major steps: (1) describing individual student course taking, and (2) describing the structural features of tracking systems at the school-level from individual student course taking patterns and other student assessment information. Individual student course taking can be accessed from transcript datasets which are available in each database, summarizing a given student's course taking. Transcripts are analyzed using the concept of course sequences, revealing the course-taking hierarchy across students. Starting with data on individual student course taking, I use various aggregation strategies to develop multiple measures of the structural features of tracking systems at the school-level, including inclusiveness, scope, selectivity, and mobility.

Chapter 3 develops multivariate models, selectively using measures first reported in the descriptive analysis in Chapter 2, to further address my overarching question: how is school composition related to tracking and has the balance between functional and conflict forces in the US tracking system changed over time? Again, I examine the following research questions.

(1) Is variation in US schools' tracking structures related to school-level compositional characteristics that can be attributed to different logics and determinants of tracking?

(2) How have these relationships changed over the past several decades?

By exploring these two questions, I identify how and why US high school STEM tracking systems vary across schools, and how the sources of that variation have changed over time. For example, if tracking systems are becoming more responsive to test score distributions, the US tracking systems are becoming increasingly functional (at least in that basic respect). Otherwise, if tracking systems are getting more tightly coupled with the socioeconomic distribution of each school, then it might be said that tracking systems have become increasingly dysfunctional.

2.2 Background Literature

2.2.1 Track Placement: An Organizational Perspective

In theory, track placement primarily involves grouping students based on their achievement levels. According to the official organizational logic, tracking is seen as a rational approach to tailor instruction and match students' learning needs in relatively skill-homogeneous classrooms (Rosenbaum, 1976). However, track placement is not solely determined by achievement and can be influenced by social factors such as gender, SES, and race/ethnicity, which can contribute to educational inequality. For instance, high-SES parents' involvement in track selection and higher educational expectations for their children can influence track placements (Useem, 1992; Kelly, 2004; Parker et al., 2016).

Another area of research focuses on organizational approaches that determine track placement at the school level. In particular, such research seeks to reveal the way in which school tracking systems are shaped by internal and external factors, and how educational inequality is generated in this process. To begin, it is generally understood that schools determine (1) the amount of available learning opportunities students are exposed to[2], and (2) the way in which

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[2] Of course, another important source of inequality in learning opportunities is the learning outside of school settings.

opportunities to learn are allocated among students. For example, schools determine how many differentiated learning experiences are in place for each subject. Kelly (2007) found a substantial variation in the number of vertical levels of ELA, Math, Science and Social Studies courses, using a dataset of curriculum guides from 92 North Carolina high schools. Schools also formally regulate the sorting process by adopting enrollment criteria and measures, such as prerequisites and corequisites, teacher recommendations, and minimum GPA/standard test scores requirements (Kelly, & Covay, 2008). Yet, schools are not the sole actors determining the placement process, as track placement is also constrained by a broad array of inter-correlated pedagogical, socio-political, and policy-implementation processes, creating even more variation in school curriculum tracking systems. Examining organizational approaches provides more insights into why schools adopt different tracking systems—the sources of school-to-school differences in tracking—and helps understand educational inequality generated from tracking at the school level. This section summarizes three social and organizational phenomena that shape and constrain track placement and related social theories that help explain the observed school-to-school differences in tracking systems.

2.2.1.1 Policy and Accountability

First, school tracking systems are greatly influenced by formal state and district-level policies, trends in school reform, and accountability regulations. Beginning in the 1990s, with a wave of standards-based school reform policies and push for curricular intensity, policy groups started to develop higher curricular standards for instruction and learning (National Council on Education Standards and Testing, 1992), pushing schools to place more students in higher tracks (Schiller & Muller, 2003). For example, Domina and Saldana (2012) found that over a two-decade period of change, the average high school graduate took approximately five more academic credits.

By 2004, approximately 43% of high school graduates earned credits in trigonometry or higher math courses, whereas only 19% of high school graduates in the class of 1982 completed trigonometry or higher math courses. More recent policies, such as Algebra for All, College Prep for All, and ongoing policy trends emphasizing STEM courses, aim to expand enrollment for gatekeeping courses. Yet, in practice, the implementation of formal tracking policies may be affected by accountability pressures and the lack of mandates and regulations. At-risk schools, for example, are found to be more responsive to state-level tracking policies in recent decades (Domina et al., 2016), similar to studies on accountability policies that find the most positive effects on observed achievement among at-risk schools (e.g., Lauen, & Gaddis, 2012), whereas other schools may not fully implement the tracking policies (Domina et al., 2015).

2.2.1.2 Technical and Normative Beliefs

Next, school administrators and teachers' pedagogical and normative beliefs also shape track placement processes and the way in which schools implement tracking policies at the school level. First, *technical* rationales for tracking argue that it creates a skill-homogeneous learning environment where instruction can better match students' needs and benefit them the most (e.g., Hallinan, 1994). Studies of de-tracking often find complex effects of heterogeneity on students' educational outcomes. Low-achieving students have been found to benefit from de-tracking of instructional environments in some cases (e.g., Domina et al., 2019), yet the inclusion of high-level content in skill-heterogeneous classrooms can have negative effects (e.g., Penner et al., 2015; Rosenbaum, 1999). Technical considerations of curriculum tracking concern the pedagogical challenges of teaching in a classroom with diverse course-taking readiness. In particular, teachers may be ill-prepared for teaching in skill-heterogeneous classrooms, and learning materials used in a skill-heterogeneous classroom may not be well-suited to the instructional needs of all students

(Clotfelter et al., 2015; Kelly & Covay, 2008; Loveless, 1999; Northrop, Borhseim-Black, & Kelly, 2019). Thus, school administrators and teachers who embrace such pedagogical concerns may prefer to promote highly differentiated curriculum systems.

Relatedly, educators' more general *functional* beliefs about schooling can also shape the school tracking system. Early theoretical works emphasize that schooling is an effective socializing mechanism, whereby students are sorted into learning environments that anticipate the already-differentiated occupational realm and society (Davis, & Moore, 1945; Hurn, 1993). How might this general functional paradigm of schooling affect a school's tracking system? School leadership literature finds that schools are sensitive to historical and local norms (Arum et al., 2007; Meyer, & Rowan, 2006), and decisions about tracking systems are shaped and constrained by the normative belief of functionalism (Gamoran, 2004; Watanabe, 2006). Combining technical rationales of tracking and functional beliefs of schooling, a technical/functional theory of tracking considers the role of curriculum of tracking in both facilitating instruction and responding to social stratification in the occupational structure. For example, Domina et al., (2016) found that that schools with technical-functional concerns tended to resist curriculum intensification; that is, a technical-functional concern encouraged schools with low average achievement scores or heterogenous student compositions to slow down the trends of enrolling all students in algebra and to continue to provide skill-differentiated courses.

2.2.1.3 Internal and External Political Interests

Lastly, both internal and external political interests in maintaining differentiated curriculum systems exert additional pressures on tracking practices, including placement policies and practices. External political interests affecting tracking include pressure from advantaged parents and their children who have strong preferences for tracked learning environments, where high-track classrooms provide greater learning opportunities. As theorized by the conflict paradigm of schooling, social stratification processes serve the interests of elite groups such that valuable learning opportunities are disproportionately allocated among different social groups. Studies on tracked classrooms find that students in high-track classes have access to more rigorous instruction and experienced teachers (e.g., Kelly, 2004; Kelly & Carbonaro, 2012) and higher-achieving peer students (e.g., Zimmer, 2003) than lower-track classes. This competition for status, along with meritocratic beliefs in schooling, may push high-SES families to pursue these exclusive advantages. More broadly speaking, advantaged families have a general preference for maintaining their social advantages. As theorized by the Effectively Maintained Inequality (EMI) framework, maintaining and producing inequalities are effective approaches to preserving social advantages (Lucas, 2001). Students who are consistently placed in high-track classes may secure better spots in colleges and achieve higher educational attainment (e.g., Attewell, & Domina, 2008). Thus, to maintain such educational and social advantages, high-SES children and their families may be more actively involved in promoting elaborate school tracking systems. Beyond individual negotiations and pressures associated with specific students and their parents to get into specific classes, the external political pressure associated with high-SES families also plays a role in determining the aggregate nature of tracking systems in schools serving elite families/high-SES communities. Students from high-SES families limit the accessibility to high-track curriculum, so that students from low-SES families may encounter additional barriers to high-track courses. Qualitative studies of school leadership find that high-SES families have greater political and economic power to influence tracking practices (e.g., Lewis, & Diamond, 2015), and as a result, high-SES schools experience more pressure to maintain highly differentiated curriculum systems.

In fact, research on de-tracking policies often finds that advantaged students and their families resist de-tracking trends (e.g., Well, & Oakes, 1996) and even push schools to create new forms of distinctions (e.g., Domina, et al., 2016).

Another form of political interest in tracking, internal political interests, pertains to teachers' preference for teaching in high-track classes. Teachers typically prefer teaching high-track classes (Carey & Farris, 1994), in part, for justifying their teaching abilities and seniority (e.g., Finley, 1984; Kelly, 2004). Thus, teachers may also have political interests in preserving a differentiated curriculum system to secure inherent track placement for themselves as well.

2.2.2 Theories of Tracking: Linking Tracking with School Characteristics

Organizational analyses of tracking examine the extent to which formal policies, school technical and normative beliefs, and political interests shape and constrain tracking systems at the school level. This organizational lens also helps elucidate decision-making processes about tracking practices. In reality, each of the forces discussed above may interact with others and create even greater and more complex variations in tracking systems. For example, schools with different local normative beliefs regarding the functionalism of schooling may conceptualize students' course-taking readiness and gatekeeping courses differently (Watanabe, 2006), leading to distinct responses to external political pressures on tracking practices (i.e., elite schools may be more actively against de-tracking policies than other schools, Domina, et al., 2016). Yet, how does the organizational lens enable us to understand important variation in school tracking systems? Organizational analyses of tracking systems often attribute variation in tracking systems to ascribed school characteristics, linking tracking practices with school compositional characteristics, using social theories of schooling, namely, functional and conflict paradigms (e.g., Hirschl, & Smith, 2023; Kelly, & Price, 2011; Riegle-Crumb et al., 2019). Studies linking tracking systems with school characteristics advance an important theoretical assumption about tracking; while school and district personnel make final decisions about the provision of opportunity and criteria of allocation, that decision-making process is *responsive* to ascribed school characteristics (Lucas, & Berends, 2002).

Functional paradigms describe a rational and meritocratic view of schooling; schools prepare students with different levels of cognitive skills and effectively sort students into differentiated labor markets. This selection process is seen as a rational way to translate variations in skills and efforts into stratified social positions and occupational spheres. Rational perspectives on curriculum tracking also emphasize the pedagogical consideration of teaching in skill-homogeneous classes. If technical/functional beliefs about tracking hold in a school, Kelly and Price (2011) hypothesized that we may expect that the overall elaboration of the tracking system would be related to the achievement-heterogeneity of the student body. Thus, variation in school tracking across schools would be explained by variability of achievement scores, as well as the basic capacity to create a highly differentiated tracking system. It's not surprising to find that schools that in general have diverse distributions of course-taking readiness have a tracked learning environment in place (e.g., Kelly, & Price, 2011; Long et al., 2012), as the creation of skill-homogeneous classes is theorized as a technical and logical response to a diverse student body.

In contrast to technical/functional explanations of tracking, first, *opportunity hoarding* theory describes the inter-group conflict between, for example, high-SES families and working/poor families. The access to valuable resources is secured and limited to in-group members, yet the systematic barriers block the access to the same resources and exclude out-group members using social boundaries (Tilly, 2000). Opportunity hoarding theory serves as a viable theoretical framework to examine the way in which educational inequalities are generated due to tracking, as it describes how learning opportunities are disproportionately allocated among different social groups. Kelly and Price (2011) hypothesized that if opportunity hoarding processes held in a school, a more highly elaborated tracking system would be associated with a more diverse distribution of family background (e.g., greater variation in family SES, race/ethnicity). Finally, *status competition* describes the competition for better educational attainment and labor force success within middle-class and high-SES families to maintain their advantages (Brown, 2001; Collins, 1979). Different with respect to the form of conflict, status competition process speaks to an **intra-group** competition. Such competition processes reflect the preferences of pursuing competitive education among middle-class families (Useem, 1991) due to a "fear of falling" (Ehrenreich, 1989). Driven by status competition, middle- and professional-class families much more actively pursue the best possible college placement than working-class and poor families (Baker, & Stevenson, 1986). Kelly and Price (2011) hypothesized that elaborated tracking policies would be linked to lower proportions of minority and low-SES students, if the school compositional effect on tracking was explained by status competition.

Applying all three tracking theories, Kelly and Price (2011) found that school compositional measures related primarily to the technical-functional explanation and status competition theory were associated with school-to-school variation in elaboration of tracking policies. Schools with compositional characteristics including greater variation in achievement scores, capacity to create a highly differentiated tracking system, and fewer minority and low-SES students were found to provide highly differentiated tracking systems with limited access to high-track course-taking experiences. Although it's nearly impossible to fully measure the actual motivations of school administrators and parents during the policy-making and implementation process, studies of social theories of tracking provide (1) a theoretical foundation for examining the link between tracking systems and school characteristics, and (2) a framework for understanding the complex organizational approaches of tracking practices. This analysis adopts this theoretical lens to examine the school-to-school differences in tracking over the course of 1982-2013.

2.2.3 Organizational Dimensions of Tracking

In Oakes' (1985) seminal book, she asserts that, "…many schools claim that they do not track students, but it is the rare school that has no mechanism for sorting students into groups that appear to be alike in ways that make teaching them easier…" (page 3). In many cases, an adequate measure of school curricular differentiation must move beyond simplistic categorizations of tracking practice (e.g., classifying schools as tracked or untracked schools, or labeling schools as vocational, general, or academic tracks). Schools create various learning experiences by regulating different tracking policies, applying curricular standards differently, and offering different content in courses. Sørenson's (1970) original theoretical work on organizational differentiation in school systems argued that school tracking systems varied along four organizational dimensions: inclusiveness, selectivity, electively, and scope. These dimensions remain relevant in contemporary research, although they are often not applied precisely as originally articulated by Sorensen for various reasons (e.g., a specific interest in mobility, lack of availability of student-level achievement data, etc.) Examining dimensions of tracking enables us to understand how structural characteristics of schools' tracking practice might relate to student achievement growth and school-to-school differences in the nature of tracking and its outcomes.

2.2.3.1 Inclusiveness

Inclusiveness is defined as the extent to which high-status learning opportunities are available to students. In practice, researchers often measure inclusiveness as the share of the student body that is assigned to the highest track (usually what would align with "the college preparatory track," even as that is itself often not clearly defined in a given school). In the US, schools vary in the extent to which they provide rigorous course content for students (Domina, & Saldana, 2012). A high inclusivity school exposes all, or as many as possible, students to academically rigorous course content (Kelly, 2007), whereas a low inclusivity school reserves rigorous instruction and course content for only the highest achievers. For example, studies on school sector effects on course taking show greater inclusiveness and academic press in Catholic schools (Carbonaro, & Covay, 2010; Xu, & Kelly, 2020). Austin (2020) found that even as curriculum intensification policies (e.g., Algebra for all) enrolled more low-SES students in rigorous math courses, their course-taking was not increased in other subject areas, or they even compensated for more challenging math courses by reducing their course-taking level in other subject areas, notably, science courses! ELA course taking, on the other hand, stayed high and stable across datasets. Turning to the possible effects of inclusiveness, in general, many scholars theorize that schools with high inclusivity will have higher average achievement growth, since large college preparatory tracks offer high levels of academic press to more students. However, as Gamoran (1992) argued, extremely high inclusivity may diminish the total benefits of academic press on the mean achievement gain by creating new stigmas among low achieving students. Snow (1991) also found that, in high inclusivity schools, adjusting instruction to accommodate low-achieving students in class may undermine high-achiever's learning process.

In this project, I use both the original definition of tracking inclusiveness (proportion of students in the high-track), along with school-mean course sequence level. I term these measures collectively, “level-related measures of tracking.” It’s obvious that, in the era of curriculum intensification, we should observe an increase in tracking inclusiveness over the past 40 years, but I will provide new estimates using a transcript-based coding in both math and science. In the multivariate models, the associations between tracking inclusiveness and both functional factors and conflict factors will be empirically interesting and are difficult to predict, as the changes in tracking inclusiveness can be motivated/influenced by both functional (e.g., schools may “track down” students with lower prior achievement to better fir their academic needs) and conflict factors (e.g., the competition for status may expand to all students). In the multivariate models, I will begin by examining the extent to which tracking inclusiveness is associated with school-level functional factors and how that association has changed over time. Then, after considering the functional factors, I will examine the extent to which tracking inclusiveness is associated with conflict factors. It’s worthwhile to note that the remaining variation between schools in inclusiveness, after controlling for both functional and conflict factors, might be conceptualized as the variation in academic press (i.e., school-level normative emphasis on academic climate, excellence and “conformity to specified academic standards,” McDill et al., 1986; see also Lee, & Smith, 1999).

2.2.3.2 Selectivity: Differentiation and Skill Homogeneity

Sørenson (1970) defined selectively as, “the amount of homogeneity that educational authorities intend to produce by [track] assignment[s]” (page 362). This was never a particularly clear concept because it references intentions, and potentially confounded multiple features. Gamoran (1992) argued that a highly selective tracking system has two features: it produces substantial gaps between groups in terms of selection criterion (i.e., in a system with three tracks, average student achievement level would be very different in those three tracks), and the variance in achievement within each level is small (homogeneity of achievement, see also Hallinan, 1994). Under this definition, we would expect high between-track inequality in achievement and rigor of instruction, as teachers adjusted instruction to a homogenous group of students. However, while Gamoran (1992) stuck close to Sorensen's original conceptualization, measuring selectivity in terms of the "selection result", Kelly (2007) emphasized that Sorensen's definition of selectivity referred to "the intended outcomes of tracking system, not the means by which this outcome is achieved," and clearly, the original definition confounds the sorting of students with the number of levels present in the system to begin with. A highly selective school sorts students into tracks strictly by achievement criteria, while the number of available tracks may moderate the selectivity. He then suggests that considerations of selectivity should consider both the number of options available and assignment criteria, revising Sørenson's (1970) original approach.

Subsequent work has generally adopted Kelly's (2007) revised approach to selectivity related dimensions of tracking. Domina et al. (2019) considered both result-oriented measures and intended outcome-oriented measures of selectivity. In this work, the degree of curricular differentiation was defined as the number of distinct curricular positions in the organization, which is theoretically equivalent to Kelly's (2007) conceptualization of the number of options available. One may expect, related to the degree of curricular differentiation, that in highly differentiated systems teachers place much emphasis on developing skill-specific instruction. Domina et al. then defined classroom skills homogeneity as the degree to which "organizations assign students to different settings based on salient observed characteristics" (Domina et al., 2019). Thus, as a second measure of selectivity, they generated the seventh-grade test-score homogeneity within eighth-grade classrooms to measure selectivity at eighth grade. The application of panel data is methodologically preferred in creating the later measure.

In the era of curriculum intensification, I also expect that the sorting process has become less related to achievement over the course of this study because higher-level courses are generally open to more students regardless of prior achievement. Moreover, similar to tracking inclusiveness, I examine the extent to which tracking selectivity is associated with school-level functional factors, including achievement heterogeneity and school size, and how that association may have changed over time. First, a functional logic of tracking may motivate schools to tailor their sorting process to better fit the achievement distribution of the student body. In addition to the achievement distribution, the extent of curricular differentiation may also be responsive to school size, as larger schools have been found to have more highly differentiated curriculum systems (Kelly, & Price, 2011). Furthermore, after considering the functional factors, I will also examine the extent to which tracking selectivity is associated with conflict factors.

2.2.3.3 The Electivity Realm: Mobility

Electivity is defined as the extent to which students' individual choice impacts track placement. Usually, a student's track placement is determined by factors such as prior achievement, course-taking experiences, or teacher recommendations, yet some schools may consider student preference or enable students to choose the courses. However, Gamoran (1992) argued that even within schools that had a formal policy to allow student choice, students' track placements were highly impacted by school authorities, as teachers generally recommend a "right" choice based on performance. Students' self-perceptions of whether they select their tracking placement provides some evidence on electivity in the early tracking literature. In Jones, Vanfossen, and Ensminger's (1995) study on students' perception on tracking, they reported two thirds of students believe they chose their track placements, and they argued that students who believe that they choose their tracking placement were more likely to be motivated. Gamoran (1992) also observed a similar proportion of students who believed that they selected their track placements. He then argued that schools with a more elective (measured as the proportion of students who believed that they choose their tracking placement) tracking system produced overall higher math achievement. However, as Kelly (2004) argued, student choice can also exacerbate existing inequality by introducing a parental involvement effect, and thus choice unto itself is not clearly functional or dysfunctional.

Relatedly, although not listed in Sørenson's (1970) original domains, tracking mobility captures a similar aspect of tracking. Kelly (2007) argued that electivity was closely related to the amount of track mobility over time, as students were more likely to move upward or downward along the track "ladder" in schools with greater electivity. The concept of mobility featured prominently in Rosenbaum's (1976) classic study of tracking. Rosenbaum provided an example of a "tournament style" tracking system at Grayton High. Despite the official rhetoric among school staff that mobility was common and expected, upward mobility in Grayton High was extremely rare, whereas students frequently moved downward from high-track classes to low-track course work. Subsequent studies observed a similar pattern of tournament-style tracking systems (e.g., Domina et al., 2019; Lucas, & Good 2001). Domina and his colleagues, for example, found 41% of students in their sample experienced downward mobility from eighth grade to ninth grade in mathematics, and 34% of students experienced downward mobility in ELA. In contrast they observed much less upward movement from the eighth grade low track to the ninth grade middle track or from eighth grade middle track to the ninth grade high track. It's commonly argued that exposure to high-mobility tracking systems may boost students' achievement by matching students' capability with instruction. Tournament-style mobility, however, is likely to depress this achievement boost and create achievement inequality (e.g., Domina et al., 2019).

In this project, absent any way to measure choice directly, I consider upward and downward mobility separately to capture different aspects of the flexibility of tracking systems. In the era of curriculum intensification, I expect a decrease in downward mobility over the course of 1982-2013, whereas the trend for upward mobility might not be obvious. For downward mobility, I will explicitly focus on how conflict forces might be associated with downward tracking mobility. In contrast, I do not anticipate any relationships between functional factors and downward mobility. For example, if downward mobility increases as the proportion of low-SES students in a school increase, the practice of tracking students down is suggestive of conflict forces. Therefore, I will examine the extent to which downward mobility is associated with school-level conflict factors and how any association has changed over time, controlling for functional factors. On the other hand, upward mobility may be associated with both functional and conflict factors. However, here I argue that the level of upward mobility itself (rather than associations with school composition) is a more salient measure of functionalism as schools "open up" learning opportunities through mobility. Yet, the association between conflict factors and any remaining variation in upward tracking mobility may indicate that upward mobility is restricted for, for example, low-SES students.

2.2.3.4 Tracking Scope

Tracking scope is narrowly defined as the extent to which students' track placement is vertically consistent across all subject areas. According to this definition, in schools with high (or we might say "wide,") track scope, students that are assigned to the high track in one subject (e.g., in ELA) are highly likely to be assigned to the high track in another subject (e.g., Math). Some of the correlation in tracking across subjects can be explained by shared cognitive skills (e.g., mathematics and science share quantitative reasoning skills), with additional correlation more policy driven. In practice, Kelly and Price (2011) found that school course policies related to tracking scope included course corequisite policies and block schedule policies, which both required students to enroll in courses of the same track level simultaneously. They reported that 20% of schools in their sample had a block schedule policy such that it was nearly impossible to enroll, for example, in AP English without enrolling in AP US History. Kelly and Price (2011) also considered cross-subject prerequisite policies (e.g., a math pre-requisite for a science course) as an indicator of high tracking scope since high-track courses were limited to students who completed prerequisite courses. In many European and Asian school systems, students are placed into overarching track placements where they are exposed to the same level of instruction in all subject areas (Lucas, 1999). In the US, Lucas (1999) reported that the US school system turned from an overarching tracking system to a system that enabled schools to track students on the basis of individual subject areas; this has become an oft-cited claim about tracking systems. Yet, he did not examine actual school policies, which often indicate otherwise and would temper such a firm conclusion about system change.

Theoretically, schools with wide track scope are more likely to exhibit salient between-track inequality in achievement as students are exposed to differentiated learning experiences for more subject areas and longer time periods. Gamoran (1992) found that the negative effect of tracking on low-track students was magnified in schools with wide track scope. Moreover, wide scope may also limit the school's ability to flexibly adjust students' track placement based on students' learning outcome and capacities (Hallinan, 1994), because rigorous corequisites are in place.

In this project, I will consider both scope between two closely related subject areas, which is likely to strongly reflect the impact of correlated achievement, and scope between two disparate subject areas, which less obviously reflects correlated achievement. I will use the correlation between math and ELA course sequence (M-E) and the correlation between science and ELA course sequence (S-E) to measure scope between disparate subjects. For tracking scope between two related subjects, I will use the correlation between math and science course sequence (M-S). In examining school-to-school variation in scope, I will primarily focus on the relationship between conflict-related measures of composition and scope, examining the extent to which both M-E, S-E, and M-S tracking scope is associated with conflict factors (e.g., SES heterogeneity), after controlling for achievement heterogeneity and school size[3].

2.3 Analytic Strategy

2.3.1 Sequential measures of individual course taking

Building on Kelly (2009), Stevenson et al. (1994), my previous work (Xu, & Kelly, 2020), and other scholarship using transcript data (e.g., Riegle-Crumb, & Grodsky, 2010) this project

[3] A more obvious functional logic for tracking scope is that subject-area differences in achievement between students correspond to differences in course taking. Due to data limitation however, in this analysis, I only have constant measures of math achievement across all databases. Thus, I argue that remaining variation in correlated course taking beyond math achievement heterogeneity may potential be evidence of conflict forces. Later in analysis, I am able to examine the association between tracking scope and correlated achievement for one cohort.

aggregates students' cumulative math and science course taking to capture school-level organizational dimensions of tracking. This process starts with assigning individual course codes to each available course from NCES transcript datasets. NCES uses the Classification of Secondary School Courses (CSSC) to classify courses transcribed from the 1982 (HS&B), 1992 (NELS:88), and 2002 (ELS:2002) cohorts, and the School Courses for the Exchange of Data (SCED) to classify courses from the 2013 cohort (HSLS:09). The complete description of the coding process for individual courses is shown in Appendix A. To capture students' cumulative mathematics course taking, I assigned each student a unique Mathematic Course Sequence (MCS) code indicating the difficulty level of the combination of courses taken by the end of 12th grade. The MCS codes start with 1–less than algebra I and end with 9–calculus or higher, often based on identification of joint courses (e.g., Level 3 is Algebra I and Geometry). Students with higher MCS values have deeper and richer mathematic learning experiences than students with lower values. The full cumulative Mathematics Course Taking codes are shown in Table 2.1.

Table 2.1 Cumulative Mathematic Course Sequence (MCS) Codes

Mathematic Course Sequence (MCS)	Content
1	Less than Algebra I
2	Algebra I or Geometry, but not both
3	Algebra I and Geometry
4	Algebra I or Geometry, with at least one transition course
5	Algebra II
6	Algebra II with at least one math elective course
7	Algebra III or Trigonometry, but not both
8	Algebra III and Trigonometry
9	Calculus or higher

Different in some respects from math courses, science courses vary in their disciplinary content (e.g., biology, chemistry, and physics, often referred to as the "big-three" in the popular press). The measure of Science Sequence Level considers both 1) sequential course difficulty level and 2) their disciplinary content (e.g., biology, chemistry, or physics, or often referred as “big-three”). The student-level Science Sequence (5 levels) is measured as follow,

1– Student took no big-three courses

2– Student took only one disciplinary category from big-three (e.g., only biology courses, but no chemistry or physics course)

3– Student took two disciplinary categories from big-three (e.g., biology and chemistry course, but no physics course), without higher-level courses

4– Student took all of the big-three courses (biology, chemistry, and physics), without higher-level courses

5– Student took two or three disciplinary categories from big-three with at least one higher-level course.

Higher-level courses are defined as courses that *at least* provide a detailed understanding of a specific general field (e.g., Chemistry II), or introduction to a post-introductory sub-field (e.g., Inorganic Chemistry). The full cumulative Science Course Taking codes are shown in Table 2.2.

Table 2.2 Cumulative Science Course Sequence (SCS) Codes

Science Course Sequence (SCS)	Content
1	Student took no big-three courses (Physics, Chemistry, Biology)
2	Student took only one disciplinary category from big-three (e.g., only biology courses, but no chemistry or physics course)
3	Student took two disciplinary categories from big-three (e.g., biology and chemistry course, but no physics course), without higher-level courses
4	Student took all biology, chemistry, and physics courses, without higher-level courses
5	Student took two or three disciplinary categories from big-three with at least one higher-level courses.

2.3.2 Organizational dimensions of tracking

I then create a set of measures of school-level organizational dimensions of tracking based on individual measures of course sequences. First, I consider tracking inclusiveness as the percentage of students who took high-level courses. Math inclusiveness is measured as the percentage of students who reached Level 7 Sequence (Algebra III or Trigonometry, but not both) or higher Math Course Sequence. To determine this criterion, I considered both the basic rigor of courses, as well as the proportion of students who did and did not take courses (and thus the variability a given criterion captures). For example, students who reach Level 9 math Sequence took multiple high-level courses, but the percentage of students who reach Level 9 may be extremely low for many schools, in particular for early cohorts. Thus, reaching Level 9 may not be a good criterion to determine math inclusiveness as it doesn't capture much variability across students or schools. Science inclusiveness is measured as the percentage of students who reached Level 5 or higher Science Sequence. Later in this chapter, I discuss the differences between using Level 5 and Level 4 to determine science inclusiveness based on more detailed descriptive results.

Tracking selectivity is measured as the intraclass correlation (ICC) calculated from a large one-way ANOVA between achievement scores and track placements. The ICC is the Pearson product-moment correlation computed over all possible pairs of observations that can be constructed within groups. The ICC measures the extent to which the variation on student standardized achievement scores at 9th grade is explained by students' track placements.

Tracking scope is measured as the correlated track placement between a pair of subjects. In this analysis, I examine three pairs of subjects. First, I consider the correlation between math and science course sequence that captures the correlated track placement between two closely related subjects. Next, I consider the correlations between math and ELA, and science and ELA course sequences, capturing the correlated track placement between two distinct subjects.

To measure track mobility, I first examine the "typical" mathematic course-taking trajectory from grade 9 to grade 12 and calculate the mean increase in MCS code by subtracting grade 9 MCS code from grade 12 MCS code. The mean increase in MCS code is 4.4., meaning, on average, students gain four and half levels during high school. I then pick an interval of increase in MCS code from 3 to 6 as the "typical" trajectory. Students who gain less than 3 levels are counted as downwardly mobile and students who gain more than 6 levels during high school are counted as upwardly mobile. The percentage of students who experience mobility is then calculated as the measure of mobility. Alternatively, instead of examining the trajectory across the entire high school, I also consider the mobility between two adjacent grade levels for each student. I choose to examine the trajectory-based measures as the main measure of mobility as it captures the mobility across the entire high school and thus conceptually produces a more general measure than the alternative one. Table 2.3 summarizes these measures of the organizational dimensions of tracking. Independent measures will be derived from HSLS:09, ELS:2002, NELS:88, and HS&B survey research.

Table 2.3 Measures of the organizational dimensions of tracking

Organizational dimensions of tracking	Measures
Inclusiveness	Percentage of students who took Level 7 or higher Math courses or Level 4 or higher Science courses
Scope	Correlation between math/science and ELA course sequence
Selectivity	Intraclass correlation (ICC) calculated from large one-way ANOVA between student standard achievement score and tracking placement
Mobility	Percentage of students who experiencing mobility (Mobility is defined as departure of typical trajectory)

2.4 Results

2.4.1 Descriptive Statistics: Mathematics Tracking

2.4.1.1 Mean Sequence Level

Table 2.4 summarizes descriptive statistics of school-mean measures of **Mathematics** tracking by cohorts, including various organizational dimensions of tracking. To capture the overall course-taking rigor for each cohort, I calculate the grand mean of school-mean Math Course Sequence Level. To address the issue of measurement error and reliability shrinkage due to the unbalanced data structure of NCES longitudinal data, I calculate the cohort-specific multilevel reliability among schools with same (or similar) school size, using the *loneway* command in STATA. The school-specific multilevel reliabilities are then used as school-level analytic weights to generate the descriptive statistics. Weighted and unweighted descriptive measures are listed side-by-side for comparison in Table 2.4.

What is the mean level of course taking and how has it changed over time? As shown in Table 2.4, Row 1, the weighted cohort mean of school-mean Math Course Sequence for 1982 (HS&B) and 1992 (NELS) high school graduates are below Level 5–Algebra II (3.70 and 4.79, respectively), whereas the weighted grand mean for school-mean Math Course Sequence of 2004 (ELS) and 2013 (HSLS) high school graduates rise dramatically to 5.60 and 6.26, respectively.

Table 2.4 Descriptive Statistics of School-level Measures of Organizational Dimensions of Mathematics Tracking by Dataset (n=3620 schools, multilevel reliabilities used as analytic weights)

	HS&B (n=920)		NELS (n=1050)		ELS (n=720)		HSLS (n=930)	
Measures of Tracking	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
1. School-mean Math Sequence Level								
Mean	3.70	3.66	4.79	4.77	5.60	5.58	6.26	6.24
Standard Deviation	1.35	1.33	1.53	1.57	1.38	1.39	1.28	1.28
2. Inclusiveness								
Mean	.235	.232	.350	.347	.470	.468	.600	.598
Standard Deviation	.202	.201	.257	.262	.249	.251	.233	.234
3. Selectivity								
Mean	.506	.515	.510	.513	.457	.459	.420	.420
Standard Deviation	.253	.253	.291	.292	.226	.227	.216	.217
4. Tracking Scope between Math and Science								
Mean	.467	.471	.585	.599	.491	.493	.532	.533
Standard Deviation	.253	.254	.238	.246	.236	.240	.224	.223
5. Tracking Scope between Math and English								
Mean	.431	.438	.514	.527	.442	.448	.439	.440
Standard Deviation	.253	.255	.244	.252	.215	.219	.212	.212
6. Upward Mobility								
Mean	.092	.091	.080	.078	.116	.116	.177	.176
Standard Deviation	.131	.130	.129	.131	.147	.147	.198	.198
7. Downward Mobility								
Mean	.563	.570	.415	.417	.293	.295	.198	.200
Standard Deviation	.230	.228	.251	.260	.228	.232	.178	.180
8. All Mobility								
Mean	.656	.661	.494	.496	.409	.411	.375	.376
Standard Deviation	.219	.217	.258	.265	.259	.261	.234	.235

NOTE: Sample size is rounded to the nearest 10 as required by NCES.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”

Continuing to consider the improvement in the overall math curriculum rigor shown in Row 1 of Table 2.4 further, the mean of school-mean Math Course Sequence in the 2013 cohort was one and a half levels (1.49) higher than students in the 1992 cohort. This difference is approximately half of the difference between, for example, completing Algebra II (Level 5) and completing Algebra III and Trigonometry (Level 8) for high school. The school-mean Math Course Sequence in the 2013 cohort was a remarkable two and a half levels higher (2.56) than 30 years ago. Figure 2.1 visualizes the increasing trends by overlapping all four density distributions of school-mean Math Course Sequences. Kernel density estimations are calculated and plotted for smooth curves. As shown in Figure 2.1, the Kernel density distributions for all four cohorts are approximately normal and the peak of the distributions move from Level 3–taking both Algebra I and Geometry, but not higher (HS&B) to over Level 6–Algebra II with at least one higher-level elective course (HSLS), indicating a trend of curriculum intensification. Table 2.4, Row 1 also shows that the school-level standard deviation of Math Course Sequence Level decreases, in the context of a rising mean, from 1.53 (NELS) to 1.28 (HSLS), indicating that, on average, school-to-school differences in sequence level became smaller in the 2013 cohort than earlier cohorts.

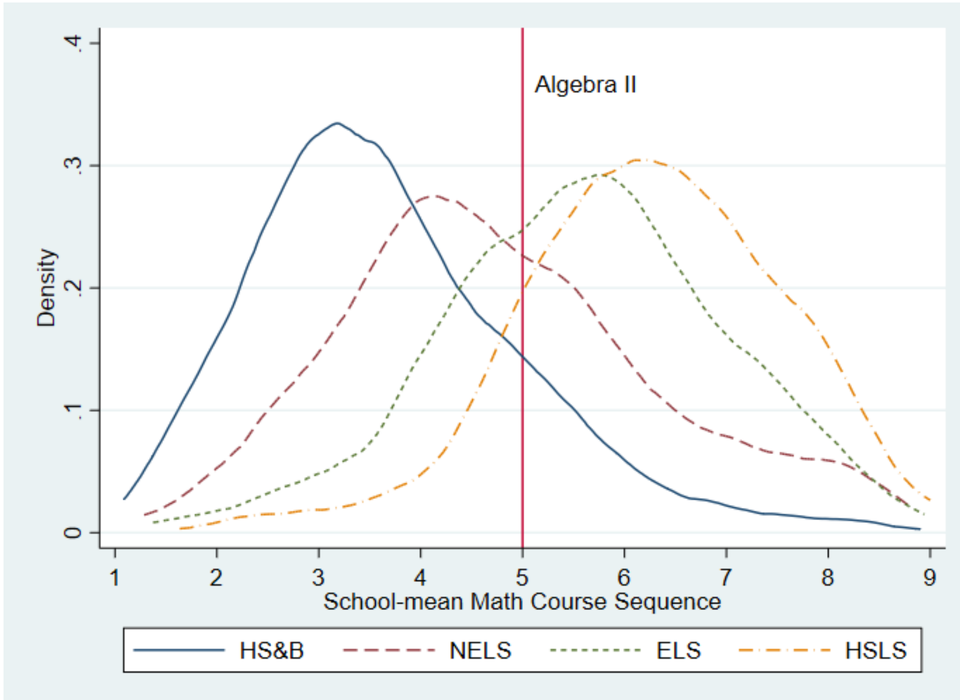

Figure 2.1 Kernel Density Distribution of School-mean Math Course Sequences (MCS) by Datasets. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.1.2 Inclusiveness

Mathematics *Tracking inclusiveness* is measured as the percentage of students who completed Level 7 (Algebra III or Trigonometry, but not both) or higher Math Course Sequence. Table 2.4, Row 2 summarizes the cohort-means of school tracking inclusiveness. As shown in

Table 1, Row 2, schools enrolled approximately only one fourth of (23.5%) students into Algebra III, Trigonometry, or higher courses in the 1982 cohort, whereas this percentage went up to 35.0% in the 1992 cohort and 47.0% in the 2004 cohort. In the 2013 cohort, schools, on average, enrolled nearly two thirds of students into higher-level math courses. Figure 2.2 shows the visualization of the density distribution of school tracking inclusiveness by cohorts. As shown in Figure 2.2, the density distributions of the 1982 and 1992 cohort are positively skewed with the peak at approximately 20%, indicating that the majority of schools in the 1982 and 1992 cohorts enrolled less than one third of students in higher-level math courses. The peak of the distribution moves greatly from the 1982 cohort (HS&B) to the 2013 cohort (HSLS). By the 2013 cohort (HSLS), the majority of schools now enroll more than 60% of students in higher-level math courses (and the distribution is now even somewhat negatively skewed). Table 2.4, Row 2 also shows that the school-level standard deviation of math inclusiveness decreases from .257 (NELS) to .233 (HSLS), indicating that, school-to-school differences in math tracking inclusiveness in the 2013 cohort were smaller than in the 1992 cohort.

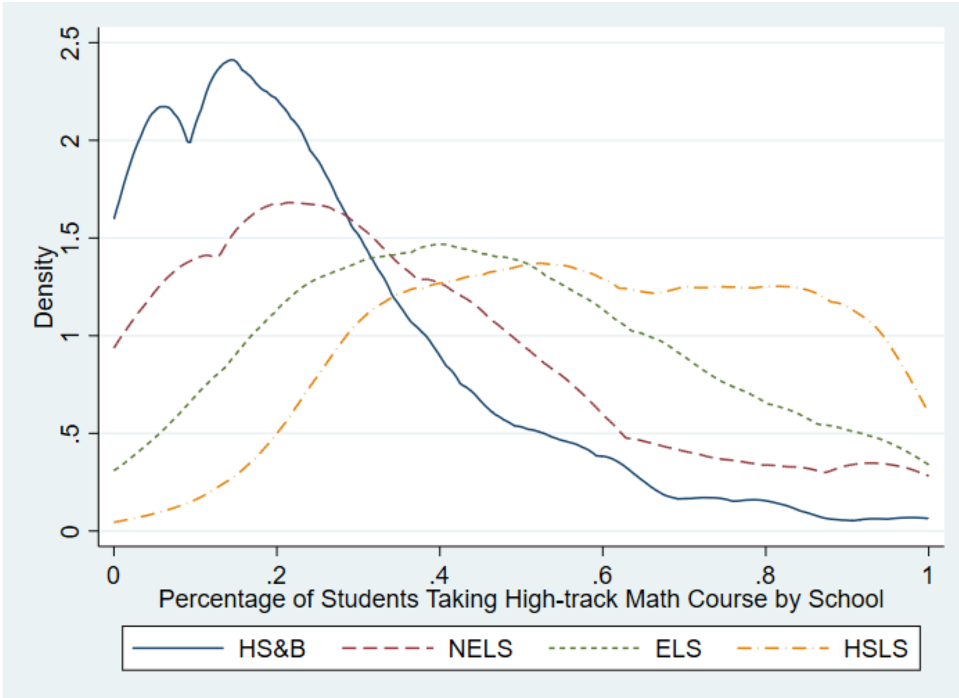

Figure 2.2 Kernel Density Distribution of Mathematics Tracking Inclusiveness by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.1.3 Selectivity

Mathematics *Tracking selectivity* is measured as the intraclass correlation (ICC) calculated from a large one-way ANOVA between the student math standardized achievement score and track placement. The ICC measures the extent to which the variation in math achievement at 9th grade is explained by student track placements. Table 2.4, Row 3 summarizes the cohort-mean of school tracking selectivity. As shown in Table 2.4, Row 3, on average, US high school tracking systems became less selective based on achievement since the 1992 cohort, changing from .510 in the 1992 cohort to .420 in the 2013 cohort, whereas students from the 1982 cohort experienced a similar level of tracking selectivity with the 1992 cohort. Figure 2.3 visualizes this decreasing trend of tracking selectivity. As shown in Figure 3, the shape of the density distribution of tracking selectivity changes from negative skewed to approximately normal, indicating an overall decreasing trend in US high school tracking selectivity. Table 2.4, Row 3 also shows that the school-level standard deviation of math tracking selectivity decreases from .291 (NELS) to .216 (HSLS), indicating that, on average, between-school stratification in selectivity in the 2013 cohort was smaller than for early cohorts.

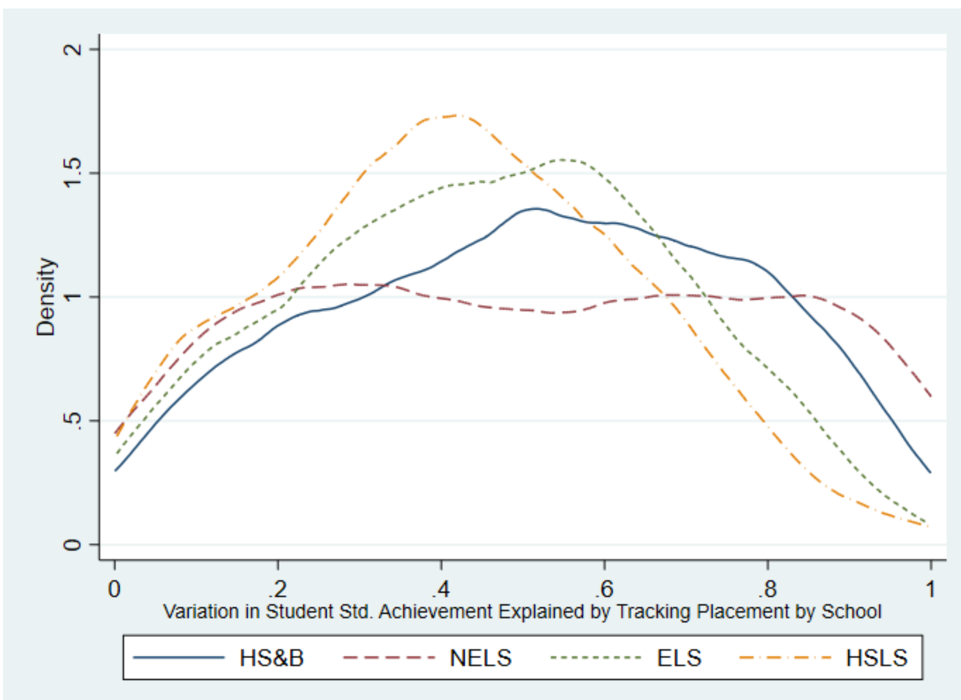

Figure 2.3 Kernel Density Distribution of Mathematics Tracking Selectivity by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School

Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.1.4 Tracking Scope

Math and Science *Tracking scope* is measured as the correlation between students' Math Course Sequence code and Science Course Sequence code within each school. Table 2.4, Row 4 shows that the cohort-mean math-science tracking scope remains at a moderate level over the course of 1982-2013, ranging from .467 to .585. I also calculated tracking scope between math and ELA course taking using the correlation between students' Math Course Sequence and ELA track placement. ELA track placement is simply measured as the most rigorous ELA course taken during high school using curriculum rigor provided by NCES. Students who completed at least one Enriched/advanced, Honors, or College level ELA course are labeled as high track; students who only completed Basic/remedial or General level ELA course are labeled as low track. This binary measure captures the basic variation in ELA course taking across students and, while not as fine-grained as the other transcript-based measures in this study, is useful for calculating a simple measure of tracking scope. Table 2.4, Row 5 shows that tracking scope between math and

ELA also remains moderate, ranging from .431 to .514, over the period of this study. Previous research has found greater Math-ELA scope (e.g., .67 from Domina et al., 2019).[4]

Moreover, as shown in Table 2.4, Row 4, the Math-Science tracking scope first went up from .467 (HS&B), then went down from .585 (NELS) to .491 (ELS) and went back up to .532 (HSLS). Table 1, Row 4 also shows that the school-level standard deviation of math-science tracking scope stays around .23 level, indicating that, on average, school-to-school differences in scope remained stable across cohorts.

[4] There are a few possibilities that might explain this difference in findings. First, Donima et al., (2019) used a sample from 23 CA middle schools and the calculated math-ELA scope may not be comparable to the scope calculated from a representative sample of US schools. Second, the measure of math course-taking track has nine levels in this analysis, compared to Domina et al.'s three-level measure. This may create more variability across students in terms of their math course-taking levels and lower the math-ELA scope.

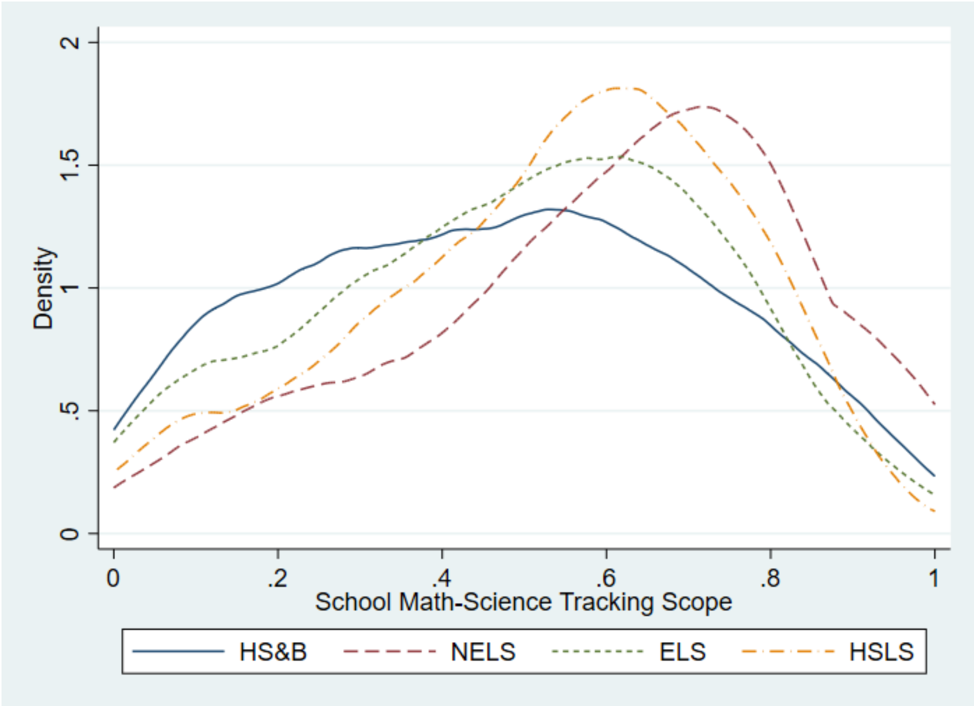

Figure 2.4 Kernel Density Distribution of Mathematics Science Tracking Scope by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

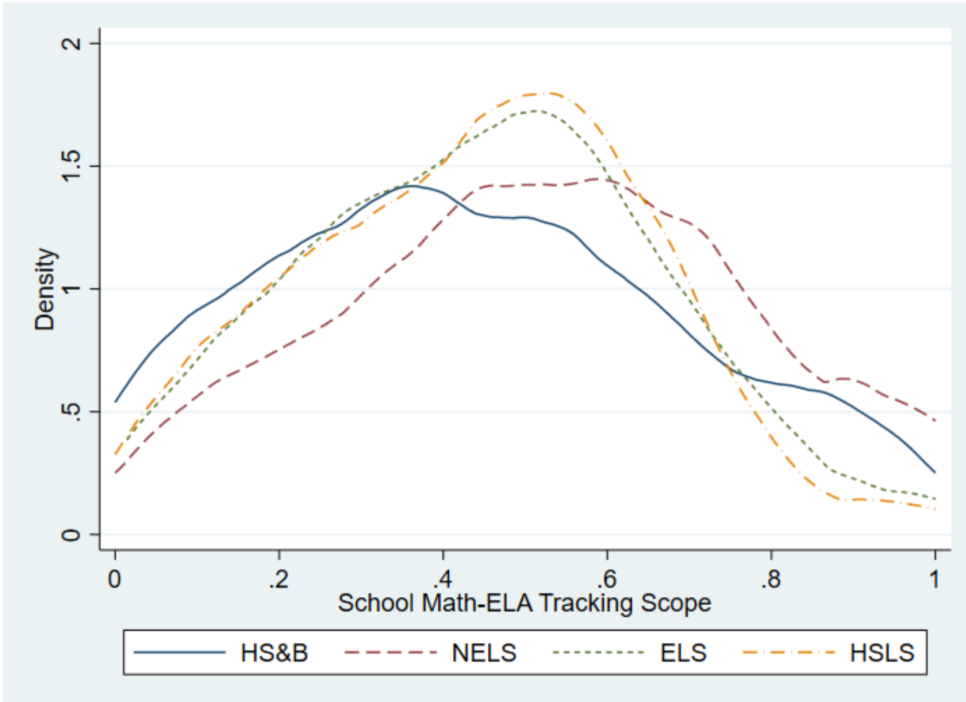

Figure 2.5 Kernel Density Distribution of Tracking Scope between Math and English by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.1.5 Track Mobility

Finally, I use the "typical" course-taking trajectory to examine Math track mobility. Recall that in this analysis, track mobility examines the extent to which an individual student's course-taking trajectory moves away from the "typical" course-taking trajectory. For example, a student who only took Informal Math (Level 1) during 9th grade but completed Trigonometry and Analytical Geometry (Level 8) before 12th grade is labeled as upwardly mobile (moving 7 levels). Another student who already took Algebra II (Level 5) before 10th grade but only complete Algebra III (Level 7) at 12th grade is considered downwardly mobile (moving 2 levels).

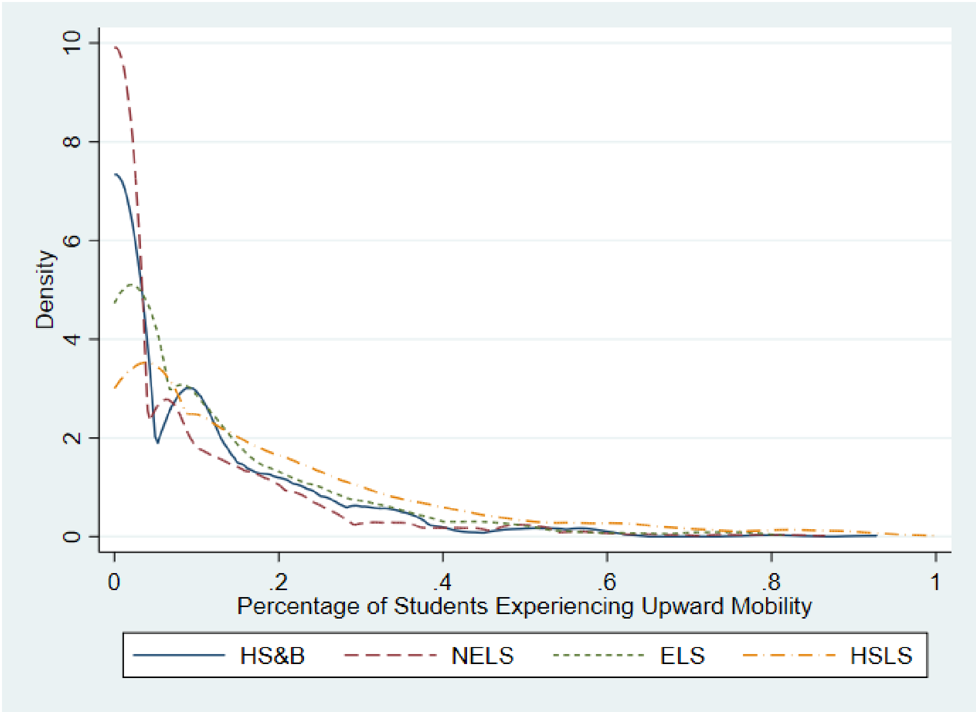

Figure 2.6 Kernel Density Distribution of Mathematics Upward Tracking Mobility by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

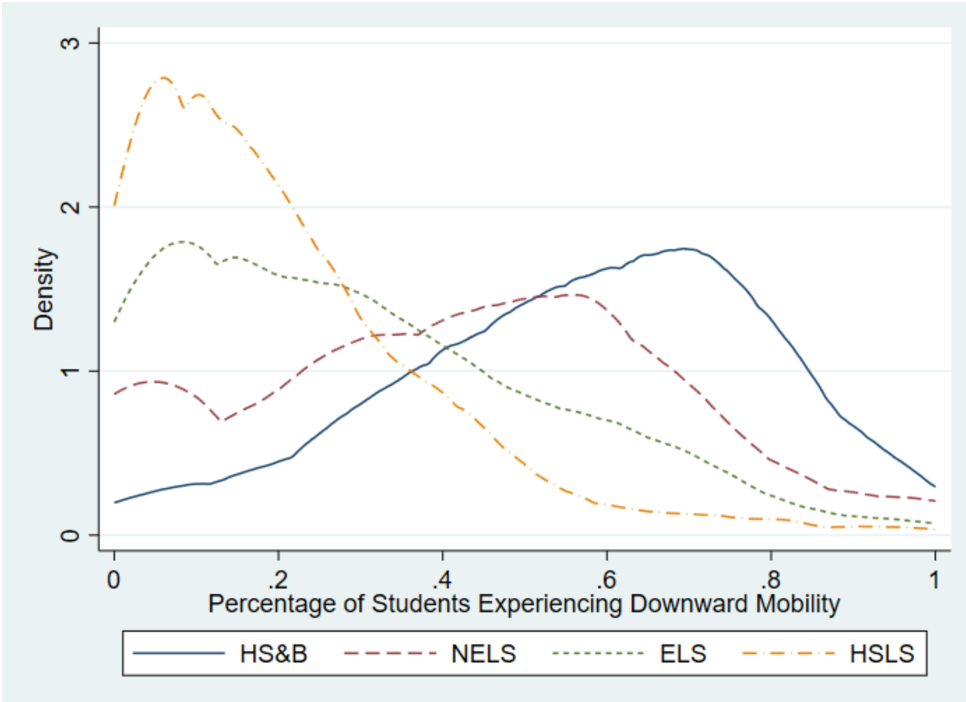

Figure 2.7 Kernel Density Distribution of Mathematics Downward Tracking Mobility by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

School-level tracking mobility is measured as the percentage of students who experience upward mobility or downward mobility. Table 2.4, Rows 6,7, and 8 summarize the cohort-mean of upward track mobility, downward track mobility, and all track mobility, respectively. As shown in Table 2.4, Row 6, on average, schools only provided approximately 9% and 8% of students with opportunity for upward mobility in the 1982 and 1992 cohorts, respectively. This percentage went up substantially in the 2013 cohort such that, on average, over one sixth (17.7%) of students can move upwardly in math. Figure 2.6 visualizes this trend. As shown in Figure 6, although all three density distributions of upward mobility are skewed positively, the high peak at around 0.0% moved dramatically down from the 1982 and 1992 cohorts to the 2013 cohort, indicating that many more schools in 2013 cohort provided at least minimal opportunity for moving up the course taking hierarchy. However, as shown in Table 1, Row 6, the school-level standard deviation of upward mobility also increases from .129 (NELS) to .198 (HSLS), indicating that, on average, school-to-school differences in upward track mobility in the 2013 cohort were greater than the 1982 and 1992 cohorts. For downward mobility, as shown in Table 1, Row 7, on average, schools tracked over 55% and 40% of students down in the 1982 and 1992 cohorts, respectively. Thirty years later, this percentage was cut by two thirds with only 20% of students moving down the track hierarchy. As shown in Figure 2.7, the shape of the density distribution of downward mobility went from normal to positively skewed, indicating that schools, on average, moved fewer students down to the lower track. Moreover, Table 1, Row 7 shows that the school-level standard deviation of downward mobility also decreases from .251 (NELS) to .178 (HSLS), indicating that, on average, between-school stratification in downward track mobility were smaller than the 1992 cohort.

2.4.1.6 Correlation Matrix of Dimensions of Tracking

Table 2.5 examines the correlation matrix between all school-level measures of Mathematics tracking, with a panel for each cohort. Figures 2.8 to 2.11 visualize the correlations among all dimensions of tracking. The correlation matrix captures the extent to which organizational dimensions are empirically associated within each cohort. First, level-related measures are tightly correlated with each other (school-mean Sequence Level and tracking inclusiveness). As shown in Table 2.5, Row 2, the correlation coefficients between Variable 1–

School-mean Math Sequence Level and Variable 2–Inclusiveness are extremely high for all four cohorts (.82, .88, .83, and .84 for HS&B, NELS, ELS, and HSLS, respectively), indicating a strong positive relationship between tracking inclusiveness and overall school emphasis on rigorous academic curriculum.

More importantly, dimensions of tracking structure (i.e., selectivity, scope, and mobility) are only moderately or even weakly associated with other dimensions. Table 2.5 shows that the correlations between tracking selectivity and scope in most cohorts are around a .15 level (Column 3 in each panel), indicating a fairly weak relationship between selectivity and scope. Tracking selectivity has even weaker relationships with track mobility for all cohorts, suggesting that, in general, tracking selectivity may have different fundamental determinants. Math-science scope and math-ELA scope are moderately correlated in the 1992, 2004, and 2013 cohorts, showing that, at least some schools have overarching tracking scope across different subject areas. This relationship, however, is weaker in the 1982 cohort. Math-ELA scope has moderate relationships with downward mobility in the 1982, 1992, 2004 cohorts, indicating that schools in early decades had a somewhat more "overarching" tracking structure. Yet, such structure became weaker in the 2013 cohort.

Moreover, the strength of correlations between level-related measures and tracking structure varies across dimensions. Tracking inclusiveness and mean sequence are closely negatively associated with downward track mobility in the 1982, 1992, and 2004 cohort, indicating that schools with, on average, lower math curriculum rigor tend to track more students down along the course-taking hierarchy. These correlations went down to moderate strength in the 2013 cohort, and it's likely due to the fact that fewer students experienced downward mobility in high schools. However, the correlations between Variable 1– School-mean Math Sequence Level and Variable

3–Selectivity are fairly weak, ranging from .06 to .09. Therefore, unlike tracking inclusiveness, there is virtually no relationship between tracking selectivity and school-mean Math Course Sequence Level.

Table 2.5 Correlation Matrix of School-level Measures of Organizational Dimensions of Mathematics Tracking (n=3620 schools)

	HS&B (1982 cohort)							NELS (1992 cohort)						
	1[a]	2	3	4	5	6	7	1	2	3	4	5	6	7
1. Mean Sequence														
2. Inclusiveness	.82							.88						
3. Selectivity	-.02	.05						.07	.11					
4. M-S Scope	-.02	.01	.08					-.16	-.13	.07				
5. M-E Scope	-.07	-.01	.18	.18				-.26	-.19	.08	.32			
6. Upward Mobility	.30	.48	.01	-.04	.01			.28	.41	.09	-.11	-.07		
7. Downward Mobility	-.78	-.61	.10	.10	.17	-.36		-.80	-.63	-.02	.24	.31	-.18	
8. All Mobility	-.61	-.32	.11	.08	.18	.26	.80	-.64	-.41	.03	.18	.27	.32	.88
	ELS (2004 cohort)							HSLS (2013 cohort)						
	1[a]	2	3	4	5	6	7	1	2	3	4	5	6	7
1. Mean Sequence														
2. Inclusiveness	.83							.84						
3. Selectivity	.05	.12						.11	.13					
4. M-S Scope	.07	.07	.18					.05	.02	.15				
5. M-E Scope	-.17	-.14	.16	.28				.02	-.01	.13	.31			
6. Upward Mobility	.12	.29	.06	-.01	.04			.37	.41	.04	-.01	-.01		
7. Downward Mobility	-.63	-.41	.04	.11	.25	-.11		-.50	-.37	.01	.16	.14	-.22	
8. All Mobility	-.49	-.19	.08	.10	.24	.47	.82	-.10	.04	.04	.12	.10	.63	.61

a. Variable number: 1– School-mean Math Sequence Level; 2–Inclusiveness; 3–Selectivity; 4–Tracking Scope between Math and Science; 5–Tracking Scope between Math and English; 6–Upwards Mobility; 7–Downwards Mobility; 8–All Mobility

NOTE: Sample size is rounded to the nearest 10 as required by NCES.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

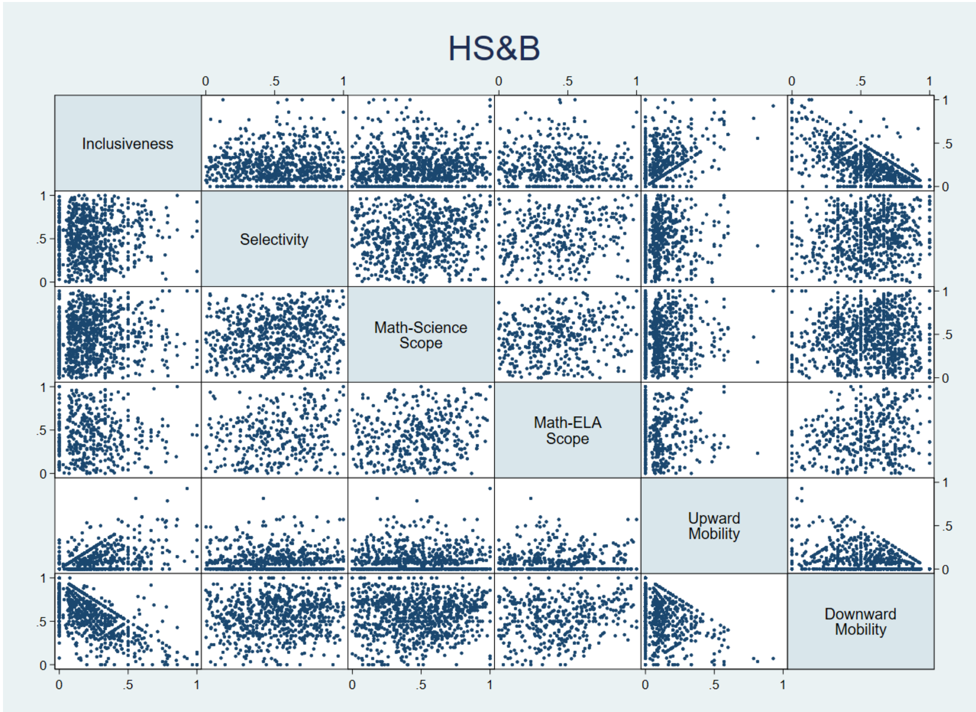

Figure 2.8 Scatter Plot Matrix of Selected Organizational Dimensions of Math Tracking for HS&B. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

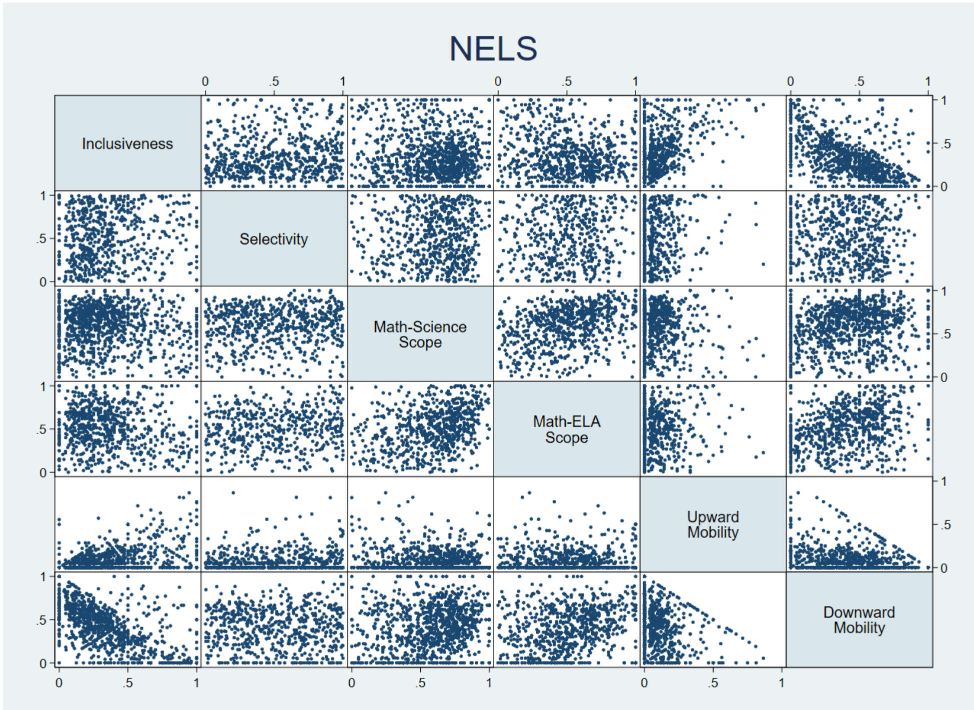

Figure 2.9 Scatter Plot Matrix of Selected Organization Dimensions of Math Tracking for NELS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

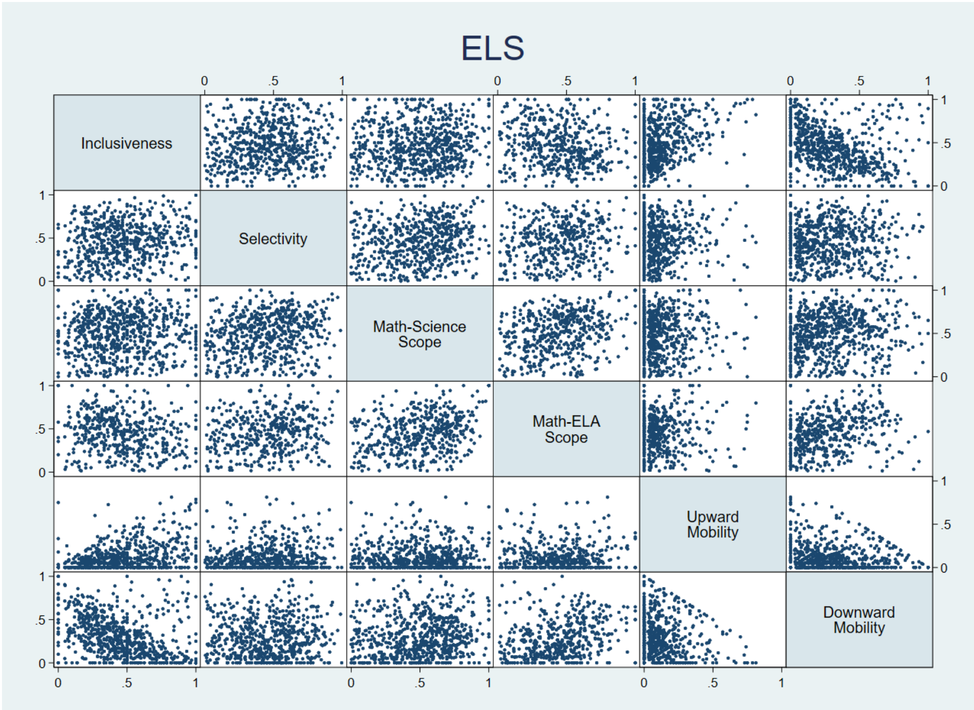

Figure 2.10 Scatter Plot Matrix of Selected Organization Dimensions of Math Tracking for ELS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

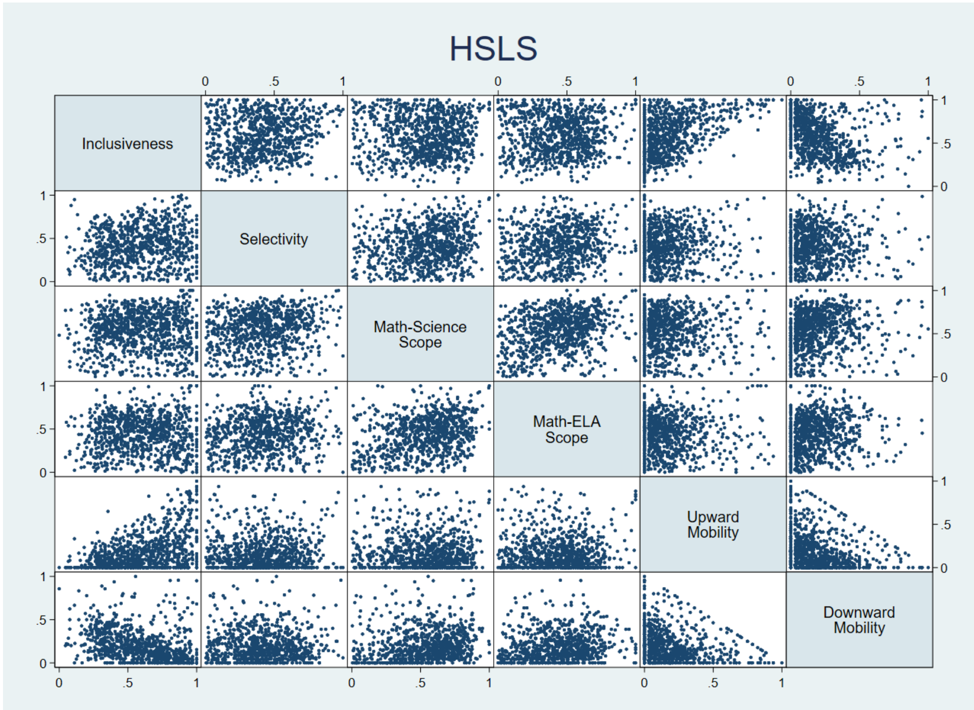

Figure 2.11 Scatter Plot Matrix of Selected Organization Dimensions of Math Tracking for HSLS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.2 Descriptive Statistics: Science Tracking

2.4.2.1 Mean Sequence Level and Total Courses Taken

Table 2.6 summarizes descriptive statistics of school-mean measures of **Science** tracking by cohorts, including various organizational dimensions of tracking. To capture the overall course-taking experience for each cohort, I calculate the grand mean of school-mean Science Course Sequence Level. As shown in Table 2.6, Row 1, the weighted cohort mean of school-mean Science Course Sequence increases from 2.35 (HS&B) to 3.80 (ELS) and slightly decreases to 3.75 (HSLS). In general, the Table 2.6, Row 1 shows an improvement in the overall science curriculum rigor from the 1982 cohort to the 2004 cohort and the school-level emphasis on a rigorous academic curriculum in science is stable in the subsequent decade. Figure 2.12 visualizes the Kernel density distribution of school-mean science sequence level by cohort. As shown in Figure 2.12, the density distribution of the 2004 cohort and the 2013 cohort are nearly identical, whereas the peak of the distribution for the 1982 cohort is almost two levels lower than these two cohorts. Table 2.6, Row 1 also shows that the school-level standard deviation of school-mean science sequence level stays around .6 level, indicating that, on average, students from all four cohorts experienced similar levels of between-school stratification in the average level of science course taking. To further unpack the trends of science course taking across cohorts, I calculate the school-mean total number of science courses taken. As shown in Table 2.6, Row 2, on average, the average student took a full three additional science courses across the cohorts represented here, from 2.50 (NELS) to 5.88 (HSLS).

Table 2.6 Descriptive Statistics of School-level Measures of Organizational Dimensions of Science Tracking by Datasets (n=3620 schools, multilevel reliabilities as analytic weights)

	HS&B (n=920)		NLES (n=1050)		ELS (n=720)		HSLS (n=930)	
Measures of Tracking	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted
1. School-mean Science Sequence Level								
Mean	2.35	2.35	3.43	3.43	3.80	3.80	3.75	3.75
Standard Deviation	.550	.544	.619	.640	.592	.596	.607	.608
2. School-mean Total Number of Science Courses Taken								
Mean	2.50	2.49	4.82	4.83	5.14	5.16	5.88	5.88
Standard Deviation	.732	.731	1.59	1.63	1.60	1.64	1.91	1.91
3. Inclusiveness (Level 5 as high-level science sequence)								
Mean	.119	.119	.248	.247	.348	.347	.436	.434
Standard Deviation	.150	.150	.224	.232	.260	.264	.223	.224
4. Inclusiveness (Level 4 and 5 as high-level science sequences)								
Mean	.148	.147	.449	.447	.609	.607	.654	.652
Standard Deviation	.163	.162	.253	.261	.253	.257	.234	.235
5. Selectivity								
Mean	.427	.435	.446	.451	.343	.344	.313	.315
Standard Deviation	.247	.250	.276	.278	.224	.225	.191	.192
6. Tracking Scope between Math and Science								
Mean	.467	.471	.585	.599	.491	.493	.532	.533
Standard Deviation	.253	.254	.238	.246	.236	.240	.224	.223
7. Tracking Scope between Science and English								
Mean	.373	.378	.482	.492	.395	.400	.388	.389
Standard Deviation	.252	.255	.240	.247	.222	.228	.200	.200
8. Upward Mobility								
Mean	.169	.170	.087	.087	.171	.170	.170	.169
Standard Deviation	.191	.192	.138	.143	.188	.189	.180	.180

NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection"

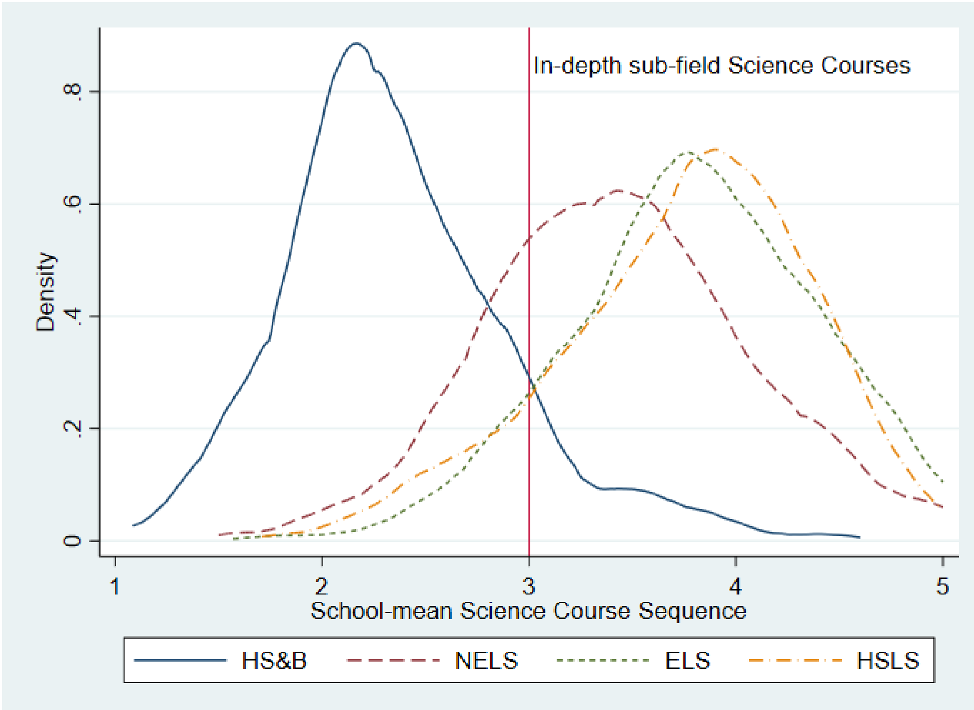

Figure 2.12 Kernel Density Distribution of School-mean Science Course Sequences (SCS) by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.2.2 Inclusiveness

Science *Tracking inclusiveness* is measured as the percentage of students who completed Level 5 (Student took two or three disciplinary categories from big-three with at least one higher-level courses) Science Course Sequence. Table 2.6 Row 3 summarizes the cohort-mean of school tracking inclusiveness. As shown in Table 2.6, Row 3, schools enrolled approximately only 12% and 25% students into at least two disciplinary categories with one higher-level course (level 5) in the 1982 and 1992 cohorts, whereas this percentage went up to one third (34.8%) in the 2004 cohort. In the 2013 cohort, schools, on average, enrolled over 40% of students (43.6%) into at least two disciplinary categories with one higher-level course. Figure 2.13 shows the visualization of the density distribution of school tracking inclusiveness by cohorts. As shown in Figure 2.13, the density distribution of the 1992 cohort is positively skewed with the peak at approximately 15%, indicating that the majority of schools in the 1992 cohort enrolled less than 15% of students in high science track. The peak of the distribution moves greatly from the 1992 cohort to the 2013 cohort. In the cohort 2013, the approximately normal distribution indicates that half of the schools enrolled more than 40% of students into the high-track courses in science. Table 2.6, Row 3 also shows that the school-level standard deviation of science inclusiveness slightly increases from .150 (HS&B) and .224 (NELS) to .260 (ELS) but returns to the .22 level in HSLS, indicating that, on average, the school-to-school differences in science tracking inclusiveness went up first, peaked at the 2004 cohort, and went down in the 2013 cohort.

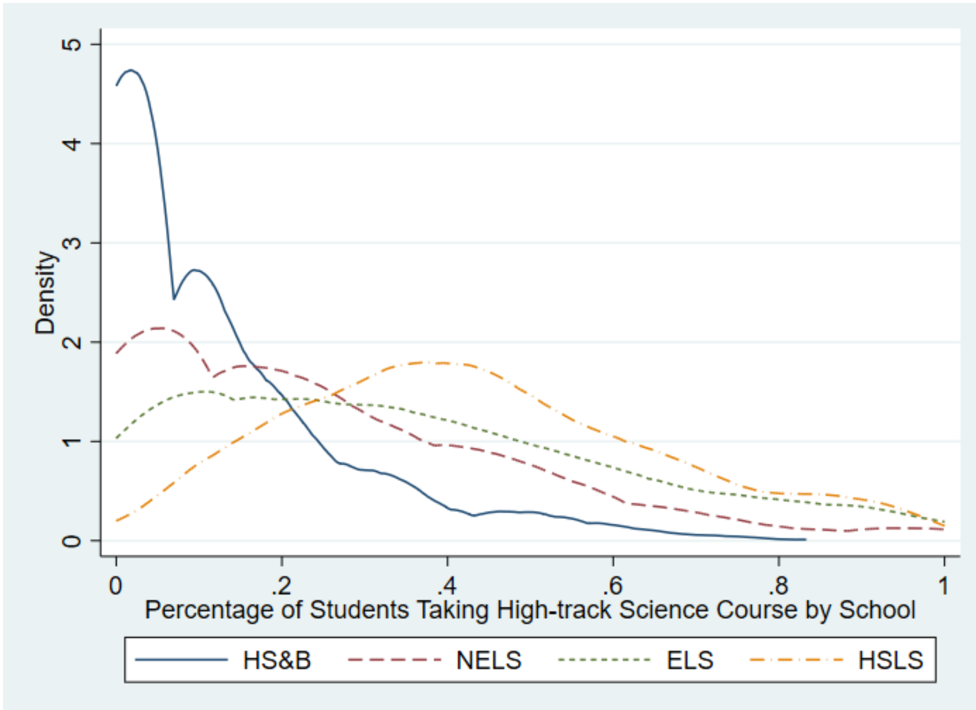

Figure 2.13 Kernel Density Distribution of Science Tracking Inclusiveness by Dataset.DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

To check the robustness of the measure of science tracking inclusiveness, I also calculate the science inclusiveness using a different definition for the high science track. As shown in Table 2.6, Row 4, if both Level 4 (Student took all biology, chemistry, and physics courses, without higher-level courses) and Level 5 are considered as high science track, the science inclusiveness increases from 14.8% in HS&B to 65.4% in HSLS, indicating a very similar trends as in Table 2.6, Row 3.

2.4.2.3 Selectivity

Science *Tracking selectivity* is measured as the extent to which the variation on student math standard achievement score at 9th grade is explained by students' Science track placement. Table 2.6, Row 5 summarizes cohort-mean of school science tracking selectivity. As shown in Table 2.6, Row 5, on average, the US high school tracking system became less selective based on achievement since the 1992 cohort, changing from .446 in the 1992 cohort to .313 in the 2013 cohort. Science tracking selectivity slightly went up from the 1982 cohort to the 1992 cohort. Figure 2.14 visualizes this decreasing trend of science tracking selectivity. As shown in Figure 2.14, although the shape of the density distributions of tracking selectivity remains positively skewed across cohorts, the distribution of HSLS shows a much higher peak, indicating many more school science curriculum systems are less selective in the 2013 cohort. Table 2.6, Row 5 also shows that the school-level standard deviation of math tracking selectivity decreases from .276 (NELS) to .191 (HSLS), indicating that, on average, school-to-school differences in science tracking selectivity in the 2013 cohort were smaller than earlier cohorts.

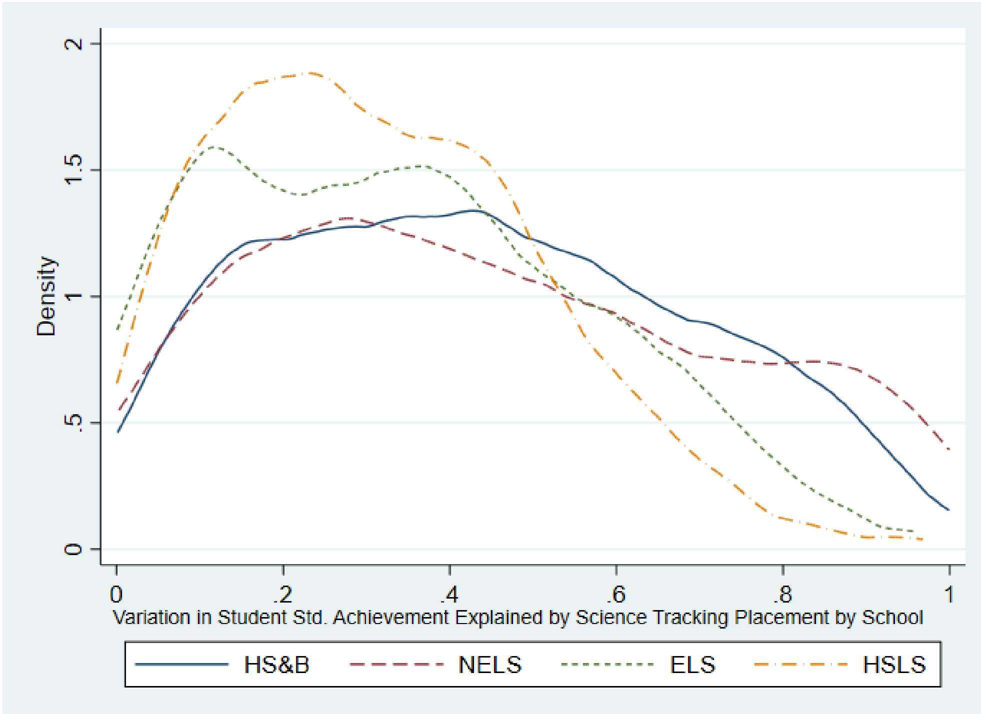

Figure 2.14 Kernel Density Distribution of Science Tracking Selectivity by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.2.4 Track Mobility

Finally, to measure **Science** *track mobility*, I first examine the "typical" science course-taking trajectory from grade 9 to grade 12 for each student by subtracting the lowest Science Course Difficulty code from the highest code. The five-level Science Course Difficulty code is used to consider sequential courses difficulty level when constructing Science Course Sequence Level and it has the following meaning,

1– Course provides basic concepts on specific field (e.g., Biology I)

2– Course is based on level 1 course, providing a more detailed understanding on specific field, or introduction to a sub-field (e.g., Biology Advanced Study)

3– Course provides an in-depth study on a specific sub-filed (e.g., Anatomy)

4– Course provides a higher-level comprehensive study of specific field (e.g., AP Biology)

5– In addition to level 4, course requires higher-level interdisciplinary knowledge to finish (e.g., AP Physics C: Electricity and Magnetism)

In HSLS, 62% of students do not move any level whatsoever from 9th grade to 12th grade, staying at the same difficulty level throughout high school. Since the "typical" science course-taking trajectory is "staying at the same level", downward mobility cannot be defined the same was as in math, although the total number of courses taken partially captures something like downward mobility. To measure upward mobility, I count students who gained more than 1 level during high school as upwardly mobile. Approximately, in HSLS, 17% of students were upwardly mobile.

School-level science track mobility is then measured as the percentage of students who experience upward mobility. Table 2.6, Row 8 summarizes the cohort-mean of science upward track mobility. As shown in Table 2.6, Row 8, on average, schools only provided approximate 9% of students with opportunity for upward mobility in science in the 1992 cohort. This percentage went up substantially in the 2004 cohort with, on average, 17.1% of students moving up in science. In the 2013 cohort, this percentage remained at 17.0%. Inconsistent with the larger trend, in the 1982 cohort, 16.9% of students experienced science upward mobility.

Figure 2.15 visualizes this trend. As shown in Figure 2.15, although all four density distributions of upward mobility are skewed positively, the high peak at around 0.0% moved dramatically down from the 1992 cohort to the 2004 and 2013 cohort, indicating that many more schools in the 2004 and 2013 cohort provided at least minimal opportunity for moving up the course taking hierarchy. However, as shown in Table 2.6, Row 8, the school-level standard deviation of upward mobility also increases from .138 (NELS) to .188 (ELS) and .180 (HSLS), indicating that, on average, between-school stratification of science upward mobility in the 2004 and 2013 cohorts were greater than earlier cohorts.

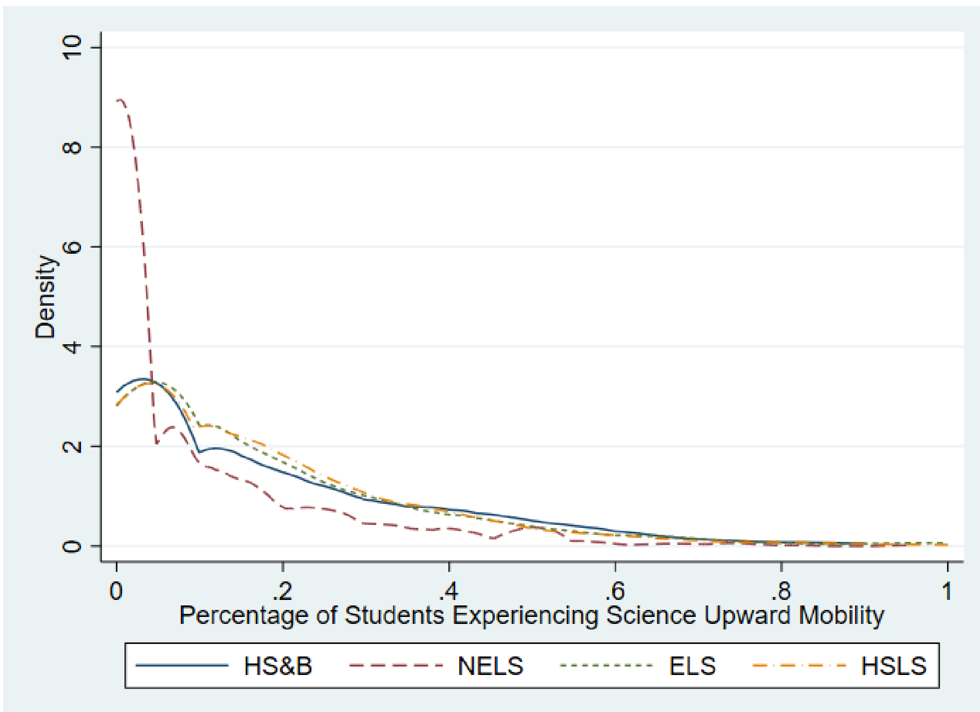

Figure 2.15 Kernel Density Distribution of Science Upwards Tracking Mobility by Dataset. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education

Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.4.2.5 Correlation Matrix

Table 2.7 examines the correlation matrix between all school-level measures of science tracking by cohorts. Again, the correlation matrix captures the extent to which organizational dimensions of science tracking are empirically associated within each cohort. Figures 2.16 to 2.19 visualize the correlations among all dimensions of tracking. Similar to the Mathematics correlation matrix, the correlation coefficients between Variable 1– School-mean Science Sequence Level and Inclusiveness are extremely high for all cohorts (.90 level for inclusiveness using Level 4 as high science track, and .70 level for inclusiveness using Level 5 as high science track), indicating a strong positive relationship between tracking inclusiveness and overall school emphasis on rigorous science academic curriculum. The school-mean science sequence also has a strong relationship with the mean number of science courses taken in the 1982 cohort. However, this correlation decreased to a .2 level in later cohorts. This is likely due to the fact that students took more science courses in the 1992, 2004, 2013 cohorts, reducing the relationship between number of courses taken and course sequence levels.

Moreover, dimensions of tracking structure are weakly to moderately related to other measures of structure. First, tracking selectivity has moderate relationships with tracking scope for all four cohorts, but has extremely weak relationships with upward track mobility. This is similar with the correlations between math selectivity and other measures of tracking structure. Math-science scope and Science-ELA scope are also moderately correlated for all cohorts. Recall that

Math-science scope also has a moderate relationship with Math-ELA scope, showing some evidence that schools may loosely place students into similar Math, Science and ELA tracks. Tracking scope, however, is only weakly associated with science upward track mobility.

Moving to the correlation between level-related measures and tracking structure, I find that the correlation between Variable 1– School-mean Science Sequence Level and Variable 5– Selectivity is fairly weak. Therefore, unlike tracking inclusiveness, there is virtually no relationship between tracking selectivity and school-mean Science Course Sequence Level. I also find a weak to moderate positive relationship between science tracking inclusiveness and upward track mobility in the 1982, 1992, 2004, and 2013 cohort, at .31, .33, .48, and .54, respectively, indicating that schools with higher science inclusiveness tend to have stronger upward mobility. This relationship is weaker in the 1982 and 1992 cohort, suggesting that these two dimensions of tracking may have different fundamental determinants; the strength then goes up to a moderate level in later decades. Overall, correlation analysis explicitly addresses whether measures of dimensions of tracking may reflect an underlying construct of a highly elaborated tracking system. Yet, this analysis indicates that the various dimensions of tracking are only moderately or even weakly associated.

Table 2.7 Correlation Matrix of School-level Measures of Organizational Dimensions of Science Tracking (n=3620 schools)

	HS&B (1982 cohort)							NELS (1992 cohort)						
	1[a]	2	3	4	5	6	7	1	2	3	4	5	6	7
1. Mean Sequence														
2. Number of Courses	.70							.26						
3. Inclusiveness 4	.78	.46						.90	.23					
4. Inclusiveness 5	.67	.36	.88					.75	.16	.64				
5. Selectivity	-.03	-.03	-.00	-.00				.01	-.01	.02	.07			
6. M-S scope	-.04	-.06	.06	.09	.27			-.17	-.11	-.14	-.07	.12		
7. S-E Scope	.05	-.01	.07	.10	.26	.29		-.08	-.08	-.11	.04	.18	.34	
8. Upward Mobility	.08	-.05	.23	.31	.10	-.00	.07	.06	0.5	.10	.33	-.01	-.04	-.05

	ELS (2004 cohort)							HSLS (2013 cohort)						
	1	2	3	4	5	6	7	1	2	3	4	5	6	7
1. Mean Sequence														
2. Number of Courses	.11							.23						
3. Inclusiveness 4	.91	.14						.90	.22					
4. Inclusiveness 5	.71	.05	.53					.70	.19	.62				
5. Selectivity	.00	.00	.03	.02				-.03	-.02	-.04	.08			
6. M-S scope	-.23	-.02	-.21	-.12	.16			-.15	-.09	-.12	-.12	.17		
7. S-E Scope	-.11	-.05	-.10	-.08	.15	.24		-.16	-.05	-.16	-.07	.22	.23	
8. Upward Mobility	.25	.07	.22	.48	.00	-.05	-.03	.41	.19	.32	.54	.13	-.04	.11

a. Variable number: 1– School-mean Science Sequence Level; 2–School-mean Total Number of Science Courses Taken; 3–Inclusiveness (Level 4 and 5 as high-level science sequences); 4– Inclusiveness (Level 5 as high-level science sequences); 5–Selectivity; 6–Tracking Scope between Math and Science; 7–Tracking Scope between Science and English; 8–Upwards Mobility

NOTE: Sample size is rounded to the nearest 10 as required by NCES.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

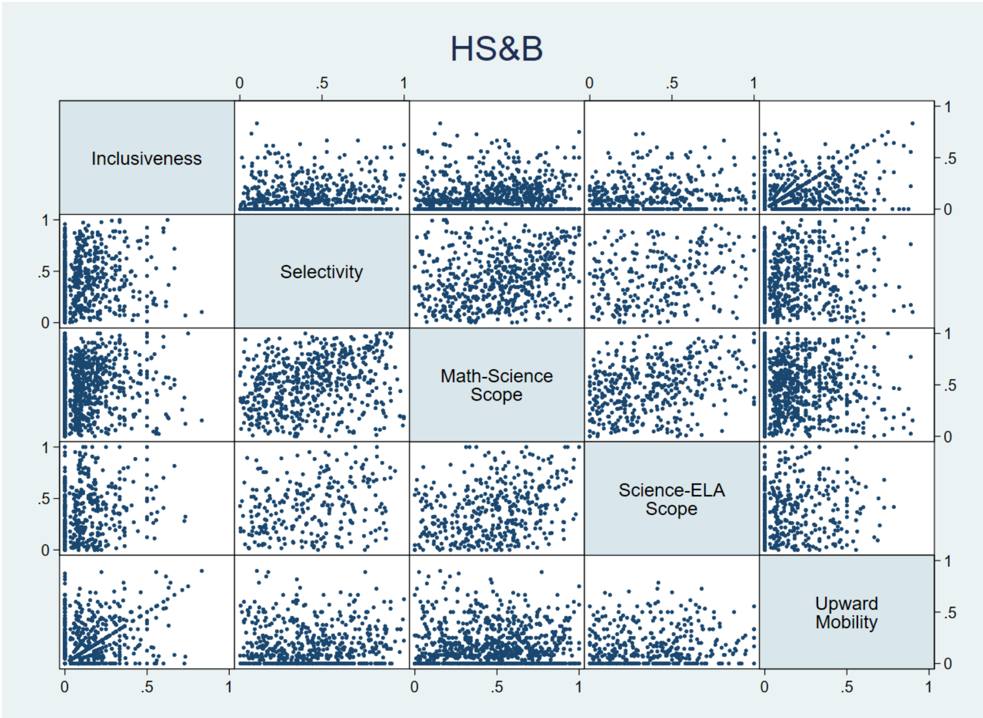

Figure 2.16 Scatter Plot Matrix of Selected Organization Dimensions of Science Tracking for HS&B. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

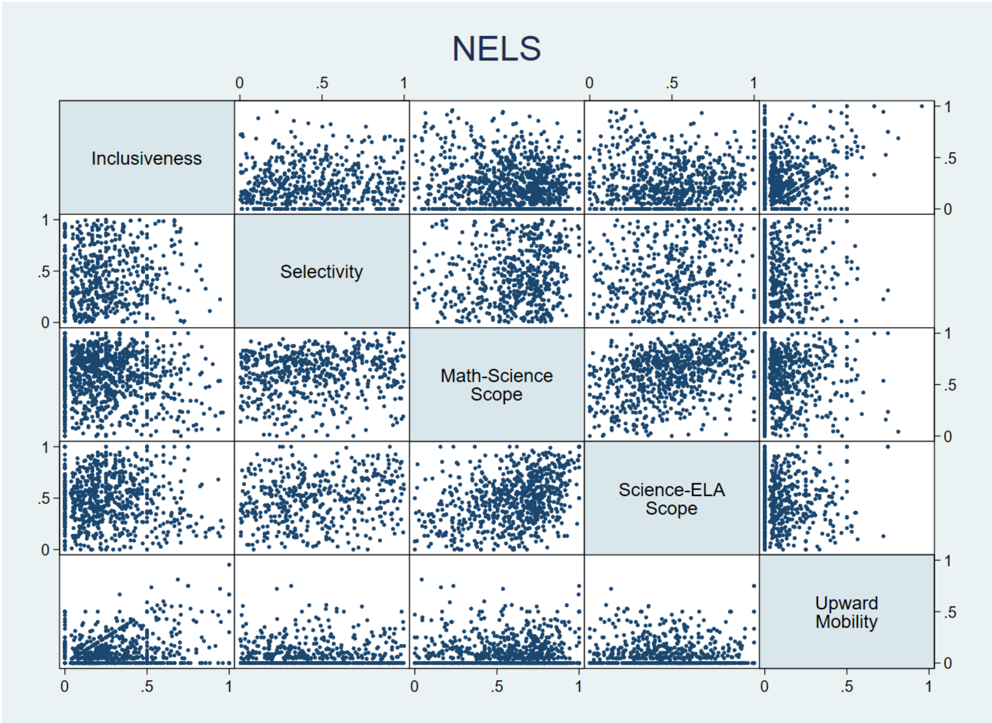

Figure 2.17 Scatter Plot Matrix of Selected Organization Dimensions of Science Tracking for NELS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

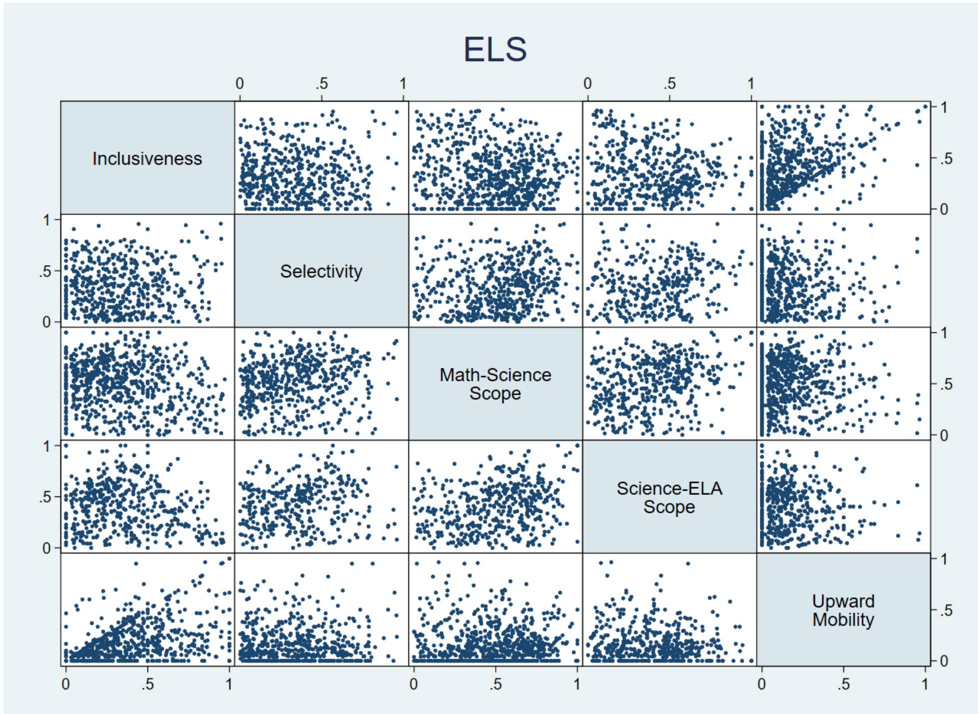

Figure 2.18 Scatter Plot Matrix of Selected Organization Dimensions of Science Tracking for ELS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

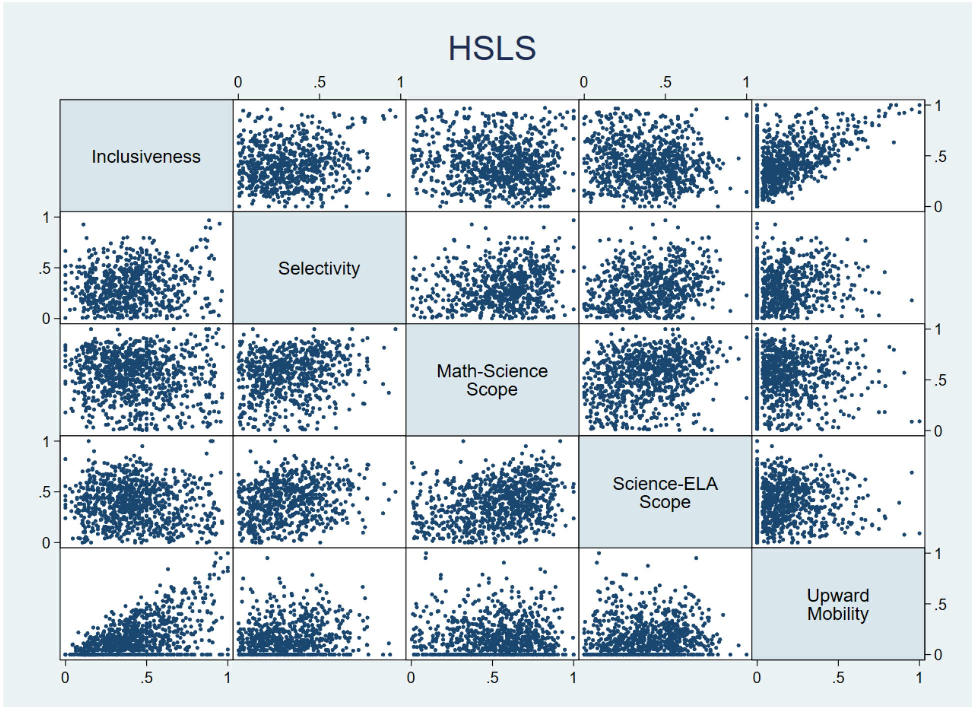

Figure 2.19 Scatter Plot Matrix of Selected Organization Dimensions of Science Tracking for HSLS. DATA SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

2.5 Discussion and Conclusion

In Chapter 2, I created a comprehensive measurement scheme of organizational dimensions of tracking and explored trends in US tracking systems over the period 1982-2013. Considering school-mean Course Sequence Level and tracking Inclusiveness as level-related measures of tracking, US high school students, on average, now take more rigorous STEM courses than decades ago (although my window of observation does not include the most recent years). In particular, school-mean math sequence level rises by almost 70% from 1982 to 2013 and math inclusiveness goes up by 155% over the same period of time. Moreover, considering the fact that the standard deviation of school-mean math sequence level and inclusiveness have both become smaller in later decades, US high schools not only provide more opportunity to learn in math, but also vary less across schools in later decades. Science sequence level and inclusiveness increase by 65% and 263%, respectively, but unlike in math, the standard deviation of science sequence level and inclusiveness also became greater in the 2004 and 2013 cohorts.

Regarding the structure of tracking systems, in general, US high school tracking systems have become less elaborate with less selective and more flexible tracking systems in place. More specifically, math tracking selectivity drops from a .50 level in the 1982 and 1992 cohorts to a .4 level in the 2013 cohort and science tracking selectivity goes down from over .40 to a .30 level in 2013. Moreover, I find that the variation in both math and science tracking selectivity across schools (captured by the standard deviation) decreased over the past decades. In terms of upward track mobility, both math and science upward mobility doubled from approximately 8% in the 1992 cohort to 17% in the 2013 cohort. However, the standard deviation of math upward mobility also went up over the past three decades, from a .13 to a .20 level. Recall that one interpretation of upward mobility is that it captures the extent to which schools flexibly match students' readiness to track placements. This analysis of track mobility shows that while schools on average “open up” more learning opportunities in recent decades, school-to-school differences in OTL also become greater. Tracking scope, on the other hand, remains at around a .50 level across cohorts.

Examining the extent to which individual dimensions of tracking are conceptually related to other dimensions, I first find that school-mean sequence level and tracking inclusiveness are closely correlated. As expected, these associations may indicate that the overall emphasis on rigorous academic curriculum and placing more students into high-level courses usually go together. More importantly, this chapter also contributes to the discussion of whether schools tend to have overarching strong or weak tracking systems. Here, schools with “strong” tracking system have high selectivity, wide scope, and low mobility, whereas a “weak” tracking system has low selectivity, narrow scope and moderate mobility. Early empirical studies found evidence that schools tended to have overarching strong curriculum tracking system (e.g., Rosenbaum, 1976). From the curriculum policies/guides perspective, Kelly and Price (2011) found higher-level inter-dimension correlations than this study, indicating that dimensions of tracking in many US high schools hang together; that is, for example, schools with wide scope tend to also have high-level selectivity. In this chapter, I find that dimensions of tracking structure are only moderately or even weakly associated with other dimensions, suggesting that individual dimensions of tracking don’t usually work together. In particular, math and science tracking selectivity are orthogonal to all other dimensions of tracking. However, I find some evidence that scope and track mobility are weakly-to-moderately correlated. For example, I find moderate relationships between Math-ELA scope and downward mobility in the 1982, 1992, and 2004 cohorts. Both Math-ELA scope and downward mobility perhaps more directly capture the extent to which school tracking systems constrain learning opportunities than more ambiguous organizational dimensions. For this reason, I focus on these constructs in particular in some subsequent analyses. Thus, the moderate correlations between Math-ELA scope and downward track mobility support notions of "strong" and "weak" tracking systems, but many other associations do not.

To show the complexity of school-to-school differences in dimensions of curriculum tracking, I pick two pairs of typical schools from the 2013 cohort to discuss here. Schools from each pair are located within the same state, serve nearby neighborhoods, and have similar compositional characteristics. State information is hidden and compositional characteristics (% of poor and % of white) are rounded to the neatest 10% for confidentiality purposes. As shown in Table 2.8, Pair A schools are predominantly white public schools where most students are from high-SES families and are located in Suburban areas of a Northeastern state. The STEM tracking system of School A1 is highly selective as this school ranks extremely high in both math and science tracking selectivity, whereas School A2 has a moderate level of STEM tracking selectivity. Schools A1 and A2 also differ in math and science tracking inclusiveness. School A1 ranks quite high in math inclusiveness but moderately in science inclusiveness, whereas School A2 ranks low in math inclusiveness but high in science inclusiveness. Regarding track mobility, both Schools A1 and A2 rank moderately. Pair B schools are predominantly white private schools with most students from high-SES families and are located in metropolitan areas of a Midwestern state. School B1 ranks extremely low in math and science selectivity and scope, showing a flexible school tracking system with presumably few prerequisites and corequisites in place. Yet, science mobility and inclusiveness of School B1 are quite low, indicating that some restrictions in track placement exist simultaneously. School B2, on the other hand, promotes a relatively more elaborate tracking system with greater selectivity and scope. But School B2 also has higher track mobility and inclusiveness, showing some flexibility of their tracking system. Overall, although these typical school cases are chosen purposefully, and inferences should be derived first and foremost from the prior descriptive trends and associations, example school pairs from Table 2.8 show that (1) within a school, individual dimensions of tracking do not always work together, and (2) even schools that share similar compositional characteristics may be very different in their tracking systems.

Table 2.8 Pairs of schools from the 2013 cohort selected to illustrate limited covariance in dimensions of tracking, percentile rank on each dimension among all schools from the 2013 cohort

Schools	Urbanicity	% Poor[5]	% White	Sector	Math Selectivity	MS Scope	Math Upward Mobility	Math Inclusiveness	Science Selectivity	Science Upward Mobility	Science Inclusiveness
A1	Suburban	10%	80%	Public	92nd	61st	36th	79th	79th	66th	43rd
A2	Suburban	10%	80%	Public	48th	45th	47th	16th	50th	43rd	81st
B1	City	10%	80%	Private	5th	1st	44th	70th	13th	30th	40th
B2	City	0%	80%	Private	49th	72nd	51st	92nd	31st	99th	79th

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

[5] State information is hidden and compositional characteristics (% of poor and % of white) are rounded to the neatest 10% for confidentiality purposes.

3.0 Multivariate Analysis of Social Determinants of Tracking

3.1 Introduction

In Chapter 3, I turn to developing multivariate models, selectively utilizing organizational measures of tracking first reported in the descriptive analysis in Chapter 2, to address my overarching question: how is school composition related to tracking and has the balance between functional and conflict forces in the US tracking system changed over time? Building on the theoretical framework of Kelly and Price (2011) and other related empirical studies on the structure of tracking systems (e.g., Domina et al., 2019; Kelly, 2007), I examine associations between organizational dimensions of high school STEM curriculum tracking (school-mean course-taking level, selectivity, scope, and mobility) and school compositional factors (e.g., achievement heterogeneity, percentage of advantaged students, and racial/SES diversity), both in pooled cross-section and in changes over-time. Are observed school-to-school differences in tracking practice and changes in tracking practices more obviously related to easy-to-document functional motivations for tracking or to dysfunctional social forces of tracking? For example, schools may promote curriculum tracking to increase efficiency by creating skill-homogeneous instructional environments, or schools with a high proportion of advantaged students may create especially elaborated tracking systems in response to opportunity hoarding or status competition processes. Ultimately, these associations seek to describe where the basic structure of a school's curriculum tracking system comes from.

3.2 Analytical Strategy

3.2.1 Dependent Variables

Dependent variables in this empirical chapter are directly derived from the descriptive measures of organizational dimensions of Mathematics and Science tracking, created in Chapter 2. To further unpack different aspects of the US secondary education tracking system, I classify dependent variables into two major analytical categories in the subsequent model estimations, *level-related measures of tracking* and course-taking patterns that reveal the *structure of tracking*. Level-related measures of tracking contain various dependent measures that are related to overall Sequence Level, including school-mean Sequence Level, math and inclusiveness, and mean number of science courses. Tracking structure captures different dimensions of tracking in which schools vary in terms of the overall elaboration of tracking, including selectivity, scope, and mobility. Or stated differently, collectively these measures can be used to identify the overall "strength" of the tracking system. I also put the variance of Sequence Level within the school into this category because the variance examines the extent to which students are exposed to different course-taking experiences. I should note that the primary intent of defining analytical categories in this way is to organize the presentation of results and following discussion. The dependent measures within each analytic category may have different sources of variation; I am not claiming they indicate, reflectively, a latent construct.

I also made a few extra modifications to certain measures of tracking. First, for parsimony, I include only Level-5 Science inclusiveness (only Level 5– "Student took two or three disciplinary categories from big-three with at least one higher-level courses" as high-level science sequence) as a dependent variable in this chapter. Second, I drop the combined measure of mobility (All mobility), both because it combines two very disparate outcomes for students, and because the majority of mobility is downward (e.g., total and downward mobility are correlated .88 in NELS).

3.2.2 Model Specification

To address Research Question 2-1, I first examine the basic association between school-level compositional characteristics and tracking measures by running a series of time-pooled regression models without any statistical controls. *Basic association* models have the following general form,

$$Y_i = \alpha_0 + \delta K_i + \varepsilon_i$$

where Y_i are various school-level measures of tracking at school i. K_i parameters are school-level functional and dysfunctional factors at school i, one factor at a time.

To further answer Research Question 2-2, I run *time-pooled models* with the following general form.

$$Y_i = \alpha_0 + \delta X_i + \pi M_i + \theta Z_i + \varepsilon_i$$

where Y_i are various school-level organizational dimensions of tracking at school i. X_i is a vector of school-level technical-functional factors. M_i is a vector of school-level conflict factors and will be added after X_i. Z_i are school-level covariates. The estimation of δ and π addresses Research Question 2-1.

Then, to address the Research Question 2-2, I first run series of regression models to estimate the school-level organizational dimensions of tracking with only year indicators as independent variables. These *categorical trend models* have the following form,

$$Y_i = \alpha_0 + \beta_1 Coh_{1982} + \beta_2 Coh_{2004} + \beta_3 Coh_{2013} + \theta Z_i + \varepsilon_i$$

where Y_i are various school-level organizational dimensions of tracking at school i, $Coh_{1982} \sim Coh_{2013}$ represent the year when high school transcripts were collected for each cohort (1983, 2004, and 2013). Coh_{1992} (represents NELS) is used as reference year and not in the model. The estimation results of $\beta_1 \sim \beta_3$ capture the cohort effect in relation to the reference year. Coh_{1992} is chosen as the reference year because the measurement of dimensions of tracking is more reliable than Coh_{1982}. Z_i is school-level covariate.

Alternatively, I also run *linear trend models* with an ordinal time indicator to capture the overall trend of each organizational dimension of tracking. These models have the general form,

$$Y_i = \alpha_0 + \beta Coh + \theta Z_i + \varepsilon_i$$

where Y_i are various school-level organizational dimensions of tracking at school i, Coh is a time indicator, centered at cohort 1992. This linear trend models also serve as the baseline trend model in the subsequent model estimation. I also run the baseline trend analysis without school-level covariates and the results will be provided in the supplemental information.

Then, to examine whether changes in tracking practices are more obviously related to functional motivations for tracking, I run *cohort-interaction models*:

$$Y_i = \alpha_0 + \beta Coh + \delta X_i + \gamma(Coh \times X_i) + \theta Z_i + \varepsilon_i$$

where Y_i are various school-level organizational dimensions of tracking at school i. Coh are single cohort indicators (NELS as reference cohort as well), X_i is a vector of school-level technical-functional factors. $Coh \times X_i$ is an interaction matrix indicating the cross product between cohorts and functional factors. δ is the estimated effect of X_i on Y_i at reference cohort (i.e., 1992 in this analysis). The estimation of γ can be used to determine whether changes in tracking practices are more or less obviously related to functional motivations for tracking. If γ is a positive value, the *total* estimated effect of X_i on Y_i , $(\delta + \gamma)$, will be larger than the estimated effect at the reference year, indicating the changes in tracking practices are more obviously related to functional motivations for tracking.

After controlling for all functional factors, I will add a vector of conflict factors. The *full cohort-interaction model* has the following specification:

$$Y_i = \alpha_0 + \beta Coh + \delta X_i + \gamma(Coh \times X_i) + \pi M_i + \rho(Coh \times M_i) + \theta Z_i + \varepsilon_i$$

where Y_i are various of school-level organizational dimensions of tracking at school i. Coh is the cohort indicators (NELS as reference cohort as well), M_i is a vector of school-level conflict factors. $Coh \times M_i$ is an interaction matrix indicating the cross product between cohorts and conflict factors. π is the estimated effect of M_i on Y_i at reference cohort (i.e., 1992 in this analysis). The estimation of ρ can be used to determine whether changes in tracking practices are more or less obviously related to conflict motivations for tracking, after controlling for all functional factors. If ρ is a positive value, the *total* estimated effect of M_i on Y_i , $(\pi + \rho)$, will be larger than the estimated effect at the reference year, indicating the changes in tracking practices are more obviously related to conflict force of tracking.

Across the different studies examined here, and within each study, the number of students sampled in each school varies considerably. As such, the data structure is unbalanced, with different levels of sampling error in the school-level outcomes and predictors I examine. To begin to address this differential school-level reliability, I calculate the cohort-specific multilevel reliability for each school based on the within-school sample size, using the *loneway* command in STATA. The estimated multilevel reliabilities are then stored and used as school-level analytic weights (*aweight* in STATA) to estimate models.

3.3 Results

3.3.1 Level-related measures of tracking

Table 3.1 to 3.9 report findings concerning *level-related* measures of tracking, including mean Math Course Sequence Level, using various model-building strategies. All models include each school's multilevel reliability as analytic weights. Table 3.1 reports the unconditional association between Mathematics and Science level-related measures of tracking and each element of school composition from (averaging over) the years 1982-2013. These models provide a baseline estimation of the relationship between school compositional characteristics and school-level organizational dimensions of tracking, without any statistical controls. Table 3.2 examines the correlations among all dependent variables.

Next, Table 3.3, 3.4, and 3.5 report the time-pooled model partial associations between measures of school composition and level-related outcomes throughout the period 1982-2013. Table 3.3 and 3.4 focus specifically on mean Math Course Sequence Level, using a streamlined (Table 3.3) and saturated (Table 3.4) specification respectively. Table 3.5 summarizes the time-pooled model estimation for all level-related measures of tracking, using the model specification reported in Table 3.4, Model 6. Tables 3.1 to 3.5 are used to address the first research question of this chapter: is variation in US schools' tracking system related to school-level compositional characteristics that might signal different tracking mechanisms?

Table 3.6 reports the baseline *time trend* of all level-related measures of tracking, using both linear trend models and categorical trend models. Finally, Table 3.7, 3.8, and 3.9 report cohort-interaction models for level-related measures of tracking. Table 3.7 and 3.8 focuses on mean Math Course Sequence Level, while table 3.9 shows results for other level-related measures of tracking, using the full-model specification reported in Table 3.8, Model 6. Keep in mind, the overall reduced-form effect of individual school compositional factors is reported in 3.1. Table 3.7, 3.8, and 3.9 are used to address the second major research question of this chapter: how has the relationship between school tracking systems and school composition changed over the past 40 years?

3.3.1.1 Baseline, Time-Pooled Association

Table 3.1 summarizes the baseline association between level-related measures of tracking and school compositional factors, on average, during the period 1982-2013. Each cell from Table 3.1 reports the regression coefficient, standard error, and standardized beta from an unconditional regression estimation of each level-related measure of tracking using only one school compositional factor.[6]

Table 3.1 ***Unconditional Association*** **between School-level Mathematics and Science Level-related Measures of Tracking and school composition, 1982-2013 (n = 3620 schools)**

	1. Math Mean Sequence	2. Math Inclusiveness	3. Science Mean Sequence	4. Mean Number of Science Courses	5. Science Inclusiveness
1. Achievement Heterogeneity	.106***	.016***	.024***	.114***	.011***
	(.014) [a]	(.002)	(.007)	(.017)	(.002)
Std. Beta	.126	.115	.058	.114	.090
R-square	.016	.013	.003	.013	.008
2. School Size (9-12 grade)	-.017***	-.002***	-.008***	.009*	-.000
	(.004)	(.001)	(.002)	(.004)	(.001)
Std. Beta	-.082	-.07	-.075	.038	-.013
R-square	.007	.005	.006	.001	.000
3. School-mean Achievement	.164***	.027***	.044***	.043***	.016***
	(.004)	(.001)	(.002)	(.006)	(.001)

[6] Coefficients reported in Table 3.1 are weighted using the estimated multilevel reliability for each school. Coefficients have no major differences with unweighted model estimations.

Std. Beta	.538	.541	.298	.121	.349
R-square	.289	.293	.089	.015	.122
4. School-mean SES	1.865***	.300***	.657***	.707***	.182***
	(.051)	(.008)	(.027)	(.069)	(.008)
Std. Beta	.522	.516	.379	.168	.346
R-square	.272	.266	.144	.028	.120
5. Percentage of non-free lunch	1.129***	.189***	.254***	-.759***	.058**
	(.125)	(.020)	(.061)	(.149)	(.019)
Std. Beta	.157	.161	.073	-.089	.054
R-square	.025	.026	.005	.008	.003
6. Percentage of white	.710***	.097***	.189***	-.378***	.036*
	(.094)	(.015)	(.046)	(.111)	(.014)
Std. Beta	.128	.107	.070	-.058	.044
R-square	.016	.011	.005	.003	.002
7. Shannon Index of Race Diversity	.388***	.073***	.237***	1.029***	.081***
	(.079)	(.013)	(.038)	(.091)	(.012)
Std. Beta	.085	.098	.106	.191	.121
R-square	.007	.010	.011	.036	.015
8. SES heterogeneity	.241*	.043*	-.050	.394~	.046~
	(.115)	(.025)	(.089)	(.217)	(.027)
Std. Beta	.122	.084	-.059	.130	.098
R-square	.076	.025	.013	.034	.028

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

According to functional theories of tracking, level-related measures of course taking should be strongly related to school-mean achievement. I find school-mean achievement is indeed positively associated with school-mean Math Course Sequence, Math inclusiveness, and, to a lesser extent, school-mean Science Course Sequence (Table 3.1, Row 3). Although treated elsewhere in the analysis as important compositional variables related to functional theories of tracking, achievement heterogeneity and school size are not expected to have a substantial functional association with level-related measures in Table 3.1 (I consider measures of heterogeneity further below). Examining the magnitude of the associations, Table 3.1 Row 3 shows that a one standard deviation difference in school-mean achievement is positively associated with a .522 and .641 standard deviation increase in school-mean Math Course Sequence level and Math inclusiveness, respectively, but is associated with only a .298 standard deviation difference in school-mean Science Course Sequence level.[7]

Is the basic level of course taking in a school also associated with status competition? According to status competition theory, students from middle- and professional- class families may compete with their peers, pursuing higher-track course-taking experiences with the ultimate goal of getting into elite colleges and maintaining their social status. In this section, I consider school-mean SES, percentage of White students, and percentage of non-poor students as school-level measures that may reveal the effects of status competition, although the results in Table 3.1 are fully unconditional, and thus also carry functional effects through their association with achievement. As shown in Table 3.1, Row 4, 5, and 6, both math and science level-related measures of tracking are positively associated with school-mean SES, percentage of non-free lunch recipients, and percentage of White students (with the exception of mean number of science courses), indicating a potential intra-group competition process that are associated with the mean level of course-taking rigor. Similar to the effects of school-mean achievement, the standardized

[7] I also conducted discrete change calculations between schools at the 75th percentile and schools at the 50th percentile. The predicted Math school-mean Course Sequence level for schools at the 75th percentile of mean achievement are, on average, .58 levels higher than schools at the 50th percentile of mean achievement. The predicted difference in Science Course Sequence level is only .15 between schools at the 75th percentile of mean achievement and schools at 50th percentile.

beta reported in Table 3.1, Row 5 indicates that the strength of the baseline associations for percent non-poor and white are stronger in math than science (.157 vs. .037). [8]

Returning to measures of compositional heterogeneity, conceptually, functional and conflict theories would anticipate associations between these measures and the *dispersion* in course taking within a school more so than the mean level of course taking. Nevertheless, as shown in Table 3.1, Row 1,7, and 8, all three measures of heterogeneity are in fact positively associated with various level-related measures of tracking in these unconditional models. The standardized beta reported in Table 3.1, Rows 1, 7, and 8 show that the strength of the associations for heterogeneity measures is at approximately the .10 level which is similar to the strength of associations for percent white and percent non-poor. One explanation for the various heterogeneity effects is that these are picking up aspects of the achievement distribution not captured by the mean. Later I consider additional moments of school-level achievement (square and cubic terms). In those analyses (Table 3.4 and 3.3), I still find that these measures of heterogeneity are positively associated with mean level of course taking even after considering functional factors and the effects of status competition. These results may indicate heightened competition processes among students in general, somehow evoked by the presence of status heterogeneity of various kinds, that in fact are associated with the mean course-taking rigor, an explanation I return to (along with other possible mechanisms) following the full set of results.

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[8] Discrete change calculations indicate that schools at the 75th percentile of percentage of non-poor students are predicted to have a .14 level higher school-mean Math Course Sequence than schools at the 50th percentile; this difference is only .03 of a level for school-mean Science Course Sequence.

Overall, during the period of 1982-2013, on average, school-mean course-taking level is associated with various measures of school composition that reflect functional factors as anticipated. Compositional features such as percent non-free lunch, and percent white are also associated with course taking level, reflecting an unknown mix of status competition and functional effects in these basic associations. Additionally, compositional features of schools we typically theorize to affect the distribution of course taking, appear to be related to the mean level of course taking as well, at a similar level to compositional features theorized to produce status competition.

3.3.1.2 Time-pooled Model of Partial Associations

Moving to analysis of partial associations, I rely on three analyses to investigate the relationship between achievement composition as a functional factor, the set of status competition factors, and compositional measures of heterogeneity, and tracking outcomes. First, Table 3.2 shows the correlation matrix of school composition measures. Second, to simplify and clearly illustrate the unique effects of school composition related to functional factors, status competition, and heterogeneity measures, specifically, Table 3.3 reports model estimations using only school-mean achievement, and summary scales for status competition variables and measures of heterogeneity. Of course, such models are glossing over a lot of information and potentially missing some key nuance in the findings, but they are useful for exposition. Thereafter, Table 3.4 reports more saturated models with the multiple compositional measures reported simultaneously (e.g., both school-mean SES and school percent free-lunch), and multiple moments of the achievement distribution of the school.

Table 3.2 Correlation Matrix of School Composition Measures

	Mean Achi.	Size	Mean SES	% White	% non-poor	Achi. Hetero.	SES Hetero.
Mean Achievement							
School Size	-.03						
Mean SES	.67	-.09					
Percent White	.33	-.31	.39				
Percent non-poor	.43	-.10	.59	.52			
Achi. Heterogeneity	.14	.13	.02	.03	-.02		
SES Heterogeneity	.08	.14	-.03	-.10	-.06	.21	
Race Diversity	-.00	.32	-.09	-.53	-.22	.14	.15

NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

As shown in Table 3.2, school-mean achievement is strongly correlated with school-mean SES and has a moderate relationship with percent white and non-poor, indicating that in the baseline associations, these measures related to status competition process (e.g., % white) may in fact be carrying functional effects through their relationship with school-mean achievement. School-mean SES has moderate to high positive relationships with other status competition factors, percent white and non-poor, but has weak or no relationship with heterogeneity measures. This is important to subsequent analyses because 1) the status competition factors do not for the most part carry the effect of heterogeneity measures, and 2) there is a statistical as well as theoretical motivation to group these measures. The relationships among heterogeneity measures, albeit weak, are consistently positive and stronger than their associations with status competition factors.

Is school-mean course-taking rigor in the US secondary education sector, over the period 1982-2013, most associated with technical-functional processes, status competition within advantaged students in a school, or perhaps competition among students in general (evoked by the presence of status heterogeneity)? Table 3.3 and 3.4 report time-pooled associations between school composition and school-mean Math Course Sequence Level, using theoretically meaningful summary scales (Table 3.3) or more saturated combinations/groupings of variables (Table 3.4).[9] The simplified exposition in Table 3.3 makes clear relationships potentially obfuscated by covariance between similar measures (e.g., school-mean SES and % free lunch, etc.).

Table 3.3 *Time-pooled Model* Estimation of School-level Math Mean Course Sequence Level using school-mean Achievement, Status Competition scale, and Heterogeneity Scale, 1982-2013 (n = 3620 schools; School-level Covariates includes school size,[b] sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. School-mean Achievement	.151***			.153***	.144***	.144***
	(.005) [a]			(.006)	(.005)	(.006)
2. Status Competition Scale		.437***		-.045		.009
		(.050)		(.047)		(.047)
3. Heterogeneity Scale			.464***		.244***	.245***
			(.045)		(.041)	(.042)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.329	.200	.227	.350	.353	.357

a. Robust Standard errors in parentheses
b. School size included as covariate only in models for level-related outcomes, elsewhere it is conceptually related to assessing functional explanations.
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department

[9] Additionally, Table 3.2 is also structured to be consistent with later tables, with variables such as school size (grouped with the functional factors) expected to be more strongly related to the structure of tracking than the level.

of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Table 3.3, Models 1–3 report the effect of school-mean achievement (as the principle functional measure expected to affect mean levels of course taking), a status-competition scale, and a heterogeneity scale, controlling for school covariates (e.g., school sector, urbanicity, sampled percent white),[10] while Models 4 and 5 consider status competition and heterogeneity, after controlling for school-mean achievement. Model 6 is the full model. To construct the summary scales, I first create the standardized form for each independent variable, and then calculate the mean of these standardized variables. Table 3.4 has the same model specifications, but has more saturated representation of independent variables, providing more robust comparisons of R-square across models.

Table 3.4 *Time-pooled Model* Estimation of School-level Math Mean Course Sequence Level using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Functional Factor						
1. School-mean Achievement	.236			.357	.161	.232
	(.380) [a]			(.440)	(.381)	(.451)
2. Achievement ^ 2	-.003			-.004	-.002	-.002
	(.008)			(.009)	(.008)	(.009)
3. Achievement ^ 3	.000			.000	.000	.000
	(.000)			(.000)	(.000)	(.000)
4. School Size	-.006			-.009*	-.011**	-.013***
	(.004)			(.004)	(.004)	(.004)
Status Competition						
5. School-mean SES		2.170***		1.459***		1.491***
		(.076)		(.086)		(.089)
6. Percentage of White		-.723***		-.413**		-.104

[10] School size is included as a covariate in this table only, later school size is used as a key functional measure related to various tracking structure outcomes.

		(.157)		(.147)		(.157)
7. Percentage of non-free lunch		-1.641***		-1.806***		-1.788***
		(.170)		(.159)		(.159)
Heterogeneity Measures						
8. Achievement Heterogeneity			.098***		.070***	.051***
			(.016)		(.014)	(.014)
9. SES Heterogeneity			.326*		-.272	-.133
			(.175)		(.179)	(.176)
10. Shannon Index of Race Diversity			.764***		.550***	.444***
			(.092)		(.082)	(.089)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.330	.285	.263	.403	.395	.438

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

As shown in Table 3.3, Model 1, on average, during the period 1982-2013, school-mean achievement is positively associated with mean Math Couse Sequence Level, and the coefficient remains positively significant after controlling for the status competition scale and/or the heterogeneity scale in subsequent models, which is consistent with functional explanations for school-to-school variation in mean course taking. The total effect of functional process is quite large; the R-square is .392 just from school-mean achievement and other school-level covariates. Note that while scales are labeled for simplicity as, e.g., "status competition scale," status competition is an underlying and unseen process/mechanism, while the scale is just a measure of composition. Model 2 reports the effect of more obvious conflict forces on mean Math Course Sequence Level, while Model 3 shows the partial association with school heterogeneity that was not originally theorized to affect mean course taking outcomes. As shown in Model 2, the status competition scale is positively associated with mean level. However, after controlling for school-mean achievement and the heterogeneity scale in Model 6, status competition has no significant relationship with school-mean mathematics course taking. A statistically significant effect of school-mean SES emerges in Table 3.4, but given the association with % non-free lunch, which is off-setting, the total effect of the status competition related variables is quite small; the R^2 rises from .33 to .40 from Model 1 to Model 4 in Table 3.4.

Table 3.3, Model 3 shows a significant positive relationship between the heterogeneity scale and mean Math Course Sequence Level, this effect remains positive and significant after controlling for school-mean achievement and the status-competition scale. To begin to interpret this relationship, it may be useful to build on previous arguments about the effects of status competition. The association between the status competition scale and school-mean course-taking rigor likely reveals a competition process *within advantaged students* in a school. I would further suggest that the association between the heterogeneity scale reflects a similar competition process, but among *all students* in that school in general. Here I hypothesize that competition for status is made more salient by the heightened status variation, in various ways, in the school population. The R-square rises from .33 to .39 from Model 1 to Model 5 in Table 3.4. The R-square change between Model 1 and 4 (7.3%) is similar to the change between Model 1 and 5 (6.5%), indicating that status competition process and heterogeneity measures contribute almost equally to the total school-to-school differences in mean course-taking level.

Although I have thus far focused on one level-related measure, the mean level of math course taking in the school, four additional level related measures are available. Table 3.5 reports those results using the same model specification as Model 6 in Table 3.4. Overall, the results are similar across the different school-level course taking outcomes, although the associations with science course taking are consistently weaker than with math. The R-squares for Math models are higher than Science models (over a .4 level for math and around a .2 level for science). This is likely due to the fact that schools vary less in mean Science course-taking level than in Math course-taking level. [11]

Table 3.5 Summary of *Time-pooled Model* Estimation of School-level Mathematics and Science Level-related Measures of Tracking using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Math Mean Sequence	2. Math Inclusiveness	3. Science Mean Sequence	4. Mean # of Science Courses	5. Science Inclusiveness
Functional Factor					
1. School-mean Achievement	.232	-.000	.189	1.169~	.093
	(.451) [a]	(.060)	(.255)	(.674)	(.076)
2. Achievement ^ 2	-.002	.000	-.004	-.025~	-.002
	(.009)	(.001)	(.005)	(.014)	(.002)
3. Achievement ^ 3	.000	-.000	.000	.000~	.000
	(.000)	(.000)	(.000)	(.000)	(.000)
4. School Size	-.013***	-.002**	-.007***	.001	-.002*
	(.004)	(.001)	(.002)	(.006)	(.001)
Status Competition					
5. School-mean SES	1.491***	.231***	.798***	1.452***	.189***
	(.089)	(.015)	(.048)	(.119)	(.015)
6. Percentage of White	-.104	-.027	.096	.060	-.025
	(.157)	(.027)	(.094)	(.231)	(.026)
7. Percentage of non-free lunch	-1.788***	-.271***	-.753***	-2.002***	-.201***
	(.159)	(.027)	(.083)	(.222)	(.025)
Heterogeneity Measures					
8. Achievement Heterogeneity	.051***	.008***	.013~	.060**	.004~

[11] In Chapter 2, Table 2.1, for example, the weighted coefficient of variation (Standard deviation divided by the mean) of school-mean Math Course Sequence for the 1992 cohort is .32, whereas the coefficient of variation of school-mean Science Course Sequence is only .17.

	(.014)	(.002)	(.007)	(.019)	(.002)
9. SES Heterogeneity	-.133	-.021	-.148	.222	.004
	(.176)	(.028)	(.094)	(.230)	(.029)
10. Shannon Index of Race Diversity	.444***	.073***	.397***	1.115***	.091***
	(.089)	(.015)	(.050)	(.124)	(.015)
School Covariates	Yes	Yes	Yes	Yes	Yes
R-squared	.438	.436	.280	.216	.234

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Overall, perhaps most important to understanding school-to-school variation in the mean level of course taking, the technical-functional process appears to be the strongest factor associated with mean course-taking level, on average, during the period of 1982-2013. In addition, a greater density of advantaged students, as well as heterogeneity in the student body, are associated with higher average levels of course taking (and almost equally so). Although not the only possible mechanism, these findings are consistent with theories of status competition, and considering the effect of heterogeneity, possibly evidence of a more pervasive process of competition evoked by heterogeneity.

3.3.1.3 Baseline Trend and Cohort-interaction Model

Table 3.6 reports the baseline time trends of level-related measures of tracking using both linear trend models and categorical trend models. As shown in Table 3.6, Row 1, overall, as reported by other researchers using different but related measures over a shorter period (e.g., Domina, & Saldana, 2012), the average course-taking level increased substantially throughout the period 1982-2013.

Table 3.6 *Baseline Trends* of School-level Mathematics and Science Level-related Measures of Tracking using Linear Trend Model and Categorical Trend Model, 1982-2013 (n = 3620 schools; School-level Covariates includes school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Mean Math Sequence	2. Math Inclusiveness	3. Science Mean Sequence	4. Number of Science Courses	5. Science Inclusiveness
Panel 1: Linear Trend Model (Cohort centered at 1992)					
1. Cohort (centered at 1992)	.812***	.116***	.422***	.979***	.100***
	(.021) [a]	(.004)	(.010)	(.026)	(.004)
2. School-level Covariates	Yes	Yes	Yes	Yes	Yes
R-square	.413	.359	.419	.392	.253
Panel 2: Categorical Trend Model (NELS as reference)					
3. HS&B	-1.164***	-.130***	-1.084***	-2.322***	-.131***
	(.065)	(.011)	(.028)	(.074)	(.011)
4. ELS	.660***	.092***	.322***	.258***	.091***
	(.068)	(.012)	(.029)	(.077)	(.011)
5. HSLS	1.347***	.225***	.274***	.934***	.175***
	(.064)	(.011)	(.028)	(.073)	(.011)
6. School-level Covariates	Yes	Yes	Yes	Yes	Yes
R-square	.419	.360	.541	.457	.255

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

School-mean Math Course Sequence level increased by, on average, .81 of a level every decade; that is approximately 2.4 levels (.81 ×3 = 2.43, or a 2.43 ÷ 9 = 26.6% relative increase) out of a 9-level Course Sequence scale over the period of this study (Table 3.6, Cell 1-1). School-mean Science Course Sequence Level goes up by, on average, .42 of a level every decade, and by approximately 1.3 levels throughout the period 1982-2013. Keep in mind that Science Course Sequence is only on a 5-level scale, a 1.3 level rise in Science Course Sequence Level is approximately a 26.0% increase out of a 5-level scale, similar in that metric to math. Inclusiveness measures the percentage of students who complete high-level math or science courses, and is, therefore, a more intuitively scaled measure. Table 3.6, Row 1 reports that, on average, schools track 12% more students to high-level math courses and 10% more students to high-level science courses every decade. It's worthwhile to note that all dependent measures are at the school level, but these baseline trends models are interpretively almost identical to student-level analyses because school-level measures are aggregated from student-level measures. R-square statistics reported in Table 3.6 range from the .25 to .50 level, indicating a quite large contribution from cohort-to-cohort differences, relative to school-to-school differences within each cohort.

Is the basic course-taking level in a school more or less related to the apparent technical-functional process, status competition within *advantaged* students, and measures of heterogeneity (revealing I argue, competition among *all* students in general), over the period of 1982-2013? Table 3.7 and 3.8 examine the interaction effects between cohorts and school composition on school-mean Math Course Sequence Level. Consistent with time-pooled partial association models, I consider the same theoretically meaningful summary scales in streamlined models in Table 3.7 and more-saturated combinations/groupings of dependent variables in Table 3.8.

Table 3.7 *Cohort-Interaction* Model Estimation of the Trends of School-level Math Mean Course Sequence Level using school-mean Achievement, Status Competition scale, and Heterogeneity Scale, 1982-2013 (n = 3620 schools; School-level Covariates includes school size[b], sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. Cohort (centered at 1992 cohort)	.765***	.883***	.783***	.654**	.820***	.692**
	(.196) [a]	(.020)	(.023)	(.248)	(.200)	(.257)

2. School-mean Achievement	.129***			.105***	.134***	.109***
	(.005)			(.006)	(.005)	(.006)
3. School-mean Achievement× Cohort	-.001			.002	-.001	.002
	(.004)			(.005)	(.004)	(.005)
4. Status Competition Scale		.864***		.487***		.469***
		(.046)		(.046)		(.046)
5. Status Competition Scale× Cohort		-.092***		-.091**		-.090**
		(.027)		(.030)		(.031)
6. Heterogeneity Scale			-.045		-.195***	-.161***
			(.044)		(.041)	(.040)
7. Heterogeneity Scale× Cohort			.074*		.002	.007
			(.033)		(.029)	(.030)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.539	.501	.429	.567	.543	.570

a. Robust Standard errors in parentheses

b. School size included as covariate only in models for level-related outcomes, elsewhere it is conceptually related to assessing functional explanations.

*** p<.001, ** p<.01, * p<.05, ~ p<.1

NOTE: Sample size is rounded to the nearest 10 as required by NCES.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.8 *Cohort-Interaction Model* Estimation of the Trends of School-level Math Mean Course Sequence Level using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. Cohort (centered at 1992 cohort)	1.434	.657***	.447***	1.439	3.492	2.067
	(7.589) [a]	(.089)	(.125)	(8.121)	(8.204)	(8.695)
Functional Factors						
2. School-mean Achievement	.490			.811	.766	.967~
	(.454)			(.504)	(.502)	(.543)
3. School-mean Achievement × Cohort	-.068			-.107	-.181	-.136
	(.451)			(.487)	(.485)	(.518)
4. Achievement ^ 2	-.008			-.015	-.013	-.017
	(.010)			(.011)	(.010)	(.011)
5. Achievement ^ 2 × Cohort	.002			.003	.004	.003
	(.009)			(.010)	(.010)	(.010)
6. Achievement ^ 3	.000			.000	.000	.000

	(.000)			(.000)	(.000)	(.000)
7. Achievement ^ 3 × Cohort	-.000			-.000	-.000	-.000
	(.000)			(.000)	(.000)	(.000)
8. School Size 9-12 grade	-.003			-.008*	.000	-.006
	(.004)			(.004)	(.004)	(.004)
9. School Size × Cohort	.005*			.006*	.007*	.006*
	(.002)			(.003)	(.003)	(.003)
Status Competition						
10. School-mean SES		1.674***		1.174***		1.177***
		(.072)		(.078)		(.080)
11. Mean SES × Cohort		-.132*		-.376***		-.374***
		(.057)		(.072)		(.074)
12. Percentage of White		-.113		.056		-.072
		(.142)		(.134)		(.140)
13. Percentage of White × Cohort		.004		.065		-.001
		(.073)		(.075)		(.092)
14. Percentage of non-free lunch		-.066		-.329*		-.312~
		(.163)		(.157)		(.160)
15. Percentage of non-free lunch × Cohort		.094		.245*		.279*
		(.119)		(.113)		(.115)
Heterogeneity Measures						
16. Achievement Heterogeneity			.018		-.017	-.019
			(.016)		(.015)	(.015)
17. Achievement Heterogeneity × Cohort			-.010		-.004	-.002
			(.012)		(.011)	(.011)
18. SES heterogeneity			.103		-.334*	-.201
			(.173)		(.156)	(.153)
19. SES heterogeneity × Cohort			.626***		.185	.182
			(.142)		(.126)	(.127)
20. Shannon Index of Race Diversity			-.163~		-.309***	-.255**
			(.095)		(.085)	(.086)
21. Shannon Index of Race Diversity × Cohort			.035		-.114*	-.077
			(.059)		(.058)	(.071)
22. School-level Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.540	.535	.421	.588	.553	.591

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Here, I focus on the cohort interaction coefficients in Table 3.7 and 3.8. School-mean achievement has a very stable effect on school-mean Math Course Sequence Level, with no statistically significant interaction terms in Table 3.7, Model 1, 4, 5, and 6. The effect of status competition on school-mean Math Course Sequence Level decreases, as the cohort-interaction with the scale of status competition has significant negative effects on math Course Sequence Level in Table 3.7, Model 2. These coefficients persist in Model 4 and 6 where I consider the partial effects of functional process and/or the heterogeneity scale. The R-square rises from .413 in the baseline trends model to .535 in Table 3.8, Model 2. Lastly, Table 3.7, Model 3 reports the cohort-interaction estimation using only heterogeneity scale and its interaction with cohort. Although Model 3 may suggest an increasing trend in the effect of heterogeneity, after considering both school-mean achievement and status competition processes in Model 6, the effect of heterogeneity on school-mean Math Course Sequence Level becomes stable across cohorts.

Results from Model 3.7 indicate, first of all, that technical-functional processes remain a strong factor that links to the school-mean math course-taking level throughout my period of study, even considering the changing effects of other compositional factors. One feature of American education over this period has been the rise in measured achievement of students (e.g., Lee, & Reeves' 2012 study on reading and math achievement trends over the period of 1990-2009 using NAEP data). Thus, I expect changes in the level of achievement to partially explain trends in course taking. The R-square change from the baseline trends model (Table 3.6, Cell 1-1) to Table 3.7, Model 1 is .13, indicating a moderate contribution from considering the level of achievement at each cohort, on average. [12] School size, despite having no effect on course-taking level in time-pooled models, is increasingly related to math Course Sequence Level, as reported in Table 3.8, Model 6. Next, the effect of the scale of status-competition becomes weaker in later cohorts. Additionally, Table 3.8 reports that this trend is primarily driven by the declining effect of school-

[12] I also run a baseline model with only cohort fixed effect and level of achievement. The R-square is .529 which indicate a similar amount of contribution just from the level of school-mean achievement at each cohort.

mean SES (Model 2, 4, and 6). Nevertheless, given the fact that the coefficient of the interaction term is much smaller than of the main effect, I find that status competition processes within advantaged students in a school remains a conflict force that drives up mean course taking even into the 2010s, which I later show specifically in sensitivity analyses. Lastly, Table 3.7 shows no evidence that the effect of heterogeneity changes substantially across cohorts. The effect of SES heterogeneity appears to go up in Table 3.8, Model 3, but later in Model 6, however, the cohort-interaction terms for all three measures of heterogeneity show stable effects on school-mean Math Course Sequence Level. Table 3.9 reports the model estimations of all five level-related measures of tracking, using the same model specification as Model 6 in Table 3.8. Overall, the results are similar across different level-related outcomes. School-mean achievement has stable effects on level-related measures of tracking, except for math inclusiveness (Table 3.9, Row 3). The effects of various measures of competition related to status competition processes on school-mean Math and Science Course Sequence Level and number of science courses also have decreasing trends over cohorts (Row 11 and 13).[13]

[13] Moreover, school-mean science Course Sequence Leve, in particular, has significant negative relationships with the cohort-interaction terms of achievement heterogeneity and race diversity, indicating an apparent decreasing trend of the effect of heterogeneity over cohorts. However, the effects of heterogeneity on all other level-related measures are pretty stable over cohorts.

Table 3.9 Summary of *Cohort-Interaction Model* Estimation of the Trends of School-level Mathematics and Science Level-related Measures of Tracking using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Math Mean Sequence	2. Math Inclusiveness	3. Science Mean Sequence	4. Mean # of Science Courses	5. Science Inclusiveness
1. Cohort (centered at 1992 cohort)	2.067	3.102*	-.689	13.384	-.255
	(8.695) [a]	(1.299)	(4.634)	(11.893)	(1.355)
Functional Factors					
2. School-mean Achievement	.967~	.173*	.631*	2.459***	.176*
	(.543)	(.071)	(.249)	(.533)	(.073)
3. School-mean Achievement × Cohort	-.136	-.192*	.040	-.811	.013
	(.518)	(.077)	(.273)	(.713)	(.080)
4. Achievement ^ 2	-.017	-.003*	-.013*	-.050***	-.003*
	(.011)	(.002)	(.005)	(.011)	(.002)
5. Achievement ^ 2 × Cohort	.003	.004**	-.000	.017	-.000
	(.010)	(.002)	(.005)	(.014)	(.002)
6. Achievement ^ 3	.000	.000*	.000*	.000***	.000*
	(.000)	(.000)	(.000)	(.000)	(.000)
7. Achievement ^ 3 × Cohort	-.000	-.000**	.000	-.000	.000
	(.000)	(.000)	(.000)	(.000)	(.000)
8. School Size 9-12 grade	-.006	-.001	-.003~	.009~	-.000
	(.004)	(.001)	(.002)	(.005)	(.001)
9. School Size × Cohort	.006*	.000	.004**	.009*	-.000
	(.003)	(.000)	(.001)	(.004)	(.000)
Status Competition					
10. School-mean SES	1.177***	.184***	.587***	.931***	.140***
	(.080)	(.014)	(.041)	(.102)	(.015)
11. Mean SES × Cohort	-.374***	-.013	-.201***	-.315**	.006
	(.074)	(.013)	(.040)	(.110)	(.013)
12. Percentage of White	-.072	-.005	.198*	.510**	.002
	(.140)	(.024)	(.080)	(.181)	(.024)
13. Percentage of White × Cohort	-.001	-.019	-.225***	-.626***	-.026~
	(.092)	(.016)	(.052)	(.124)	(.015)
14. Percentage of non-free lunch	-.312~	-.072**	-.145~	-.484*	-.049~
	(.160)	(.027)	(.085)	(.201)	(.027)
15. Percentage of non-free lunch × Cohort	.279*	-.005	.548***	.950***	.035~
	(.115)	(.020)	(.062)	(.161)	(.020)
Heterogeneity Measures					
16. Achievement Heterogeneity	-.019	-.001	-.020**	-.035*	-.004~
	(.015)	(.002)	(.007)	(.017)	(.002)
17. Achievement Heterogeneity × Cohort	-.002	.000	-.023***	-.017	-.002
	(.011)	(.002)	(.006)	(.015)	(.002)
18. SES heterogeneity	-.201	-.037	-.219**	.009	-.024
	(.153)	(.026)	(.076)	(.180)	(.025)
19. SES heterogeneity × Cohort	.182	-.009	.093	.195	.010
	(.127)	(.023)	(.067)	(.173)	(.023)
20. Shannon Index of Race Diversity	-.255**	-.022	.010	.097	-.005
	(.086)	(.014)	(.045)	(.109)	(.014)
21. Shannon Index of Race Diversity × Cohort	-.077	-.009	-.147***	-.120	.001

	(.071)	(.012)	(.039)	(.100)	(.011)
22. School-level Covariates	Yes	Yes	Yes	Yes	Yes
R-square	.591	.543	.528	.436	.355

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

3.3.1.4 Summary of level-related analysis

Considering all model estimations of level-related measures of tracking, both time-pooled models and cohort-interaction models reveal substantial relationships between level-related measures of tracking and school-level compositional characteristics that may signal different tracking mechanisms. Time-pooled models provide the broadest summary look at school-to-school differences in mean course-taking level over the period of 1982-2013.[14] In particular, I find that the technical-functional process is the strongest factor associated with mean course-taking level, on average, during the period of 1982-2013. The competition process within *advantaged students* in a school is also positively related to school-mean course-taking level. In addition to that, I further argue that the competition among *all students* in general is also associated with mean level. The cohort-interaction models examine how these relationships change throughout the period of this study. Both technical-functional processes and measures of heterogeneity have stable effects on level-related measures of tracking, whereas the effect of status competition processes becomes weaker in later decades.

[14] Time pooled models also consider the cohort-to-cohort error inherently induced by each specific NCES study by averaging the cohort-specific measures.

3.3.2 Tracking Structure

Tables 3.10 to 3.24 and Supplementary Tables B.1 and B.2 report model estimation results concerning various dimensions of math and science *tracking structure*, including the variance of Course Sequence within the school, tracking selectivity, tracking scope, and track mobility. Collectively, these organizational dimensions of tracking structure speak to the overall elaboration of the curriculum tracking system in US high schools. Table 3.10 and 3.11 report the unconditional associations between each element of school composition and measures of Math and Science structure, respectively, on average, over the period of 1982-2013. Similar to Table 3.1, Table 3.10 and 3.11 provide a baseline model estimation of the relationship between school composition and school-level organizational dimensions of tracking, without considering any statistical controls.

Next, Tables 3.12 to 3.18, and Appendix Table 8 report the time-pooled partial associations between tracking structure outcomes and school composition, on average, over the period of 1982-2013. Table 3.12 specifically focuses on the variance of students' Math Course Sequence within the school using streamlined model specifications, as the variance of Math Course Sequence examines the most basic form of inequality in course taking within a school. Similar to Table 3.3, I consider the theoretically meaningful scales of school composition related to functional processes, status competition, and opportunity hoarding in streamlined models. Further in Tables 3.13 and 3.14, I report the streamlined model estimations of all measures of tracking structure using the full model specification reported in Table 3.12, Model 6. Supplemental Tables 3.15, 3.16, and S.1 summarize the time-pooled partial associations between school composition and measures of tracking structures using fully-saturated model specifications.

Tables 3.17 and 3.18 report the baseline time trend of all measures of tracking structure, using linear trend models and categorical trend models. Tables 3.19 to 3.23 and Appendix Table

9 report cohort-interaction model estimations of measures of tracking structure. Tables 3.19 to 3.21 focus on model estimations using streamlined model specifications, whereas Tables 3.22, 3.23, and S.2 summarize model estimation results for fully-saturated models. Finally, Table 3.24 summarizes estimated effects of school composition on measures of tracking structure from both time-pooled models and cohort-interaction models, using symbols to qualitatively summarize the direction and consistency of relationships from 1982 to 2013. In Table 3.24, green triangles represent increasing effects over time of school composition consistent with different logics of tracking on the multiple dimensions of tracking structure investigated here, whereas red upside-down triangles indicate decreasing association over time. I label stable effects throughout the period of this study with yellow squares.

3.3.2.1 Initial Evidence on Tracking Structure and School Composition: Time-Pooled Baseline Associations

Table 3.10 and 3.11 summarize the baseline association between measures of Math and Science tracking structure and school compositional factors, respectively, on average during the period of 1982-2013. Each cell from Table 3.10 or 3.11 reports the regression coefficient, standard error, and standardized beta from an unconditional regression estimation of each measure of tracking structure using only one school compositional factor.[15]

[15] Coefficients reported in Table 3.10 and 3.11 are weighted using multilevel reliabilities. Coefficients have no major differences with unweighted model estimations.

3.3.2.1.1 Evidence of a Functional Logic in the Structure of Tracking

Are various measures of tracking structure potentially responsive to technical-functional processes? The functional theory of tracking suggests that schools place students into tracked course-taking experiences to meet their instructional needs, and thus the measures of tracking structure should be responsive to the achievement distribution. Here I analyze achievement heterogeneity, as opposed to school-mean achievement used in the previous section, as a key functional determinant of tracking structure. Another conceptually important component of the functional logic of tracking is that larger schools may have greater capacity to provide students with various course-taking experiences. Under functional norms, schools with a more diverse distribution of achievement and larger student population are expected to provide students with a correspondingly diverse set of course-taking pathways, in general.

Table 3.10 *Unconditional Association* between School-level Mathematics Tracking Structure and school composition, 1982-2013 (n = 3620 schools)

	1. Variance of Math Sequence within the School	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility
1. Achievement Heterogeneity	.244***	.016***	.015***	.010***	-.009***	.007***
	(.026) [a]	(.003)	(.002)	(.002)	(.002)	(.001)
Std. Beta	.156	.118	.123	.082	-.070	.092
R-square	.024	.014	.015	.007	.005	.008
2. School Size (9-12 grade)	.028***	.001~	.002**	.001~	.003***	.000
	(.007)	(.001)	(.001)	(.001)	(.001)	(.000)
Std. Beta	.074	.038	.056	.038	.102	.001
R-square	.005	.001	.003	.001	.010	.000
3. School-mean Achievement	.006	.001	-.003***	-.007***	-.021***	.008***
	(.009)	(.001)	(.001)	(.001)	(.001)	(.000)
Std. Beta	.010	.017	-.067	-.157	-.438	.283
R-square	.000	.000	.004	.025	.192	.080
4. School-mean SES	.054	.016	-.022*	-.063***	-.245***	.074***
	(.110)	(.011)	(.009)	(.010)	(.008)	(.006)
Std. Beta	.008	.029	-.042	-.124	-.441	.218
R-square	.000	.001	.002	.015	.194	.048

5. Percentage of non-free lunch	.992***	.094***	-.045*	-.086***	-.124***	.028*
	(.229)	(.021)	(.018)	(.021)	(.020)	(.012)
Std. Beta	.076	.087	-.043	-.087	-.110	.041
R-square	.006	.008	.002	.007	.012	.002
6. Percentage of white	.506**	.075***	-.001	-.020	-.107***	.024**
	(.173)	(.017)	(.014)	(.016)	(.015)	(.009)
Std. Beta	.050	.087	-.001	-.025	-.124	.045
R-square	.002	.008	.000	.001	.015	.002
7. Shannon Index of Race Diversity	.038	-.053***	-.003	.003	-.038**	.029***
	(.143)	(.013)	(.012)	(.013)	(.012)	(.008)
Std. Beta	.005	-.077	-.004	.005	-.054	.066
R-square	.000	.006	.000	.000	.003	.004
8. SES heterogeneity	1.164***	.054	.133***	.043	.007	.085***
	(.338)	(.033)	(.027)	(.031)	(.029)	(.018)
Std. Beta	.058	.031	.083	.027	.004	.081
R-square	.003	.001	.007	.001	.000	.007

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.11 *Unconditional Association* between School-level Science Tracking Structure and school composition, 1982-2013 (n = 3620 schools)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
1. Achievement Heterogeneity	.044***	.001	.005*	.007***
	(.005) [a]	(.003)	(.002)	(.002)
Std. Beta	.136	.010	.046	.073
R-square	.019	.000	.002	.005
2. School Size (9-12 grade)	.008***	.002*	.003***	.001
	(.001)	(.001)	(.001)	(.000)
Std. Beta	.100	.053	.098	.026
R-square	.010	.003	.010	.001
3. School-mean Achievement	-.001	-.002*	-.004***	.009***
	(.002)	(.001)	(.001)	(.001)
Std. Beta	-.006	-.051	-.090	.292

R-square	.000	.003	.008	.085
4. School-mean SES	-.029	.005	-.007	.074***
	(.023)	(.011)	(.010)	(.006)
Std. Beta	-.021	.009	-.013	.197
R-square	.000	.000	.000	.039
5. Percentage of non-free lunch	-.078	.069**	-.002	.104***
	(.049)	(.023)	(.021)	(.013)
Std. Beta	-.028	.065	-.002	.135
R-square	.001	.004	.000	.018
6. Percentage of white	.051	.018	-.019	.024*
	(.037)	(.017)	(.016)	(.010)
Std. Beta	.024	.022	-.023	.041
R-square	.001	.001	.001	.002
7. Shannon Index of Race Diversity	.012	-.032*	.014	.016~
	(.031)	(.014)	(.013)	(.008)
Std. Beta	.007	-.048	.022	.034
R-square	.000	.002	.000	.001
8. SES heterogeneity	.227**	.078*	.092**	.089***
	(.071)	(.035)	(.031)	(.019)
Std. Beta	.054	.046	.059	.077
R-square	.003	.002	.004	.006

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Tables 3.10 and 3.11, Row 1 and Row 2 examine the unconditional associations of achievement heterogeneity and school size with all ten measures of tracking structure (six DVs for math and four DVs for science). According to the functional logic of tracking, I expect that the variance of Course Sequence Level within the school is responsive to achievement heterogeneity. While it may be less apparent that, under a functional logic of tracking, other dimensions of tracking structures are related to achievement heterogeneity, I expect that tracking Selectivity, in particular, is responsive to achievement heterogeneity. Selectivity speaks to the selection criteria in producing tracked homogeneous course-taking experiences. In this analysis, the measure of selectivity is intended to reflect a school's overall emphasis on students' achievement when implementing enrollment policies, even as it is not a direct measure of policies. Schools with greater selectivity are more likely to adopt more rigorous requirements for course enrollment based on achievement or course prerequisites. Under this definition, I argue that a diverse distribution of achievement within a school may motivate school administrators and teachers to implement rigorous selection processes, in order to create homogeneous course-taking environments, if the school embraces the functional logic of tracking and promotes a highly-tracked curriculum based on students' instructional needs. Schools with a homogeneous achievement distribution, instead, may not have the similar instructional concerns to promote rigorous selection criteria, and thus may have a lower level of tracking Selectivity. As shown in Table 3.10 and 3.11, Row 1, achievement heterogeneity is positively associated with the variance of course sequence level, and, to a lesser extent, tracking selectivity. The positive associations with achievement heterogeneity, as expected, may reveal the presence of a functional motivation of curriculum tracking, on average, during the period 1982-2013.

Tables 3.10 and 3.11 also report associations between school composition and scope and mobility, but functional concerns are not necessarily expected to produce *associations* between the measures of composition considered here and scope or mobility. Rather, systems with generally higher levels of mobility (i.e., the levels of mobility themselves indicate functionalism[16], not their association with school composition), and tracking scope appropriate to cross-subject achievement

[16] Even as the absolute, optimal level, what is "most functional," is unclear.

similarity[17] would be said to be more functional[18]. In contrast, later, measures of scope between disparate subjects will be considered a more obvious indicator of conflict forces. Corequisites polices for disparate subjects are rarely seen the US high schools[19], thus the observed tracking scope between two distinct subjects (e.g., scope between ELA and Math or science in this analysis) reflects the overarching inequality structure that constrains the opportunity to learn. Because schools don't actively "control" the level of tracking scope between STEM and ELA courses, I argue that such scope likely reflects conflict forces of tracking. The positive associations with these DVs observed in Table 3.10 and 3.11 may only serve as statistical controls in later models.

The functional logic of tracking also suggests that larger schools may have greater capacity to provide students with various course-taking experiences. In examining the relationships between school size and all measures of tracking structure, I argue that, in addition to the association between school size and the variance of Course Sequence, functional theories of tracking may also be supported by associations between school size and upward mobility. In this

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[17] Studies of high school curriculum guides (e.g., Kelly, 2007) find that schools usually adopt course corequisites policies to promote tracking scope between closely-related subjects, such as math corequisites for science courses or ELA corequisites for social science courses. The rationale underneath the policies is that students may need a certain set of mathematical skills to take science courses, or language skills to take social sciences courses.

[18] An obvious functional motivation of tracking scope, of course, is the correlations in abilities, but this is not the focus of this analysis. As argued by Lucas and Berends (2002), correlated ability contributes to much of the correlation across different subjects; that is, the functional logic of tracking may suggest that tracking Scope between, for example, Math and science course taking is responsive to the correlation between Math and science achievement, rather than just the distribution of Math achievement.

[19] As reported in Kelly (2007), for example, only one high school out of a sample of 92 schools explicitly required ELA corequisites for honors science courses.

analysis, mobility examines the extent to which students have the ability to move away from the typical course-taking trajectory. It's worthwhile to note that unlike other measures of tracking structure in this analysis, upward mobility partially describes the way in which schools "open up" the opportunity to learn for students, and thus has a somewhat different functional logic.[20] Schools with higher upward mobility, in particular, enable students to enroll in elective or even higher-level courses that students from other schools don't normally take at the current grade level. Therefore, in this analysis, I argue that associations between school size and upward mobility reveal functionalism. The concept of downward mobility, however, mixes the ideas that 1) downward mobility opens opportunity for students who aren't able to catch up and 2) downward mobility constrains opportunity to learn, and thus its association with school size is not a clear indicator of the functional logic of tracking.

3.3.2.1.2 Conflict Forces and the Structure of Tracking Systems

Status competition theories of tracking suggest that an intra-group competition for status is common in high-SES and elite schools and thus these schools are more likely to embrace a more elaborated tracking system to create and preserve advantage for the most-advanced students. In this section, I argue that the ascriptive status competition factors in Table 3.1 (school-mean SES, percentage of non-free lunch recipients, and percent white) imply a competitive context, overall. In addition to SES-related measures, I also consider school-mean achievement as an element that may increase intra-group competition processes within a school. The achievement-based measures

[20] Of course Upward Mobility has somewhat mixed conceptualization in this analysis in which mobility speaks to both approaches that tracking opens up opportunity and advantaged groups prioritize opportunity. I will come back to this later in this analysis.

may, in particular, capture the internal anxiety among high-achieving students of falling behind other peer students.

I begin this section by examining the most basic evidence of conflict forces of tracking. As shown in Table 3.10 and 3.11, Row 3–6, in terms of the unadjusted, baseline relationships, the variance of math Sequence within the school and math and science Selectivity are positively associated with at least one factor of status competition processes (Table 3.10, Columns 1 and 2, and Table 3.11, Column 2). These findings indicate that the status competition processes within advantaged students may, in general, be associated with the overall elaboration of tracking structure. The tracking scope between math and science, however, is not related to any status competition factors. Additionally, Tables 3.10 and 3.11 report that upward mobility are positively associated with school-mean status level, showing a more general approach though which advantaged students and parents may in fact actively seek more learning opportunities. Different with respect to other measures of tracking structure, the associations between upward track mobility and the status level speak to both the way in which the intra-group competition "opens up" more flexible course-taking practices and high-status students and families prioritize learning opportunities to obtain advantages in course taking.[21] The standardized beta indicates that the strength of the associations between upward mobility and status competition factors are at a .2 level, whereas the associations for variance of math Sequence and Selectivity are at a much lower level.

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[21] I should note that in these data we don't see *which* students are mobile. Other dimensions of tracking (e.g., scope) are more clearly related to within-school inequality. Here I only consider the level of mobility in the school as a whole.

Are highly elaborated tracking systems also common in schools with diverse student populations? Opportunity hoarding theories of tracking describe a set of unequal distribution processes, which create uneven course-taking opportunities among students from different SES, race, or ethnicity groups within a school; that is, inter-group competition is expected to be more common in schools with more diverse student populations, and thus these schools should be more likely to implement highly elaborated curriculum tracking systems. Following prior research (e.g., Kelly, & Price, 2011), I consider race and SES heterogeneity as school compositional measures that may capture the extent to which advantaged students monopolize opportunities to learn. In particular, I find in Table 3.10 and Table 3.11, Row 7, 8, SES heterogeneity is positively associated with science selectivity and tracking scope (Row 8), showing some evidence that the elaboration of tracking is related to an inter-group conflict process. The standardized beta coefficients, however, are relatively weak.

3.3.2.2 Time-pooled Model and Cohort-interaction Model of Partial Associations

Moving to the partial associations analysis, I consider both time-pooled models and cohort-interaction models to examine the relationships between the elaboration of tracking structures and school compositional factors that reveal functional, status competition, and opportunity hoarding processes. Tables 3.12 and 3.19 specifically focus on the variance of math Sequence within the school using both streamlined time-pooled and cohort-interaction model specifications, as the variance of Course Sequence examines the most basic form of inequality in course taking within a school and has the largest between-school variance among all DVs in both time-pooled and cohort-specific settings.[22] Similar to level-related measures of tracking, I first examine the effect of the theoretical summary scales of functional, status competition, and opportunity hoarding processes on all measures of tracking structure in streamlined models. Tables 3.13 and 3.14 summarize the time-pooled model estimations of all school-level measures of tracking structure using the full model specification reported in Table 3.12, Model 6, whereas Tables 3.20 and 3.21 report the cohort-interaction model estimations of all DVs using the full model in Table 3.19, Model 6. Keep in mind that the construction of summary scales is somewhat different than the set of scales I use in level-related models. Here the functional scale is the standardized mean composite of achievement heterogeneity and school size. The status competition scale combines school-mean achievement, SES, percent white, and non-poor. The opportunity hoarding scale combines race and SES heterogeneity. I then consider fully-saturated model estimations of all dependent variables in Tables 3.15 and 3.16 for time-pooled model estimations, and in Tables 3.22 and 3.23 for cohort-interaction model estimations. Fully saturated models further examine the effect of single theoretically-meaningful school compositional factors, as opposed to the effects of summary scales.

Table 3.12 *Time-pooled Model* Estimation of School-level Variance of Math Sequence within the School using Functional Scale, Status Competition scale, and Opportunity Hoarding Scale, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. Functional Scale	.498***			.448***	.503***	.450***
	(.081) [a]			(.083)	(.085)	(.087)

[22] I calculate standard deviation of measures of tracking structure among all schools for time-pooled variance and large one-way ANOVA for within-cohort variance. The variance of Math and Science Course Sequence Level have the largest within-cohort variance as well.

2. Status Competition Scale		.435***		.344***		.343***
		(.101)		(.103)		(.103)
3. Opportunity Hoarding Scale			.125		-.018	-.006
			(.080)		(.084)	(.084)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.053	.048	.042	.057	.053	.057

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.13 Summary of Time-pooled Model Estimation of School-level Mathematics Tracking Structure using Functional Scale, Status Competition scale, and Heterogeneity Scale, 1982-2013 (n = 3620 schools; School-level Covariates sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Math Sequence within the School	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility
1. Functional Scale	.450***	.038***	.016*	.008	-.016*	.011*
	(.087)	(.009)	(.007)	(.008)	(.007)	(.005)
2. Status Competition Scale	.343***	.039***	.008	-.012	-.080***	.045***
	(.103)	(.010)	(.008)	(.009)	(.008)	(.006)
3. Opportunity Hoarding Scale	-.006	-.019*	.002	-.007	-.043***	.027***
	(.084)	(.008)	(.007)	(.008)	(.007)	(.004)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.057	.032	.040	.048	.214	.080

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department

of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Table 3.14 Summary of *Time-pooled Model* Estimation of School-level Science Tracking Structure using Functional Scale, Status Competition scale, and Heterogeneity Scale, 1982-2013 (n = 3620 schools; School-level Covariates sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
1. Functional Scale	.102***	-.001	.009	.010*
	(.019) [a]	(.009)	(.008)	(.005)
2. Status Competition Scale	.015	.049***	.013	.060***
	(.020)	(.010)	(.009)	(.006)
3. Opportunity Hoarding Scale	-.008	-.007	.004	.022***
	(.017)	(.009)	(.008)	(.005)
School Covariates	Yes	Yes	Yes	Yes
R-squared	.049	.035	.030	.065

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Table 3.15 Summary of *Time-pooled Model* Estimation of School-level Mathematics Tracking Structure using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Math Sequence within the School	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility
Functional Factor						

1. Achievement Heterogeneity	.217***	.017***	.010***	.008**	-.005*	.004**
	(.033) [a]	(.003)	(.003)	(.003)	(.002)	(.002)
2. School Size	.001	.001	-.001	-.001	.001~	-.001~
	(.009)	(.001)	(.001)	(.001)	(.001)	(.000)
Status Competition						
3. School-mean Achievement	-.026	-.000	-.004**	-.006***	-.011***	.007***
	(.016)	(.002)	(.001)	(.002)	(.001)	(.001)
4. School-mean SES	.064	.008	.050**	.025	-.189***	.051***
	(.203)	(.021)	(.016)	(.020)	(.015)	(.011)
5. Percentage of White	-.224	.068~	.007	.034	.016	.017
	(.381)	(.039)	(.029)	(.032)	(.026)	(.018)
6. Percentage of non-free lunch	1.802***	.087*	.001	.019	.294***	-.101***
	(.366)	(.036)	(.029)	(.034)	(.026)	(.019)
Heterogeneity Measures						
7. SES Heterogeneity	.373	.033	.069*	.004	.015	.060**
	(.425)	(.041)	(.032)	(.038)	(.029)	(.021)
8. Shannon Index of Race Diversity	-.195	-.062**	-.020	.010	-.076***	.020*
	(.203)	(.020)	(.017)	(.019)	(.015)	(.010)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.074	.044	.055	.068	.337	.133

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.16 Summary of *Time-pooled Model* Estimation of School-level Science Tracking Structure using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
Functional Factor				

1. Achievement Heterogeneity	.034***	.001	.002	.003~
	(.007) [a]	(.003)	(.003)	(.002)
2. School Size	.004*	.000	.002~	-.001
	(.002)	(.001)	(.001)	(.000)
Status Competition				
3. School-mean Achievement	-.004	-.005**	-.007***	.009***
	(.003)	(.002)	(.001)	(.001)
4. School-mean SES	.065	.058**	.072***	.012
	(.043)	(.022)	(.020)	(.012)
5. Percentage of White	.148~	.029	.005	-.072***
	(.080)	(.039)	(.034)	(.021)
6. Percentage of non-free lunch	-.101	.154***	.032	.047*
	(.072)	(.034)	(.033)	(.019)
Heterogeneity Measures				
7. SES Heterogeneity	.123	.053	.098*	.048*
	(.083)	(.044)	(.039)	(.022)
8. Shannon Index of Race Diversity	-.020	-.026	.000	-.002
	(.046)	(.020)	(.020)	(.012)
School Covariates	Yes	Yes	Yes	Yes
R-squared	.053	.057	.049	.102

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.17 *Baseline Trends* of Measures of Mathematics Tracking Structure using Linear Trend Model and Categorical Trend Model, 1982-2013 (n = 3620 schools; School-level Covariates includes school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Math Sequence within the School	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility
Panel 1: Linear Trend Model (Cohort centered at 1992)						
1. Cohort (centered at 1992)	-.272***	-.029***	.011**	-.010*	-.118***	.030***
	(.049) [a]	(.005)	(.004)	(.005)	(.003)	(.003)

2. School-level Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.050	.029	.040	.048	.378	.073
Panel 2: Categorical Trend Model (NELS as reference)						
3. HS&B	-.391**	-.006	-.115***	-.085***	.161***	.009
	(.149)	(.015)	(.012)	(.016)	(.010)	(.008)
4. ELS	-.385*	-.050***	-.087***	-.072***	-.100***	.030***
	(.155)	(.015)	(.012)	(.014)	(.011)	(.008)
5. HSLS	-1.111***	-.084***	-.045***	-.071***	-.202***	.096***
	(.146)	(.014)	(.012)	(.012)	(.010)	(.008)
6. School-level Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-square	.059	.032	.069	.067	.382	.086

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.18 *Baseline Trends* of Measures of Science Tracking Structure using Linear Trend Model and Categorical Trend Model, 1982-2013 (n = 3620 schools; School-level Covariates includes school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
Panel 1: Linear Trend Model (Cohort centered at 1992)				
1. Cohort (centered at 1992)	.027*	-.044***	-.012**	.013***
	(.011) [a]	(.005)	(.005)	(.003)
2. School-level Covariates	Yes	Yes	Yes	Yes
R-square	.039	.058	.030	.020
Panel 2: Categorical Trend Model (NELS as reference)				
3. HS&B	-.123***	-.021	-.106***	.076***
	(.032)	(.015)	(.015)	(.009)
4. ELS	-.113***	-.100***	-.096***	.085***
	(.033)	(.015)	(.014)	(.009)
5. HSLS	.002	-.133***	-.087***	.087***
	(.031)	(.014)	(.012)	(.009)
6. School-level Covariates	Yes	Yes	Yes	Yes
R-square	.045	.068	.062	.056

a. Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1

NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.19 *Cohort-Interaction Model* Estimation of the Trends of School-level Variance of Math Sequence within the School using Functional scale, Status Competition scale, and Opportunity Hoarding Scale, 1982-2013 (n = 3620 schools; School-level Covariates includes school size[b], sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
1. Cohort (centered at 1992 cohort)	-.400***	-.261***	-.347***	-.362***	-.423***	-.384***
	(.050) [a]	(.048)	(.051)	(.050)	(.052)	(.052)
2. Functional scale	1.139***			1.083***	1.105***	1.040***
	(.132)			(.134)	(.135)	(.136)
3. Functional scale × Cohort	-.159*			-.168**	-.171*	-.165*
	(.062)			(.061)	(.067)	(.066)
4. Status Competition Scale		.558***		.464***		.469***
		(.109)		(.108)		(.108)
5. Status Competition Scale× Cohort		-.290***		-.263***		-.269***
		(.062)		(.061)		(.062)
6. Opportunity Hoarding Scale			.273**		.127	.157~
			(.092)		(.091)	(.091)
7. Opportunity Hoarding Scale × Cohort			-.016		.028	-.017
			(.065)		(.069)	(.069)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.080	.064	.057	.088	.081	.089

a. Robust Standard errors in parentheses
b. School size included as covariate only in models for level-related outcomes, elsewhere it is conceptually related to assessing functional explanations.
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.20 Summary of *Cohort-Interaction Model* Estimation of the Trends of School-level Mathematics Tracking Structure using Functional scale, Status Competition scale, and Opportunity Hoarding Scale, 1982-2013 (n = 3620 schools; School-level Covariates includes school size[b], sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Math Sequence within the School	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility
1. Cohort (centered at 1992 cohort)	-.329***	-.034***	.010*	-.015**	-.124***	.029***
	(.051) [a]	(.005)	(.004)	(.005)	(.003)	(.003)
2. Functional scale	.598***	.037***	.012~	.007	.014*	.005
	(.097)	(.010)	(.008)	(.010)	(.007)	(.004)
3. Functional scale × Cohort	-.185**	.014*	.003	.005	-.012*	.001
	(.067)	(.006)	(.006)	(.007)	(.005)	(.004)
4. Status Competition Scale	.447***	.011	.011	-.032**	-.134***	.046***
	(.110)	(.012)	(.009)	(.012)	(.007)	(.006)
5. Status Competition Scale× Cohort	-.289***	.022***	-.000	.016*	.029***	.009*
	(.062)	(.006)	(.005)	(.007)	(.004)	(.004)
6. Opportunity Hoarding Scale	.165~	-.005	-.004	-.004	.002	.012**
	(.091)	(.009)	(.007)	(.009)	(.006)	(.004)
7. Opportunity Hoarding Scale × Cohort	-.030	-.005	.005	.002	.005	.008~
	(.069)	(.006)	(.006)	(.007)	(.005)	(.004)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.081	.056	.043	.053	.451	.118

a. Robust Standard errors in parentheses
b. School size included as covariate only in models for level-related outcomes, elsewhere it is conceptually related to assessing functional explanations.
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Table 3.21 Summary of *Cohort-Interaction Model* Estimation of the Trends of School-level Science Tracking Structure using Functional scale, Status Competition scale, and Opportunity Hoarding Scale, 1982-2013 (n =

3620 schools; School-level Covariates includes school size[b], sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
1. Cohort (centered at 1992 cohort)	.022*	-.045***	-.015**	.008*
	(.011) [a]	(.005)	(.005)	(.003)
2. Functional scale	.097***	.010	.007	.005
	(.022)	(.010)	(.010)	(.005)
3. Functional scale × Cohort	-.006	-.002	.006	.003
	(.014)	(.006)	(.007)	(.004)
4. Status Competition Scale	.078***	.025*	.009	.043***
	(.023)	(.012)	(.012)	(.006)
5. Status Competition Scale× Cohort	-.083***	.009	-.000	.028***
	(.013)	(.006)	(.007)	(.004)
6. Opportunity Hoarding Scale	-.016	.010	.009	.007
	(.019)	(.010)	(.010)	(.005)
7. Opportunity Hoarding Scale × Cohort	.012	.005	.001	.023***
	(.015)	(.006)	(.006)	(.004)
School Covariates	Yes	Yes	Yes	Yes
R-squared	.062	.070	.034	.094

a. Robust Standard errors in parentheses
b. School size included as covariate only in models for level-related outcomes, elsewhere it is conceptually related to assessing functional explanations.
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.22 Summary of *Cohort-Interaction Model* Estimation of the Trends of School-level Mathematics Tracking Structure using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Math Sequence	2. Math Selectivity	3. Math-Science Scope	4. Math-English Scope	5. Math Downward Mobility	6. Math Upward Mobility

Cohort (centered at 1992 cohort)	.824	-.319***	-.114~	-.199**	-.121*	-.103*
	(.779) [a]	(.072)	(.068)	(.077)	(.052)	(.048)
Functional Factor						
1. Achievement Heterogeneity	.290***	.021***	.009**	.007~	.005*	.002
	(.038)	(.004)	(.003)	(.004)	(.002)	(.002)
2. Achievement Heterogeneity × Cohort	-.075**	.003	-.001	.004~	.001	.002
	(.027)	(.003)	(.002)	(.003)	(.002)	(.001)
3. School Size	-.002	-.000	-.001	-.001	.000	-.000
	(.009)	(.001)	(.001)	(.001)	(.001)	(.000)
4. School Size × Cohort	-.006	.001~	.001	.000	-.001**	-.001*
	(.006)	(.001)	(.001)	(.001)	(.000)	(.000)
Status Competition						
5. School-mean Achievement	.000	-.003	-.005***	-.007***	-.011***	.006***
	(.017)	(.002)	(.001)	(.002)	(.001)	(.001)
6. School-mean Achievement × Cohort	-.023	.005***	.003*	.002	.002	.002*
	(.015)	(.001)	(.001)	(.001)	(.001)	(.001)
7. School-mean SES	.402~	.033	.044*	.030	-.141***	.039***
	(.208)	(.022)	(.017)	(.021)	(.014)	(.011)
8. School-mean SES × Cohort	-.573**	-.016	-.022	-.011	.068***	.013
	(.180)	(.016)	(.016)	(.017)	(.012)	(.012)
9. Percentage of White	-.378	.077~	.034	.017	.015	.013
	(.395)	(.043)	(.032)	(.040)	(.025)	(.016)
10. Percentage of White × Cohort	.037	-.026	-.025	.013	-.000	.014
	(.229)	(.022)	(.020)	(.024)	(.015)	(.013)
11. Percentage of non-free lunch	.908*	-.043	.021	-.056	.070*	-.051**
	(.439)	(.045)	(.035)	(.051)	(.027)	(.020)
12. Percentage of non-free lunch × Cohort	.725*	.037	.020	.042	-.072***	-.040*
	(.302)	(.029)	(.025)	(.033)	(.021)	(.017)
Opportunity Hoarding						
13. SES Heterogeneity	.662	.024	.072*	-.025	.008	.034~
	(.437)	(.044)	(.034)	(.045)	(.026)	(.019)
14. SES Heterogeneity × Cohort	-.144	-.021	-.021	.040	-.021	.044*
	(.341)	(.031)	(.029)	(.034)	(.022)	(.021)
15. Shannon Index of Race Diversity	.049	-.018	-.050*	.023	.022	.004
	(.235)	(.024)	(.019)	(.025)	(.015)	(.009)
16. Shannon Index of Race Diversity × Cohort	.254	-.015	.020	.001	.024*	-.002
	(.175)	(.016)	(.015)	(.018)	(.011)	(.010)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.104	.071	.064	.076	.485	.160

a. Robust Standard errors in parentheses

*** p<.001, ** p<.01, * p<.05, ~ p<.1

NOTE: Sample size is rounded to the nearest 10 as required by NCES.

SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

Table 3.23 Summary of *Cohort-Interaction Model* Estimation of the Trends of School-level Science Tracking Structure using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	1. Variance of Science Sequence within the School	2. Science Selectivity	3. Science-English Scope	4. Science Upward Mobility
Cohort (centered at 1992 cohort)	.239	-.241**	-.261***	-.149**
	(.166) [a]	(.078)	(.075)	(.046)
Functional Factor				
1. Achievement Heterogeneity	.030***	.005	.002	.003
	(.008)	(.004)	(.004)	(.002)
2. Achievement Heterogeneity × Cohort	.001	.002	.002	.002
	(.006)	(.003)	(.003)	(.001)
3. School Size	.004*	-.000	.001	-.001
	(.002)	(.001)	(.001)	(.000)
4. School Size × Cohort	-.000	-.001	.000	-.000
	(.001)	(.001)	(.001)	(.000)
Status Competition				
5. School-mean Achievement	.001	-.006***	-.009***	.006***
	(.004)	(.002)	(.002)	(.001)
6. School-mean Achievement × Cohort	-.009**	.003*	.004**	.004***
	(.003)	(.001)	(.001)	(.001)
7. School-mean SES	.087~	.093***	.095***	-.005
	(.044)	(.023)	(.021)	(.012)
8. School-mean SES × Cohort	-.135***	-.021	-.057***	.069***
	(.037)	(.017)	(.017)	(.011)
9. Percentage of White	.097	.029	-.002	-.027
	(.087)	(.044)	(.040)	(.021)
10. Percentage of White × Cohort	.112*	-.020	.011	-.045***
	(.050)	(.022)	(.023)	(.014)
11. Percentage of non-free lunch	.037	.036	.020	.017
	(.089)	(.045)	(.047)	(.022)
12. Percentage of non-free lunch × Cohort	.050	.014	.012	-.036*
	(.063)	(.028)	(.030)	(.017)
Opportunity Hoarding				
13. SES Heterogeneity	.180*	.036	.119*	.014
	(.087)	(.047)	(.046)	(.022)
14. SES Heterogeneity × Cohort	.053	.020	-.016	-.001
	(.071)	(.033)	(.033)	(.020)

15. Shannon Index of Race Diversity	-.098~	.016	-.007	-.008
	(.054)	(.025)	(.025)	(.013)
16. Shannon Index of Race Diversity × Cohort	.118**	.004	.017	.010
	(.040)	(.016)	(.018)	(.010)
School Covariates	Yes	Yes	Yes	Yes
R-squared	.073	.088	.058	.158

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

3.3.2.2.1 The Variance of Course Sequence Level within the School

I begin by considering the variance of Course Sequence Levels in math within the school, which I consider to be the most basic measure of course taking inequality as it summarizes the students entire high school course taking experience. As shown in Table 3.12, Model 1, the functional scale is positively associated with the variance of Math Sequence, on average, over the period 1982-2013. The coefficient remains significantly positive after considering the status competition scale and/or opportunity hoarding scale in Model 4, 5, and 6.

Later in Table 3.15, Model 1, the variance of Math Course Sequence is only associated with achievement heterogeneity, but not school size. This result is consistent with the official rationale of curriculum tracking; that is, schools with a more diverse distribution of achievement are more likely to provide students with a correspondingly diverse set of course-taking pathways. The total effect of functional processes here, however, is not quite as large as the previously reported effect on mean course-taking level (The R-square is only at a 5% level for variance of math). Model 2, 4, and 6 from Table 3.12 show significant and positive associations between the scale of status competition and the most basic form of inequality in course taking (the variance), indicating an apparent intra-group conflict force that increase the dispersion of the opportunity to learn, over the period 1982-2013, on average. Table 3.15, Model 1 shows that the percentage of non-poor students is the strongest status competition factor that is related the variance, indicating that schools with more students from advantaged families have more highly disparate course-taking experiences within the school. In contrast, the opportunity hoarding scale is positively related to the variance of Course Sequence in baseline models but does *not* appear to be related to the variance of math course taking, after controlling for functional factors. The total effects of both functional and status competition processes are quite weak, accounting for approximately less than 10% of the total variance. Note that some of the measures of tracking structure that rely on both course taking outcomes and student characteristics in their construction (e.g., selectivity) may have greater measurement error, and thus less signal in these models.

Has the most basic structure of inequality in course taking in the US secondary education system become more or less related to school composition that signals different mechanisms of tracking since 1982? Table 3.19 examines interaction effects between cohorts and school composition factors on the variance of Math Sequence, throughout the period of this study. As shown in Table 3.19, the effects of functional processes (as captured by school composition) on the variance of math Sequence within a school decrease over the course of 1982-2013, as the cohort-interaction coefficients are consistently negative in Model 1, 4, 5, and 6. The effects of school composition factors related to status competition processes also decrease since 1982. Later in Table 3.22, Model 1, the full-saturated model indicates that the effects of school-mean SES and percent non-poor have opposite trends where the effect of school-mean SES decreases but the effect of percent non-poor increases. Nevertheless, the net effect of those off-setting but conceptually and empirically related measures of family background is a decline in the relevance of school mean family background.

3.3.2.2.2 Tracking Selectivity

Tracking selectivity directly speaks to the extent to which students' course-taking experiences are affected by their prior achievement; a factor frequently targeted by course enrollment requirements. Tables 3.13 and 3.14, Models 2 reports the time-pooled model estimations of both Math and Science tracking Selectivity, respectively, using streamlined model specifications.

As shown in Table 3.13, Model 2, math Selectivity is positively associated with functional compositional factors, after considering both scales of conflict factors. Later in Table 3.15, Model 2, Math tracking Selectivity is only positively associated with achievement heterogeneity, but not school size. Recall that I have argued that, if US high schools embrace the functional logic of curriculum tracking in general, achievement heterogeneity should be associated with tracking Selectivity. Results in Tables 3.13 and 3.15 are consistent with that hypothesis. Tracking Selectivity for Science, however, is not associated with the functional scale or any functional factors in Table 3.14 or Table 3.16. This result is consistent with the baseline associations reported in Tables 3.10 and 3.11.

Is tracking selectivity in US high schools also related to less-functional sources of tracking? Status competition theories of tracking, in general, suggest that intra-group competition processes are associated with tracking structure, including tracking selectivity, after accounting for functional measures. As shown in Tables 3.13 and 3.14 (Model 2), the status competition scale is positively associated with both Math and Science tracking Selectivity, after considering other dimensions of school composition. Relatedly, tables 3.15 and 3.16 show that Math and Science tracking Selectivity are positively associated with specific measures of composition related to status competition, including school-mean SES, percent white, and percent non-poor. Opportunity hoarding processes, however, show less evidence of exerting pressure on selectivity (small negative associations in Tables 3.13 and 3.14).

Tables 3.20 and 3.21 examine time trends in the associations between tracking Selectivity and school compositional factors, using cohort-interaction models. As shown in Table 3.20, Model 2, the interaction term between the functional scale and cohort is positively associated with math selectivity, after controlling for other cohort-interaction terms and cohort-fixed effect. This indicates that functional logic of tracking becomes an even stronger concern in later decades that motivates the US high schools to adopt rigorous course enrollment processes. The cohort-interaction with the scale of status competition processes, similarly, also has a positive relationship with math tracking selectivity, indicating that the effect of the status competition scale become stronger in later decades. The effects of both the functional scale and status competition scale on science tracking selectivity, however, remain stable throughout the period of this study.

3.3.2.2.3 Tracking Scope

Tracking scope captures the extent to which students are placed into similar course-taking experiences in both closely-related and distinct subjects. As shown in Table 3.13, Model 3, tracking scope between math and science is positively associated with the functional scale, after controlling for the conflict-related measures of composition. Although not central to functional conceptualizations of tracking, there appears to be an association between achievement heterogeneity and school size, and scope. Tracking scope between STEM and ELA courses, as expected, are not related to the functional scale in Table 3.13, Model 4, and Table 3.14, Model 3. Later in the discussion section, I run a set of ancillary statistical models to examine the extent to which math-science tracking scope is appropriate to cross-subject achievement similarity for the 1992 cohort[23]. The association between math-science tracking scope and achievement correlation (net of conflict forces) may support a more functional view of promoting corequisites between math and science.

The associations between measures of composition related to conflict forces and STEM-ELA tracking scope are theoretically more important in this analysis, as this relationship captures the extent to which schools constrain opportunity to learn and promote the overall elaboration of tracking in an explicitly non-functional manner[24]. Although neither Table 3.13 nor 3.14 reports positive relationships between the status competition scale and tracking scope, the full-saturated model estimations reported in Table 3.15 and 3.16 show some significant associations. As shown in Table 3.16, Model 3, school-mean SES is positively associated with tracking scope between Science and ELA, indicating that high-SES schools, on average, promote greater scope, over the period of 1982-2013. Table 3.15, Model 3 also reports that higher school-mean SES is associated with greater tracking scope between Math and science courses.

Is tracking scope, as one of the major dimensions of curriculum tracking, also greater in heterogenous schools where inter-group competition may be highly salient? As suggested by Opportunity Hoarding theories of tracking, schools with more diverse student populations are expected to adopt an elaborate tracking system in response to the inter-group competition among families from different social groups. As shown in key results reported in Tables 3.13 and 3.14,

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[23] Only NELS (the 1992 cohort) measured 8th grade science achievement scores.

[24] Similar to the tracking scope between math and science course taking, the achievement correlation between ELA and STEM also implies a technical-functional consideration of placing students into similar ELA and STEM courses. Nevertheless, this functional consideration does not necessarily support the associations with school composition.

neither measure of tracking scope shows a significant relationship with the opportunity hoarding scale. Later in fully saturated models, Table 3.15, Model 3 shows a significant relationship between SES heterogeneity and math-science scope. Even more striking, SES heterogeneity is positively associated with tracking scope between ELA and science (Table 3.16, Model 3). Overall, time-pooled models concerning the conflict forces of tracking scope first indicate that scope is not related to both scales of conflict theories, the status competition scale and the opportunity hoarding scale. The relationships between scope and individual social factors, however, shows that school-mean SES and SES heterogeneity link to scope that likely reflect the rigor of course corequisites (and related processes) and structure inequality in course enrollment.

Has the scope of tracking systems in US high schools become more or less responsive to school composition that relates to functional and conflict forces? Tables 3.21, 3.22, 3.22, and 3.23 examine the effect of cohort-interaction terms on both math-science and science-ELA scope. Overall, Table 3.20, Model 3 and Table 3.21, Model 3 report that the effects of scales of functional and conflict processes on tracking scope are stable over time, as none of the cohort-interaction terms are significant. Later in Table 3.23, Model 3, the cohort-interaction with school-mean SES is negatively associated with tracking scope between ELA and science, indicating that the intra-group competition in high-SES schools exerts lesser pressure on promoting tracking scope in later decades.

Considering both cohort-interaction models and time-pooled model estimations, overall, school-mean SES and SES heterogeneity, and, to a lesser extent, measures of composition generally associated with functionalism, are associated with greater tracking scope, throughout the period of 1982-2013. Additionally, the competition within high-SES school became somewhat less of a concern in promoting greater tracking scope in later decades. Yet, the extent to which model estimations support the social theories of tracking remain unclear in this analysis.

3.3.2.2.4 Track Mobility

Track mobility, overall, and in theory, speaks to the extent to which schools flexibly match students' achievement, level of engagement, and self-efficacy, to track placements, as these student-level readiness factors change over time. In this analysis, of the two forms of mobility, I argue that upward track mobility is the more salient process through which schools "open up" learning opportunities, although observed rates of upward mobility may also reflect students' and parents' emphasis on academic press. In contrast, the measure of downward track mobility combines both the concept of providing appropriate instruction for low-achievers, but also represents an increasing constraint on students' learning opportunities as they move through schooling. I begin by considering the level of mobility itself (rather than associations with composition), as the level of mobility [25] directly reflects schools' overall emphasis on the functional logic of tracking.

Table 3.17, Model 6 and Table 3.18, Model 4 describe the baseline trends of math and science upward track mobility that may partially capture changes in functional motivations of tracking. As shown in these models, on average, over the period of 1982-2013, US high schools provided 3% and 1.3% more students every decade with the opportunities to move up away from

[25] Here I should note that extremely high-level of mobility could be potentially attributed to unstable curriculum systems or arbitrary implementations of curriculum policies, and thus perhaps only moderate- to high- level of track mobility relates to a functional consideration of tracking. In this analysis, I find that an average school moves 35%-50% students out of typical course-taking trajectories throughout the period of this study.

the Math and Science typical course-taking trajectories, respectively. To the extent that this mobility means capable students can pursue appropriately-challenging courses, these results may indicate tracking systems have become increasingly functional. However, these unadjusted results may also reflect an increasing emphasis on academic press and rigorous STEM courses among elite schools.

Now considering *associations* with student composition, due to heterogeneity in effects within each theoretical grouping, I focus first on Tables 3.15 and 3.16. These tables reveal some interesting findings about the associations between upward track mobility and various measures related to the potential for conflict forces[26] (e.g., school-mean SES, percent non-poor, and SES and race distributions). As shown in these models, both Math and Science upward mobility are positively associated with school-mean achievement, and SES heterogeneity; Math upward mobility is also positively associated with school-mean SES and race heterogeneity. Math downward mobility, however, is negatively associated with school-mean SES and achievement, and race heterogeneity. Overall, the time-pooled partial associations between school composition and track mobility indicate that high-SES schools and schools with diverse student population tend to have *higher* upward mobility and lower downward mobility (see also Tables 3.13 and 3.14), Importantly, in this analysis of mobility in particular, I argue that the positive associations with measures of composition related to conflict, blocked aspirations, etc., are not necessarily evidence of those social forces in this case. Keep in mind that track mobility captures a generally positive

[26] The associations of achievement heterogeneity with both forms of track mobility may not support the fundamental logic of functional theories. The positive associations with these DVs observed in Table 3.15 and 3.16 may only serve as statistical controls.

dimension of tracking structure, and one associated with a rising emphasis on academic press. Therefore, in this section, I find that school compositions traditionally hypothesized as only generative of increasing inequality may in fact have a set of more ambiguous effects on learning opportunities, at least in terms of mobility. Yet, from these findings we cannot identify *which* students are upwardly mobile. In addition to time-pooled model estimations, cohort-interaction models reported in Table 3.22, Model 6, and Table 3.23, Model 4 show that the link between higher upward mobility and schools with diverse student population is even stronger in later decades.

3.4 Discussion

Chapter 3 dives deep into the nature of the US high school curriculum tracking system in the era of curriculum intensification and provides new insights into how and why US high schools vary in tracking practices. Building on the theoretical framework of Kelly and Price (2011) and other related empirical studies on the structure of tracking systems (e.g., Domina et al., 2019; Kelly, 2007), I examine associations between organizational dimensions of high school STEM curriculum tracking (school-mean course-taking level, selectivity, scope, and mobility) and school compositional factors (e.g., achievement heterogeneity, percentage of advantaged students, and racial/SES diversity). These associations seek to describe where the basic structure of a school's curriculum tracking system comes from. Here in this analysis, I consider realized patterns of course taking that capture the actual practices of curriculum tracking from student transcript datasets (e.g., Austin, 2020) rather than school policy documents and curriculum guides (e.g., Kelly, & Price, 2011). These associations provide new insight into social theories of tracking which include technical-functional rationales, status competition theories, and opportunity hoarding theories of tracking. Consistent with Kelly and Price's (2011) analysis of single state data, in Chapter 2, I find that any given organizational dimension of tracking is only moderately or even weakly associated with other dimensions. Thus, in this chapter I proceeded by analyzing each dimension of tracking in turn.

Prior research described two over-arching organizational processes that determine students' opportunities to learn at the school level (Sørensen, 1989; see also Hanselman et al., 2022 for more recent discussion of *provision decisions* and *allocation decisions*). The first process determines the amount of total available learning opportunities, which involves decisions about course-offerings and the learning environment and academic press in each classroom. Second, schools have to make allocation decisions, deciding criteria to govern the placement process. Both organizational processes are shaped and constrained by inter-correlated micro- and macro-level factors, including (1) school resources that determine the available learning opportunities (Sørensen, 1989), (2) external political and policy pressures that influence the patterns of course-offering and placement criteria (e.g., Domina et al., 2016), (3) communities' and families' involvement in negotiating schools' tracking practices (e.g., Lewis, & Diamond, 2015), and (4) school administrators' and instructors' beliefs in curriculum tracking that shapes schools' learning and instructional environment (e.g., Oakes et al., 1997). In this analysis, I consider school composition as a contextual factor that motivates schools toward different practices of curriculum tracking. I should note that any given school compositional factor may be associated with multiple of the above processes (e.g., family involvement in tracking practices or school's response to a specific policy) that shape different aspects of a tracking system, or even offset each other. Therefore, this study discusses a broad array of relationships between tracking and school composition that further supports theoretical explanations of school-to-school differences in tracking practices.

3.4.1 Level-related measures of tracking

Using a sample of 3,620 high schools from four NCES longitudinal high school studies, my investigation of tracking first provides insights into how the overall STEM *course-taking level* (math and science school-mean course taking level and tracking inclusiveness) in schools is responsive to school compositional factors over the period of 1982-2013. The analysis of overall course-taking level quickly shows the trends of curricular intensification and the "de-tracking" practices in recent decades reported previously (e.g., Domina, & Saldana, 2012), where higher level of course taking correspond to a greater proportion of students experiencing high-track courses in high schools. In this analysis, using the specific coding process developed in Xu and Kelly (2020), I find an increasing trend in both course-taking level and tracking inclusiveness throughout the period of 1982-2013. On average, school-mean math and science course sequence level increased by .81 and .42 of a level every decade. Relatedly, schools track 12% more students to high-level math courses and 10% more students to high-level science courses every decade.

Consistent with prior empirical research concerning the technical-functional rationale of tracking (e.g., Clotfelter et al., 2015; Iatarola et al., 2011), in this chapter, I find a *stable* set of positive associations between level-related measures of tracking and school-mean prior achievement, over the period of this study. In examining the technical-functional logic of tracking, school-mean achievement level is a major technical concern of schools that should be associated with the overall course-taking level of a school, since students with higher prior achievement exhibit, in general, greater readiness to take high-track courses. Therefore, the consistent positive associations between school-mean course-taking level and prior achievement from 1982 to 2013 support technical-functional views of tracking. I should note that while a focus on a single, summary measure of the overall course-taking level appropriately reveals the positive consequences of curricular intensification practices over the recent decades, it may also in part reveal more specific changes including those that maintain inequality. For instance, in Domina et al.'s (2016) analysis of 1,524 California schools from 2003 to 2013, they found that elite schools promoted "double high tracks" in response to the state-wide de-tracking policies, creating a means to maintain differences in status and learning opportunities[27]. My measure of overall course-taking level instead captures a broader range of changes in course-taking level across the US. Later in this section, I provide more insights into the changes of structure of curriculum tracking and the way in which the associations with school composition may support different fundamental logics of tracking.

In addition to the functional-technical considerations of overall course-taking level, in this analysis, I examine the associations between course-taking level and school compositional factors concerning the conflict motivation of tracking. Over the period of this study, I find that school-mean SES, on average, is positively associated with measures of course-taking level in math and science, after controlling for prior achievement; however, these associations are generally getting

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[27] Domina's analysis also revealed a positive association between school-mean prior achievement and proportion of students enrolled into high-track 8th grade math courses (partially overall course-taking level). They further examined the change of tracking structure as a source of the rising of course-taking level and figured out that a new track above all existing tracks (8th grade algebra + geometry) might induce the increase in overall course-taking level. They then attributed the positive association between prior achievement and course-taking level to functional pressure to resist the de-tracking practices.

weaker in later decades. Such relationships demonstrate a basic inequality-generating process due to tracking; that is, even considering functional processes that match students' overall prior achievement level with instructional rigor, placement into higher-level courses still favors socioeconomically-advantaged schools. This result resonates with early arguments on the role of tracking in reproducing socioeconomic inequalities (e.g., Lucas, 1999; Oakes, 1994), although much of these studies focused on within-school inequality rather than differences across schools. To further explain this phenomenon, I argue that theories of status competition provide a conceptual explanation; that is, a general competitive environment among elite students may force up the overall course-taking level. This overall competition among high-SES families may speak to socio-political approaches where high-SES parents and students actively seek advanced courses and exert pressures on schools' accommodations and policy changes in tracking. School administrators and instructors may also respond, sometimes overly, to such external political pressures. I should note, however, in this chapter we do not see *which* students are enrolled in high-track courses. Additionally, some of the effects of school-mean SES may be capturing measurement error in achievement. Thus, this analysis considers status competition theories (and other social theories of tracking) as a summary of complicated ascriptive organizational and social approaches that collectively shape the practices of tracking, providing an explanatory perspective into the basic way in which actual tracking practices vary across schools.

This chapter also reveals the more surprising finding that course-taking at the school level has *stable* positive associations with race-ethnicity heterogeneity and, to a lesser extent, prior achievement heterogeneity, over the period of this analysis. There appears to be a relationship between the heterogeneity of the student body, broadly, and greater access to advanced learning opportunities. This relationship should not be explained by theories of opportunity hoarding, since those theories imply exclusion of particular groups from high track courses, not necessarily any change in mean level of course taking. Some other organizational and social processes may provide better explanations for this relationship. For example, in schools with heterogeneous student populations, the competitive environment among advantaged students may also expand to other students within the same school and thus increase the overall awareness of schooling. Additionally, administrators and instructors may be able to better serve disadvantaged students' instructional needs in diverse schools (Dee, & Penner, 2016) and value diversity and equity (Lewis, & Diamond, 2015) than schools with homogeneous SES, race/ethnicity, and prior achievement distributions, and therefore facilitate the overall accessibility of advanced learning opportunities.

Overall, the first part of this chapter explores school-to-school variation in course-taking levels in the era of curriculum intensification. Most importantly to the associations between level-related measures of tracking and school composition, I identified a set of consistent relationships between school-mean achievement and course-taking level, supporting a technical-functional view of curriculum tracking. Considering a rising trend of mean course-taking, I argue that technical-functional factors are strong predictors of course-taking level and tracking inclusiveness, as the relationships have not declined in later decades. Moreover, I found that schools with diverse distributions of SES, race/ethnicity, and, to a lesser extent, achievement tend to have higher mean-level of course taking. This result may suggest that diverse schools, in general, are able to better increase students' overall awareness of schooling and serve the instructional needs of disadvantaged students.

Concerning the inequalities maintained and generated due to tracking, consistent with prior studies (e.g., Domina, & Saldana, 2012; Domina et al., 2016; Klugman, 2013), this study finds some evidence that high-SES schools maintain their advantages in providing higher-level course-taking experiences. This result supports a theoretical perspective of status competition which summarizes a set of complicated organizational and socio-political processes (Collins, 1979; Ehrenreich, 1989) that push greater competition among elite students and their families. Yet, the associations between factors related to status competition and course-taking level have decreased over recent decades.

3.4.2 Tracking Structure

Using the same set of sampled schools from NCES's high school longitudinal studies, Chapter 3 further examines the associations between school composition and a set of measures concerning the essential structure of school tracking systems. These measures include the variance of course taking, tracking selectivity, scope, and mobility, which speak to realized tracking practices that both constrain learning opportunities (greater selectivity and scope), and provide more flexibility (mobility). By relating the tracking structure of a school with its compositional characteristics and explaining the associations with social theories of tracking, this analysis helps trace fundamental sources of organizational variation in tracking practices and provides more insights into the inequality-generating processes of a school due to tracking. Moreover, this analysis adds to the ongoing debate on tracking, which concerns both the pedagogical need to align students' abilities with appropriate instruction and the generative effects of tracking on social inequality (e.g., Hanselman et al., 2022; Hirschl, & Smith, 2023; Lewis, & Diamond, 2015).

Table 3.24 Symbol-based Summary of the Changing Effects of School Composition on Various Measures of Tracking Structure

	Achievement Diversity and Size	School-mean Status Level	School SES and Race Diversity
1. Variance of Math Sequence	▼	▼	×

2. Math Selectivity	▲	▲	×
3. Math-Science Scope	■	■	■
4. Math-English Scope	×	×	×
5. Math Downward Mobility	▼	×	×
6. Math Upward Mobility	■	▲	▲
7. Variance of Science Sequence	■	▼	×
8. Science Selectivity	×	■	×
9. Science-English Scope	×	▼	■
10. Science Upward Mobility	■	▲	▲

Legend:
× No effect over the period 1982-2013, on average
▲ Effects rose over the period 1982-2013
■ Stable effects over the period 1982-2013
▼ Effects decreased over the period 1982-2013

NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

3.4.2.1 Functional View of Tracking

Technical-functional theories of tracking speak to an “appropriate”, or a “responsive” pedagogical approach in coping with a diverse distribution of students’ ability and readiness within a school. Consistent with prior studies concerning the technical-functional logic of tracking (Kelly, & Price, 2011; Long et al., 2012), I find that schools with higher achievement heterogeneity, on average, tend to have greater variation in math and science Course Sequence Level and math tracking selectivity, over the course of this study. Functional theories of tracking suggest a pedagogical consideration that tracking creates a skill-homogeneous learning environment where instruction can better match students’ needs (Hallinan, 1994). Central to the theory-testing, here in this analysis, I conclude that the associations of achievement heterogeneity with the variation in course-taking level and Math tracking selectivity support an apparent functional consideration of tracking. The strength of this association, however, is relatively weak. Although expected by theories, science selectivity does not appear to be related to skill heterogeneity, indicating some other forces may somewhat drive up the selection processes. The non-finding may also be attributed to a measurement error specific to science selectivity where math achievement was used to create the measure of science selectivity (due to omission of science achievement data in some NCES studies). Moreover, the cohort-interaction models indicate a decreasing trend in the effects of such functional considerations on the variance of math course-taking level, whereas the effects on math selectivity increase.

In addition to any associations between achievement heterogeneity and the structure of tracking, empirical evidence concerning school size may support a technical-functional consideration of tracking. As theorized by Hallinan (1994), larger schools may be able to better serve students' instructional needs by having more flexible schedules and greater capacity for diverse curriculum, if schools embrace the functional logic of curriculum tracking. In contrast to that positive view (of providing a better fit with student readiness), Hanselman et al. (2022) argue that larger schools face greater pressures from diverse student populations[28], and thus such pressures may motivate schools to promote differentiated instruction (creating perhaps unnecessary stratification). Likewise, Kelly and Price (2011) find that school size is positively related to the overall elaboration of school tracking systems. In this analysis, I find little relationship between school size and measures of tracking structure (there is a small statistically

[28] In Table 3.2, I show that there are weak to moderate correlations between school size (Grade 9 to Grade 12) and various measures of school heterogeneity, including achievement, SES and race heterogeneity.

sig relationship with the variance in science course taking, but no similar relationship in math, and no relationship with any other measure of structure).

Regarding the association between tracking scope and achievement heterogeneity (e.g., Tables 3.13, and 3.14), this is not the most compelling or relevant functional analysis of scope. To explore a more pertinent functional determinant of tracking scope, I run a set of ancillary model estimations of math-science tracking scope using a measure of correlated achievement in math and science.[29] As argued by Lucas and Berends (2002), correlated ability contributes to much of the correlation across different subjects; that is, the functional view of tracking may suggest that tracking scope between Math and science course taking is responsive to the correlation between Math and science achievement, rather than just the distribution of Math achievement. Due to the availability of science achievement scores, I only run this ancillary analysis for the 1992 cohort. Table 3.26 summarizes both baseline association model and partial association models. As shown in Table 3.26, Model 1, tracking scope between math and science is positively associated with the achievement correlation. Later in partial association models, the relationship between scope and correlated achievement remains significantly positive, after considering school-level covariates and school composition related to conflict forces. This ancillary analysis provides some evidence that, at least in the 1992 cohort, math-science tracking scope is appropriate to cross-subject achievement similarity and may thus support a functional view of promoting corequisites between math and science. Comparing this ancillary analysis with the main analysis that contains the entire

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[29] To generate achievement correlation between math and science, I used “forvalue” command in STATA to loop the calculation of correlation for each school. Schools with less than three sampled students were directly excluded from this calculation. For this ancillary analysis only, I didn’t create imputed dataset to handle missing value.

sampled schools, the ancillary models reported in Table 3.26 consider the achievement correlation as a more apparent functional view of promoting greater tracking scope, and thus after considering the achievement correlation, these models may provide better insights into the associations between conflict forces and tracking scope.

Table 3.25 Summary of *Ancillary Model* Estimation of School-level Math and Science Tracking Scope using achievement correlation, school size, status-competition related variables, and measures of heterogeneity, Cohort of 1992 (n = 1050 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5
Functional Factor					
1. Achievement Correlation	.153***	.111*	.123*	.107*	.110*
	(.043) [a]	(.047)	(.050)	(.047)	(.050)
2. School Size		.002	.003	.002	.003
		(.002)	(.002)	(.002)	(.002)
Status Competition					
3. School-mean Achievement			-.002		-.003
			(.003)		(.003)
4. School-mean SES			-.016		-.011
			(.031)		(.031)
5. Percentage of White			-.021		-.013
			(.046)		(.047)
6. Percentage of non-free lunch			.030		.024
			(.057)		(.056)
Heterogeneity Measures					
7. SES Heterogeneity				.136*	.158*
				(.060)	(.062)
8. Shannon Index of Race Diversity				.000	.001
				(.030)	(.032)
School Covariates	No	Yes	Yes	Yes	Yes
R-squared	.016	.106	.110	.114	.120

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), "Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992."; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of

2002 (ELS: 2002/2004), "Base-year Survey, First Follow-up Survey, High School Transcript Study"; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), "Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection".

As an outcome, as with scope, associations with course taking mobility may be more difficult to interpret. As theorized in early literature (e.g., Rosenbaum, 1976), schools with higher level mobility might be conceptualized as "responsive" to changing student achievement, engagement, and motivation. In this analysis, I argue that the *level* of track mobility per se, especially upward mobility, rather than associations with school composition, speaks to the functional logic of tracking, as schools offer more flexibility to match students' achievement/ability to track placement. While I don't specifically examine an individual student's experience of track mobility, this analysis finds, on average, US high schools create 3% and 1.3% more opportunities of upward mobility every decade for math and science course taking, respectively. Consistent with Rosenbaum (1976) and Lucas (1999, pp. 87), this analysis argues that moving students upwardly is still extremely rare among US high schools, even in the 2013 cohort.

Concerning the inferential limitations, in interpreting the results, I should note that the realized tracking practices do not directly speak to tracking policies, and thus a functional logic of tracking may not motivate specific policy implementation processes. For example, tracking selectivity measures the extent to which students' track placements rely on their prior achievement, and may further imply schools' overall emphasis on readiness when enrolling. However, its association with achievement heterogeneity does not specifically point to policy-making processes. The interpretations of these findings should also be aware of the complexity of organizational processes, such as schools' response to curriculum policies or school professionals influencing school ethos about curriculum tracking, that shape the school tracking systems. As argued earlier, here in this section I consider the aggregated school compositional characteristics as a contextual effect that motivates schools to promote tracked instruction based on students' abilities. Additionally, it's also worthwhile to note that not every pair of relationship between achievement heterogeneity/school size and tracking structure supports a functional logic of tracking, such as the associations with tracking scope between STEM and ELA and track mobility, as these dimensions of tracking structure reflect a more apparent conflict force of tracking. As such, the interpretation of theorized technical-functional logic of tracking should be restricted to dimensions that reflect the basic pedagogical logic of tracking.

I should note that while a technical-functional process of tracking certainly speaks to an instructional preference for grouping students by ability level, such theoretical perspective does not necessarily consider the complex effects of skill-homogenous instruction on students' learning outcomes. Recent studies have found both positive (e.g., Penner et al., 2015) and negative (e.g., Domina et al., 2019), and even mixed (e.g., Nomi, & Raudenbush, 2016) effects of placing students into skill-homogenous classrooms.[30] Therefore, in this analysis, I argue that the associations between tracking structure and skill heterogeneity only suggest a technical-functional consideration of tracking held by school administrators and teachers (Clotfelter et al., 2015; Gamoran, 2004), and may not necessarily further imply that students would benefit from skill-homogenous classes.

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[30] Much of recent research on this topic has focused on the effect of de-tracking policies on educational outcomes where de-tracking efforts create skill-heterogenous classrooms. Here I transform the effect of skill-heterogenous into the effect of skill-homogenous to facilitate my argument.

Overall, both baseline and partial-association models concerning the technical-functional pathways of tracking show that the basic form of inequality in STEM course taking (the variance) and Math Selectivity are related to a conceptualization scale of functionalism. The cohort-interaction models further indicate that the basic form of STEM inequality in course taking become less associated with technical-functional logic of tracking in later decades, whereas the relationship between Math Selectivity and functionalism becomes an even stronger concern in later decades that motivates the US high schools to adopt rigorous course enrollment processes. Recall that earlier in this study, I find a stable technical-functional motivation that relates to level-related measures of tracking. Thus, in general, this chapter reveals that a rational and logical way to continuing provide students with rigorous instructions and expose students to differentiated curricular remains predominant in US high school curriculum systems. This analysis also provides some evidence that promoting greater scope between math and science is related to functional logic of tracking, at least for the 1992 cohort. The associations between school composition concerning functionalism and STEM-ELA scope and mobility, however, are not central to theory testing. While it might be difficult to explain the fundamental technical-functional logic of track mobility, this analysis argues that the level of mobility per se indicates that the US track mobility become more logical in later decades.

3.4.2.2 Conflict forces and tracking

Prior sociology research on tracking describes two general processes that generate inequality across students of different family backgrounds: 1) students enjoy educational advantages in high-track learning environments (Farkas et al., 2005; Gamoran, 1987; Kelly, & Carbonaro, 2012; Van Houtte, 2004) and 2) high-SES families have an advantage in accessing high-track courses (Kelly, 2004; Lareau, 2011; Hanselman et al., 2022). This study contributes to this argument by pointing to a tension between rational considerations of tracking and conflict forces of differentiation, disentangling these effects at the school level, and identifying patterns of inequality in specific dimensions of tracking. Tracking of course creates skill-homogeneous classrooms that may benefit instruction, but this analysis argues school-to-school differences in tracking structure may exist that go beyond functional explanations, and are explained in part by conflict mechanisms.

3.4.2.2.1 Status Competition Processes of Tracking

This section examines the extent to which dimensions of school tracking structure are responsive to school composition related to status competition processes (i.e., school-mean achievement and status level). Consistent with Kelly and Price (2011), this analysis finds that, on average, schools with a higher overall status level (higher school-mean SES and more non-poor and white students) tend to have larger variation in math course sequence levels, and to promote greater STEM tracking selectivity, over the course of this study. In particular, both unconditional models (Tables 3.10 and 3.11) and time-pooled partial association models (Tables 3.15 and 3.16) show that schools with a greater share of non-poor students tend to have larger within-school differences in math sequence and math and science tracking selectivity. Additionally, I find some evidence that math and science selectivity are positively related to percent white (Table 3.15, Model 2) and school-mean SES (Table 3.16, Model 2), respectively. As explained by status competition theories of tracking, the findings in this study might be explained by intra-group competition among students in high-SES schools that generate a more elaborated set of tracking practices. Theoretically, such competition processes reflect the preferences of pursuing competitive education among middle-class families (Useem, 1991) due to a “fear of falling” (Ehrenreich, 1989), and may further speak to a more complicated set of socio-political processes that shape the school tracking systems. For example, high-SES parents actively seek to promote differentiated course-taking environments (Alon, 2009; Welner, & Burris, 2006) and schools may respond to such external pressures (Domina et al., 2016).

Concerning forces of status competition that are associated with tracking scope, this analysis does not find strong evidence to support the theoretical link between school-mean status levels (school-mean SES, percent white and non-poor students) and scope. First, both baseline association models (Tables 3.10 and 3.11) and time-pooled partial association models with summary scales (Tables 3.13 and 3.14) show no positive relationships between scope and school composition related to status competition. Second, I examine the status competition process considering a more apparent functional view of promoting greater scope in ancillary analysis. As shown in Table 3.26, math-science tracking scope does not appear to link to any measures of status competition (Model 3 and Model 5), net of correlated achievement. The results reported in ancillary models support the main analysis in Tables 3.13 and 3.14.

Moreover, findings regarding school composition and tracking selectivity resonates with theoretical works on Effectively Maintained Inequality (EMI) framework (e.g., Klugman, 2013; Lucas, 2001; Domina et al., 2016) where maintaining and producing distinctions are theorized as effective approaches to preserve social advantages. In this study, I find that the link between status competition and math tracking selectivity is getting even stronger in more recent decades when rigorous courses are increasingly accessible; the corollary link with science tracking selectivity remains stable in the 2013 cohort. I therefore argue that, in the era of curriculum intensification, promoting greater STEM tracking selectivity may have become an effective organizational approach for elite groups to maintain their advantages in taking rigorous courses.

Overall, both baseline and partial association models show that the variance of math sequence and STEM tracking Selectivity are related to conceptualization scale of status competition, indicating an apparent intra-group conflict force that increase the dispersion of the opportunity to learn. It's worthwhile to note that Table 3.13, Model 1 also shows that the effect of functionalism is larger than the status competition scale. [31] The cohort-interaction models further show that status competition process increasingly relates to STEM tracking selectivity, whereas the variance of math sequence becomes less related to status competition forces. Recall that earlier in this chapter, concerning level-related measures of tracking, I argue that a general competitive environment among elite students may force up the overall course-taking level. This section adds that the competition environment relates to both more rigorous instruction and higher differentiated curricular. To further conceptualize this conflict process, concerning both level-related and tracking structure measures, I argue that this competition process speaks to both explicit within-school intra-group competition that relates to the differentiation, and a more general competition that motivates high-SES parents and students to actively seek advanced courses.

3.4.2.2.2 Opportunity Hoarding Processes of Tracking

This section further examines the extent to which opportunity hoarding processes explain the school-to-school differences in dimensions of tracking structure. Opportunity hoarding theories of tracking describe an inequality-generating process among different social groups in which the access to valuable learning opportunities is heightened for students from advantaged families. Considering the model estimation results, in this analysis, I argue that the forces of opportunity hoarding may in fact exert lesser pressures on promoting more elaborated tracking

[31] Because both scales are standardized, I am able to compare those two effects of conceptualization scales.

systems than status competition processes, as I find that most dimensions of tracking structure don't show consistent positive relationships with measures of school heterogeneity across models. In particular, while I find that, in baseline association models (Tables 3.10 and 3.11), both the variance of math and science course sequence and science selectivity have positive relationships with SES heterogeneity, these associations generally become non-significant later in partial association models (both in summary models reported in Tables 3.13 and 3.14 and in more-saturated models reported in Tables 3.15 and 3.16). Some other associations between tracking and measures of heterogeneity, however, do not directly examine the opportunity hoarding theory. In this analysis, I find that level-related measures and upward mobility are unexpectedly related to measures of heterogeneity. I then argue that heterogeneity may exert positive forces that "opens up" more learning opportunities.

I then briefly compare this analysis with earlier studies on opportunity hoarding. In his seminal book on tracking structure, Samuel Lucas (1999, pp.69-71) described a similar relationship between scope and SES diversity and then attributed this link to both individual actions of middle-class families to obtain high-track course-taking experiences (e.g., negotiating with teachers and administrators and requesting higher track placement for their kids, see Lewis, & Diamond, 2015) and collective political actions to preserve a highly-differentiated school tracking system (e.g., pushing back de-tracking policies or exerting external pressures on differentiated system, see Domina et al., 2016). Lucas' (1999) analysis of tracking scope pointed to mixed consequences of the efforts of dismantling overarching tracking programs and promoting subject-specific enrollment. Yet, in this analysis, I don't particularly find evidence that supports an opportunity hoarding process of tracking.

3.4.2.2.3 Conceptualizing Track Mobility

Among these model estimation results, the associations between track mobility and school composition do not specifically support the conflict sources of within-school tracking and instead have ambiguous conceptualizations of track mobility. First, this analysis finds that both the status competition within high-SES groups and a more general competition process between social groups are related to more upward mobility and less downward mobility. Thus, the conflict sources of *within-school* tracking that are originally theorized as constraints of learning opportunities may in fact have positive effect on providing more flexible tracking system. Yet, considering an overall aggregated structure of *between-school* inequality, both forms of mobility at least partially capture the extent to which school tracking systems benefit advantaged students in general and constrain the learning opportunities of low-SES students. In this study, I show that STEM upward mobility is increasingly associated with school-mean SES and percent non-poor. Relatedly, this study also finds that low-SES schools tend to track down more students than high-SES schools. These results indicate that the practices of moving up students over time and opening up more learning opportunities in fact benefit students from socio-economically advantaged schools and may reflect schools' overall emphasis on academic press. Importantly to theorizing track mobility, this result may indicate that conflict forces of tracking that are traditionally considered as sources of inter- and intra-group inequality may have more ambiguous (both positive and negative) effects of learning opportunities.

3.4.3 Implications and Limitation

Overall, Chapter 3 provides a systematic understanding of how and why US high school STEM tracking systems vary across schools, and how the sources of that variation have changed over recent decades. By connecting various organizational dimensions of tracking with basic measures of school composition, this study helps trace the fundamental sources of the key dimensions of schools' curriculum tracking systems. As an overall picture, this study finds clear evidence that school-to-school differences in tracking systems follow a fundamental functional logic of differentiation. Yet, results capturing the forces of status competition show that the US school tracking system also creates socio-economically disproportionate access to high-quality learning opportunities. Thus, I argue that this study points to the tension, and the reality created by that tension, between the pedagogical needs to align students' abilities with appropriate instruction and the generative effects of tracking on social inequality. One of the clearest implications is that research on curriculum tracking should continue to theorize tracking as due to a plural set of mechanisms and social forces. For example, research on the effects of tracking on social inequality should employ a full set of functional factors as statistical control if plausible effects are to be identified. Furthermore, this study provides more insights into the inequality-generating processes from tracking. In particular, this analysis argues that promoting greater STEM tracking selectivity in elite schools is an apparent organizational approach through which middle-class and elite families prioritize learning opportunities, in the ear of curriculum intensification.

Further research on related topics utilizing nationally representative data and educational administration data should be aware of the major limitations of the current study. First, the measures of tracking generated from transcript data do not directly speak to specific curriculum policies nor schools' guidance/impact of/on enrollment. Thus, the analytical framework used here can only inform policy implementation indirectly. Second, nationally representative data may have limited inferential ability to the effect of single policy change since tracking is a complicated and inter-correlated phenomenon; it's less likely to disentangle the effect of a single policy in such research setting. Moreover, future research may expand this analysis by considering the effects of various organizational approaches of tracking on educational outcomes and educational inequality; that is, such research may bridge the conceptual links between social processes, learning opportunities, and educational attainment. Such research setting may further identify the extent to which tracking practices both provide appropriate instruction and generate social inequality. Additionally, doing so will provide new insights into the definition of "functional" consideration of tracking; that is, to what extent the functionally-driven instructional context may benefit various educational outcomes, including achievement and attainment. Overall, this analysis contributes to the enduring question of just how functional curriculum tracking really is? It's logical that schools promote differentiated learning environments in response to diverse student populations, in particular, in the era of curriculum intensification. Yet, it's crucial to acknowledge that the extensive inequality in learning opportunities may arise when this functional tailoring of tracking system moves away from an "appropriate" level.

4.0 Social Determinants of School-to-school Differences in Opportunity to Learn, A Cross-national Study

4.1 Introduction

Cross-national empirical studies of educational inequality address an important research question: to what extent do the organizational features of school systems affect inequality in education outcomes? The research speaks to a basic concern that both policymakers and parents would like to know; that particular characteristics of school systems (e.g., the way that students are selected and grouped) may result in variation in achievement and have consequences for enlarging inequality in educational outcomes. In understanding outcomes of educational systems, researchers have examined how the level of inequality in achievement is related to the degree to which education systems stratify students through different opportunity to learn (e.g., Brunello, & Checchi, 2007; Hanushek, & Wößmann, 2006; Montt, 2011). Yet, what leads to stratified Opportunity to Learn in the first place and where are the explanations for stratified OTL in a given country likely to stem? In this analysis, I consider school-to-school differences in opportunity to learn as a major form of stratification of OTL in cross-national setting because between-school tracking is predominant in many different countries.

An important theoretical frame for this chapter, taken from classic theories of social stratification, is that there is a basic evolution of social inequality as countries develop, with certain developmental factors first increasing then decreasing inequality writ-large (e.g., both directly and through mechanisms such as the share of urban residents in a country), so the degree of inequality in schooling and other aspects of society can be understood as a departure from that "natural" trend. Much as the recent school effects literature in the summer-learning paradigm (Downey, 2020) helps frame and focus social and educational policy on the sources of test-score inequality that really matter, school-to-school differences in opportunity to learn should be understood in the context of the fundamental social forces that shape educational systems.

Following a similar theorical paradigm of curriculum tracking considered in previous chapters, this chapter further explores the functional and conflict sources of school-to-school differences in opportunity to learn. A school system may produce inequality in opportunity to learn in a functional way, as a result of variation in school academic readiness; that is, the school-to-school differences in opportunity to learn may fit the distribution of average academic readiness of each school. On the other hand, school systems may also produce excessive and dysfunctional inequality such as a tracking system that benefits high-SES students by allocating more learning opportunities. Therefore, understanding the reason behind the origin of such inequality may enable us to disentangle the total observed inequality in opportunity to learn. Finally, this chapter discusses the role of education policies concerning stratification and standardization in moderating the effect of social inequality on school-to-school differences in Opportunity to Learn.

Using a large cross-national sample with 278 observations across 67 countries/regions, dating from 1995 to 2019, this empirical study contributes to the existing cross-national studies of educational inequality in several ways. First, this study traces the fundamental origin of inequality in Opportunity to Learn across countries; that is, inequality in OTL is responsive to the basic evolution of social inequality as countries develop. The extent to which schools differ in Opportunity to Learn provided then can be attributed to both functional and conflict dimensions. Second, this analysis utilizes actual curricular content measured in TIMSS and is even more focused on the content of instruction and learning than studies focusing on course/program provision (although specific content is closely linked with course taking). Third, this study advocates a comprehensive consideration of country-level developmental factors in cross-national studies of educational inequality.

4.2 Literature Review

4.2.1 Cross-national studies on educational inequality

Studies of the institutional structure of educational systems focus on how education is organized for selection and allocation (i.e., how education systems stratify students through differential opportunity to learn), which in turn induces variation in various educational outcomes (e.g., Bol et al., 2014; Brunello, & Checchi, 2007; Buchmann, & Dalton, 2002; Buchmann, & Park, 2009; Chmielewski, Dumout, & Trautweinl, 2013; Parker et al., 2016; Van de Werfhorst, & Mijs, 2010). Closely related to the present study, foundational research has focused on characterizing curriculum tracking systems and capturing baseline country-to-country variation in tracking systems (e.g., Broaded, 1997; VanHoutte, 2004).

In his comprehensive empirical work, Montt (2011) established an overarching framework for understanding educational inequalities in the cross-national setting. In particular, Montt (2011) examined the extent to which two important dimensions of educational systems, *inequality in opportunity to learn* and *the intensity of schooling* were related to differences in achievement inequality across countries, net of variation in family background, using PISA 2006 data. The framework speaks to the important role of reducing inequality in Opportunity to Learn in decreasing the total achievement inequality and equalizing the educational inequality due to SES heterogeneity, in the cross-national setting. Among his indicators of opportunity to learn, between-school tracking practices were found to be related to inequality in achievement. Specifically, more tracking programs and earlier tracking, measured at the country level, were associated with greater inequality in achievement, after controlling for intensity of schooling and SES distribution. Although not the main focus of this chapter, Montt (2011) also considered variation in school physical resources and instructional resources as measures of inequality in Opportunity to Learn. Montt (2011) provides a compelling conceptual framework that establishes the theoretical link between variation in Opportunity to Learn and achievement inequality, an important form of educational inequality that both educators and policy makers care about (e.g., Coleman, 1966), in a cross-national research setting.

Consistent with Montt (2011), Hanushek and Wößmann (2006) found a similar association between inequality in achievement and tracking practice at the national level. Using PIRLS (for 4th grade data) and TIMSS (for 8th grade data) data, Hanushek and Wößmann (2006) found that countries experienced a greater increase in achievement inequality from 4th grade to 8th grade with highly differentiated secondary education systems, after controlling for inequality in achievement at 4th grade. The gain in achievement inequality was less dramatic among countries with less-differentiated secondary school systems. Huang (2009) found that high achieving students enjoyed mathematics achievement gains at the expense of achievement loss among low achievers in countries with greater tracking selectivity (measured as skill homogeneity). Although Huang's (2009) results were not precisely similar to Montt (2011) or Hanushek and Wößmann (2006), Huang (2009) showed that more intensive tracking at the country level may have enlarged pre-existing achievement gaps between high-achievers and low-achievers. Overall, educational systems with a greater degree of explicit stratification induce greater inequality in achievement where different students are selected and allocated to different instructional contexts.

Another set of empirical studies focuses less on the total variance in educational outcomes, and instead on the degree to which educational systems stratify students from different social origins (e.g., Ammermüller, 2005; Marks, 2005; Brunello, & Checchi, 2007; Buchmann, & Park, 2009). Brunello and Checchi (2007) examined how the effect of family background on various educational outcomes is moderated by stratification, measured as the duration of between-school differentiation within each educational system, using ECHP, ISSP, IALS, and PISA 2003 datasets. They found that the inequality in educational achievement and post-secondary enrollment induced by family background increased with greater duration of tracking (Brunello, & Checchi, 2007). They also found that the advantage of wealthier families on long-term educational outcomes (i.e., job income) was *reduced* as the length of tracking increased. In Buchmann and Park's (2009) study of the relationship between stratification and educational expectations in highly differentiated educational systems using PISA 2003, they examined two critical stratification processes to unpack the moderation effect of stratification on perpetuating and exacerbating SES inequality. First, they found that social origins were strongly related to track placement which was, in highly differentiated school systems, different types of schools. Second, they found that the types of schools that students attended were related to students' educational expectations. High SES students were more likely to enroll in academically oriented schools and thus had higher educational expectations and a better chance to realize those expectations.

Overall, research on country-level stratification systems indicate that: *more highly elaborated between-school tracking practices are associated with greater inequality in achievement growth*. However, although these studies are consistent with conflict-based theories of schooling (where e.g., high-SES students take advantage of tracked systems), they do not actually show that the tracking policies and practices are motivated by, and/or generated from conflict-based social forces. Moreover, such studies fail to explicitly address the functional and dysfunctional sources of inequality in opportunity to learn specific, measured curricular content, which will be the primary focus of this study.

4.2.2 Developmental stage, social inequality, and variation in Opportunity to Learn

In Kuznets' (1955) pioneering analysis of historical trend data from Great Britain, Germany and the US, he found an inverted U-shape relationship between income inequality (measured by the GINI coefficient) and country developmental stage (measured as GDP per Capita); that is, as countries developed (i.e., approaching advanced industrial societies), income inequality first increased, and then declined. Kuznets' (1955) analysis innovatively created an important framework that linked social inequality with a country's developmental stage. This framework was later expanded to identify the relationships between income inequality and various social developmental/structural factors beyond just GDP and GDP per capita.

In the late 1990s, François Nielsen and Arthur Alderson (1995) revisited Kuznets' framework and proposed an "internal development" model to understand the relationship between inequality and development[32] (Nielsen, 1994; Nielsen, & Alderson, 1995;1997; Alderson, & Nielson, 1999). They argued that country developmental stage should be understood in a more systematic way; that is, internal development factors should be isolated and emphasized to

[32] In additional to cross-national analyses, this model has been applied to single-country analyses, such as studies using US data (e.g., Partridge, 2005)

understand their role in *generating* social inequality as countries developed. The internal-development framework considers three major processes through which a country's development generates income inequality. First, this model identifies both between- and within- sector inequality as the labor force shifts from the agricultural sector to the industrial sector as countries develop as an important source of inequality. Both *sector dualism* (capturing income inequality due to between-sector disparities) and the *size* of the agricultural sector (capturing income inequality within sectors) are considered in this process. Second, this model considers the role of rapid population growth in producing excessive labor supply, which in turn produces income inequality. Third, the internal-development model regards the spread of secondary education as producing an increased supply of skilled labor which may ultimately contribute to a decrease in income inequality.

It's also worthwhile to note that subsequent studies using the internal-development framework focus on the modification of existing processes and adding new inequality-generating processes to understand the trends in the relationship between development and income inequality in the post-2000s era. For example, in a recent study on revisiting internal-development framework, Clark (2020) proposed several modifications on the original internal-development framework, including using sector pluralism to consider all three major employment sectors (agriculture, industry, and services), and replacing secondary enrollment with tertiary education enrollment to better reflect the supply structure of skilled labors. Clark (2020) also considered the female political participation rate, as the gender structure of political elites may shape the resources distribution. In the current study, I adopt the modification of tertiary education instead of secondary education, to better reflect the labor force structure in the current era (which will also avoid the confusion of using secondary education enrollment to understand how secondary education resources are distributed). But I stick to the definition and measurement of labor force shifts in the original framework since a binary measure of social dualism may better capture the most salient relationship between social inequality and educational inequality.

Both Kuznets' (1955) original analysis and the internal-development model of inequality (Nielsen, 1994; Nielsen, & Alderson, 1995) focus on the most essential relationships concerning development and income inequality. Can this framework be expanded to educational outcomes and be used to understand the relationships between developmental stage, social inequality, and capacity to equitably allocate educational resources (i.e., Opportunity to Learn)? Much as Cole's (2018) recent empirical study on political inequality applies the internal-development framework to examine the relationship among development, social inequality (notably income inequality), and inequality in political power, it may be useful to understanding educational systems. In this study, I argue that the internal-development framework is useful to systematically explore the relationship between the nature of society in a country and various educational outcomes and to trace the fundamental sources of educational inequality through development and social inequality. **The basic level of educational inequality (i.e., variation in Opportunity to Learn in this study) is hypothesized to be responsive to the social distribution of economic and human resources , after considering the generative effects of internal-development factors on basic social inequality (H 4-1)**. Figure 4.1 portrays this baseline model.

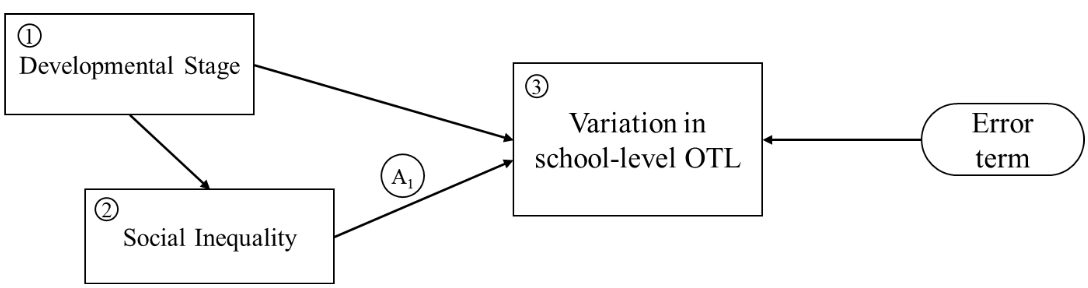

Figure 4.1 Baseline model of school-level variation in Opportunity to Learn

In this baseline model, developmental stage is related to basic social inequality, and social inequality in turn produces the variation in school-to-school differences in Opportunity to Learn. The relationship between social inequality (Box 2, which includes income inequality and unequal distribution of population) and variation in school-level opportunity to learn (Box 3) within each country is indicated with Path A_1, net of countries' actual developmental stage (Box 1) measured by three constructs from the internal-development framework. This model is helpful to trace the fundamental sources of educational inequality and identify which countries have greater, lesser, or "appropriate" inequality than anticipated/predicted from this model. For example, if the social and economic resources are clustered in urban areas in a country, it's supposed that the distribution of education resources also follows that pattern. Moreover, this baseline model establishes the conceptual framework for later analysis where I consider functional- and conflict-based explanations for between-school tracking.

4.2.3 Functional and Conflict sources of Inequality in Opportunity to Learn

The baseline model (Figure 4.1) is useful for examining the relationships between developmental stage, social inequality, and school-level variation in Opportunity to Learn across countries, and to identify any apparent excessive educational inequality. Yet, educational systems often purposefully induce variation in course taking at the school-level, in the form of between-school tracking, under a functional logic of tracking, and Figure 4.1 does not capture that process. Even more importantly, Figure 4.1 is missing any measure of achievement that might be functionally-related to between-school tracking, and helps to then reveal remaining, "dysfunctional" sources of tracking. To further unpack the functional vs. dysfunctional pathways, therefore, I again build on the literature on school-to-school differences in tracking in the US setting. In Kelly and Price's (2011) empirical work on examining the relationship between school compositional characteristics and school-to-school differences in school tracking policies, they examined both functional and conflict sources of tracking that motivated school-to-school variations in tracking policies. Functional forces are identified by the associations between dimensions of tracking and achievement heterogeneity. After adjusting for these functional factors, they then identified conflict forces, where various measures of school composition were hypothesized to motivate more elaborated tracking systems.

Here, I build on Kelly and Price's approach, but with less specificity. Technical-functional theory suggests that tracking systems enable teachers to match instruction (e.g., material, academic richness, and pace) to students' skill and target their instruction to an ability-homogeneous groups of students (Hallinan, 1994; Oakes, 1992). In the cross-national setting, functional explanations for variation in school-level Opportunity to Learn would suggest that schools structure course offerings to match students' readiness (specifically, achievement prior to secondary education). Therefore, in this study, I characterize the school-to-school differences in Opportunity to Learn in a country attributable to variation in school-mean academic readiness as functional. In contrast, conflict theories of tracking posit that advantaged students maintain their advantages through school tracking systems. For example, opportunity hoarding theory describes the inter-group conflict between, in one case, high-SES families and working/poor families. That is, students from high-SES families limit access to high-track curriculum to maintain their own advantage (e.g., Oakes, & Lipton, 1992; Wells, & Oakes, 1996). Status competition describes the competition for better educational attainment and labor force success *within* middle-class and high-SES families to maintain their advantages (Baker, & Stevenson, 1986). While it's empirically difficult to explicitly explore these two conflict-related theories in a cross-national setting due to data limitations, conflict theories suggest that, in general, after accounting for the more functional effect of variation in school readiness, the remaining relationship between social inequality and educational inequality indicates a dysfunctional pathway (A_2). Figure 4.2 shows the model with both functional and dysfunctional pathway.

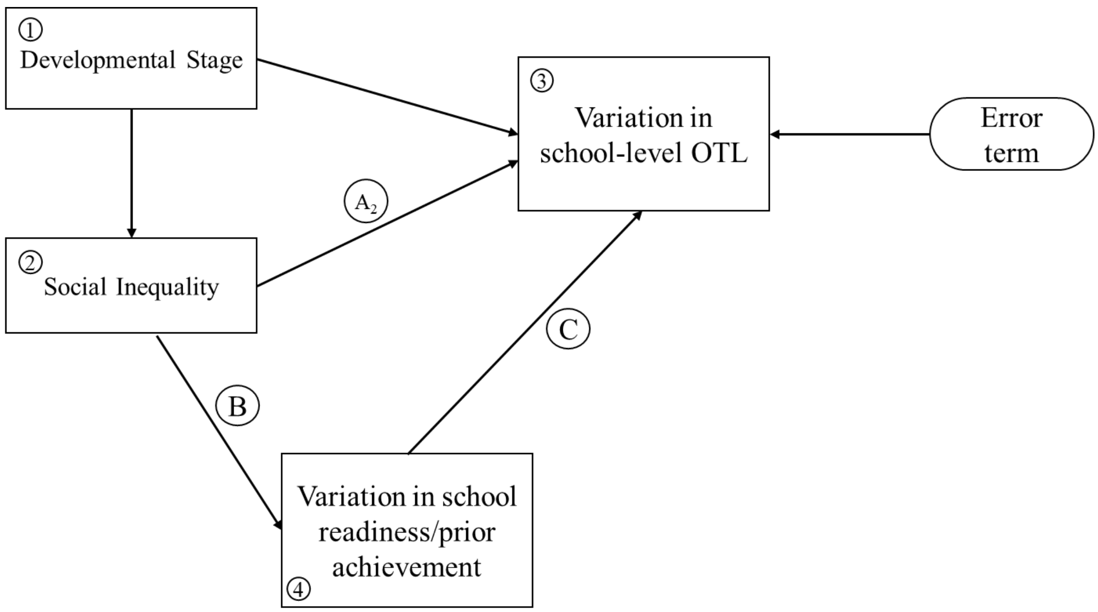

Figure 4.2 Tracing functional and dysfunctional pathways using baseline model of school-level variation in Opportunity to Learn

As such, based on the analysis of the literature and proposed frameworks, **I hypothesized that, if the variation in school-level Opportunity to Learn is motivated by functional forces, school-to-school differences in opportunity to learn will be explained by variation in school readiness/prior achievement, controlling for social inequality measures (H4-2a).** Alternatively, after considering functional forces, if the observed school-to-school differences in Opportunity to Learn are related to conflict mechanisms**, I would expect greater social inequality to be related to school-to-school differences in Opportunity to Learn (H4-2b).**

4.2.4 Education policies and practices as moderators: The role of stratification and standardization

Early studies on the relationship between education and social stratification provide a comparative framework of how differences in educational systems lead to differences in the way in which students are sorted into the labor force (e.g., Kerckhoff, 2001; Maurice et al., 1986; Müller, & Karle, 1993). Alan Kerckhoff conducted important work in this area, building off classic studies by Turner (1960) and others. Educational systems that differ in dimensions, such as stratification and standardization, vary in "capacity to structure" education trajectories (Kerckhoff, 2001). For example, In Germany, school type is clearly associated with students' post-secondary trajectories and student' occupational destinations are highly predictable once they are allocated into secondary education (Allmendinger, 1989; Kerckhoff, 2001), whereas the American comprehensive school system is known as a less explicitly stratified educational system where students' future trajectories are not explicitly mapped to enrollment in a given type of secondary school.

The moderation effects of stratification and standardization policies on relationships between family background and educational outcomes has been studied empirically. For example, Brunello and Checchi (2007) found that inequality in educational attainment and post-secondary enrollment induced by family background increased with the practice of *stratification* (measured as the duration of between-school tracking practice). Studies on the relationship between *standardization* and educational inequality, however, find that standardization has a counterbalancing effect on the relationships among between-school tracking, social origins, and inequalities in educational outcomes (e.g., Ayalon, & Gamoran, 2000; Bol et al., 2014; Horn, 2009;

Park, 2008). Park (2008), for example, found that standardization (e.g., national college entrance examination) reduced the effect of social origins on achievement inequality.

In this study, I argue that Kelly and Price's framework of educational inequality can also be used to understand the role of stratification and standardization policies in producing school-to-school differences in Opportunity to Learn. Specifically, I hypothesize that **stratification policies (e.g., longer tracking, early tracking, applying gate-keeper courses) will exacerbate the effect of social inequality on variation in school-level Opportunity to Learn, while standardization policies (e.g., national entrance/exit examination, or national curriculum standards) will attenuate this effect instead (H4-3).** Figure 4.3 illustrates this hypothesis, focusing on the direct effect of social inequality after accounting for variation in school readiness, the more obviously dysfunctional path from social inequality to opportunity to learn.

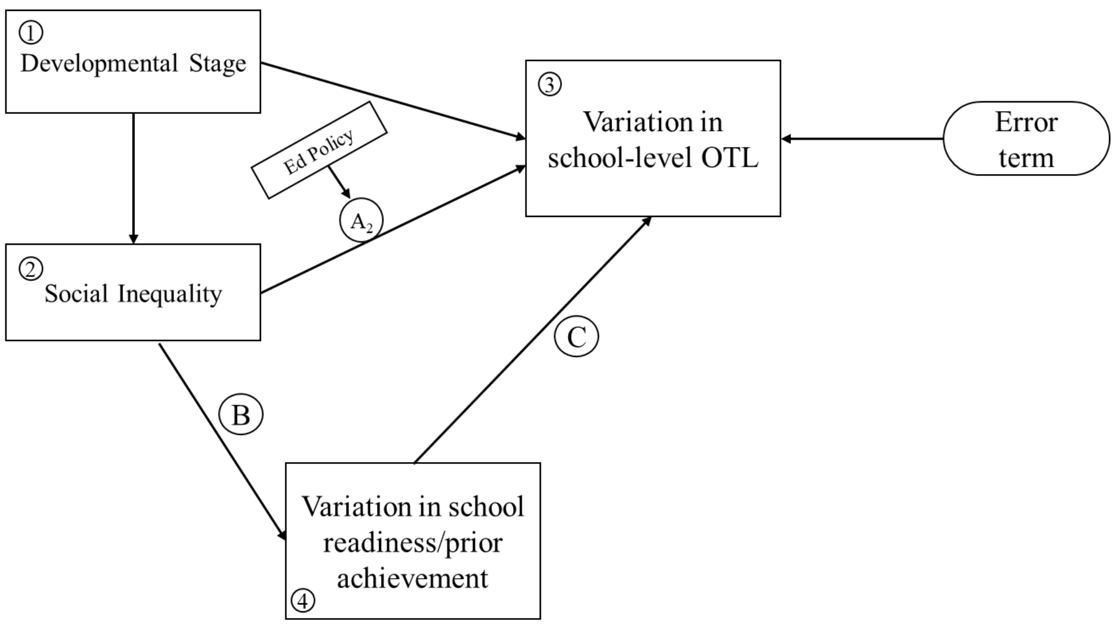

Figure 4.3 Final model of school level variation in Opportunity to Learn

It's worthwhile to note that due to data limitations, available measures of stratification and standardization are not fine-grained, making this moderation analysis weaker and more uncertain than the remainder of the model elements shown in Figure 4.2.

4.3 Analytic Strategy

4.3.1 Measurement

4.3.1.1 Dependent Measure

In this analysis, I consider school-to-school differences in Opportunity to learn to capture the country-level inequality in OTL. To measure the overall Opportunity to Learn at the school level, I calculate school-mean course-taking experiences. The measurement of student course-taking opportunity is a coding scheme that is built upon individual course-taking reports from the Trends in International Mathematics and Science Study (TIMSS). The goal for coding the difficulty level of math and science course taking is first to designate a difficulty level for each topic taught, and then produce a cumulative measure of math and science course taking at 8^{th} grade. Because the TIMSS dataset does not include transcript data, the measurement of student course-taking experiences relies on teacher-reported **curricular topic lists** for each participating student.

4.3.1.1.1 Curricular Topic Coding

For 8^{th} grade math curricular topics, I match each topic to an equivalent grade level according to a widely used curricular standard in the US, the Common Core Mathematics Standards (CCMS). Curricular topics coded as high-level math topics are usually taught in senior middle school classrooms, such as simultaneous equations or concepts of irrational numbers. The mid-level math topics (e.g., simple linear equations or basic statistics) are taught in entry-level middle school math classes. TIMSS also surveyed some basic mathematics topics that are taught before middle schools and not common in middle school math classes (e.g., computing with whole numbers). I coded these topics as low-level math curricular topics. Alternatively, I also consider middle school Algebra topics as a major mathematics domain discussed in many middle school education literatures. Thus, in the subsequent analysis, I create an alternative measure of algebra topics individually and discuss related results in robustness analysis.

Different in some respects from math topics, science curricular topics are not necessarily associated with a given grade level, especially at the middle school level. Therefore, instead of assigning a difficulty level based on grade level, the science topics code captures how deeply students have learned content during middle school. To determine the topic code for each topic, I first refer to Science Content Domain documents provided by the TIMSS team. Each topic is further described in this document by several specific learning objectives which enable me to identify how deep each topic requires students to achieve. To further understand the cognitive skill involved in each topic, I consulted an expert on science education and modified the topic codes if I initially over-estimated or under-estimated the difficulty of cognitive skills involved during instruction. Low-level science curricular topics are defined as introductory level science concepts with no high cognitive skill requirement, such as major taxonomic groups of organisms, the classification of the properties of matter, or energy forms. Middle-level science topics require the ability to apply scientific knowledge, such as the structure and function of major organs and organ systems, chemical changes, or physical changes. Finally, classes that instruct high-level science topics usually involve advanced level of cognitive skills, including the synthesis, analysis, and evaluation of science concepts and scientific principles. For example, the structure and function of cells, the role of electrons in chemical bonds, or forces and motions are classified as high-level science curricular topics.

Because TIMSS gradually modified surveyed curricular topic lists over time, I thus use three different versions of coding schemes to assign topic codes to teacher-reported curricular topics. See Appendix C for the complete coding process of individual curricular topic coding.

4.3.1.1.2 Student-level measures of course-taking experience

Each student is then assigned to a Curricular Experience (CE) code based on their overall course-taking richness and difficulty. To achieve this measurement goal, with teacher-level data, I first examine whether each surveyed curricular topic is taught in their classrooms. TIMSS asked teachers to report the extent to which each curricular topic is covered in the middle school classrooms. Teachers select a response from the following options, (1) topic is mostly taught before 8th grade[33], (2) topic is mostly taught at 8th grade, or (3) topic is not taught in middle school or just introduced. In this analysis, I consider that students are exposed to curricular topics if their teachers report that these topics are taught mostly at or before 8th grade (i.e., option 1 or 2). Second, I link teacher survey results to student files using the TIMSS Link files and examine whether students are exposed to each individual curricular topic. Depending on school curriculum systems, students may stay in one and only math/science classroom or experience different classes throughout middle school. Thus, multiple teachers may report curricular topics for a student in TIMSS. In this analysis, I consider that students are exposed to curricular topics if at least one teacher reports that topics are taught before or at 8th grade. Finally, as the final measure of students'

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[33] In some surveyed counties, 8th grade is not the final year of middle school. In this case, questionnaire is modified to corresponding grade level (e.g., 9th grade) that is applied to certain country. Here in this measurement, I always measure whether the topic is taught at or before the final year of middle school.

overall course-taking experience, I calculate the percentage of high-level[34] math and science topics learned, respectively, as the CE codes. This percentage represents the proportion of high-level topics learned out of the total number of high-level curricular topics surveyed in TIMSS. The percentage of high-level curricular topics learned considers both richness and difficulty of student course-taking experiences throughout middle schools. [35] Alternatively, I also calculate the percentage of high-level Algebra topics learned throughout middle schools.

To examine the school-to-school differences in Opportunity to Learn for each country, I aggregate student level data to the school level (mean), then calculate the variance of the school-mean CE code (MCE and SCE) for each country. I also calculate the country-mean pairwise school differences in math and science CD code by averaging the difference between each possible pair of schools for each country. Average pairwise differences capture the expected difference in the school mean CE between two randomly selected schools within a country. These pairwise differences are used for descriptive purposes, where they have a more intuitive expression than the variance.

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[34] I also calculate the percentage of mid-level and above topics learned. However, schools on average expose a lot more students to mid- and high-level curricular topics than to just high-level topics, creating less variation across schools. Schools on average expose more than 75% students to mid- and high- level curricular topics as opposed to below 60% student to high-level topics. Thus, I choose to use percentage of high-level topics learned as a main DV.

[35] I realize that due to the existence of three different versions of curricular topic coding schemes, the amount of total high-level curricular topics may differ across cohorts. Thus, I expect some unexpected year-to-year fluctuation within countries. I therefore argue that year-fixed effect is useful to control some of these variation.

4.3.1.2 Independent Measure

For independent variables, I consider four main categories of predictors: (1) internal-development factors, (2) basic measures of social inequality, (3) school-to-school differences in school academic readiness (which is functionally related to school-to-school differences in course taking), and (4) country-level stratification and standardization policies. The internal-development process is captured by development of the non-agricultural sector, higher education expansion, and the natural population increase rate. The basic level of social inequality is measured using income inequality (GINI coefficient) and a measure of rural/urban duality. School-to-school differences in school readiness are measured by the variance in students' prior achievement. And finally, educational policy is measured by three sets of dummy variables that capture the extent to which a country mandates academic-based promotion, curriculum tracking, and high-stake examinations. The full description of independent variables is listed in Table 4.1

Table 4.1 Description of independent measures

IVs	Description
Internal Developmental Factors	
GDP per capita	The GDP per capita in constant 2010 US dollar. Dataset is drawn from the World Bank.
Labor shift from agricultural sector (%)	Labor shift is calculated as the difference between the percentage of the population in rural areas and the share of agriculture, forestry, and fishing as a percent of GDP. i.e., how impactful is the rural economy compared to its population share Both population data and GDP data are drawn from the World Bank.
Size of non-agricultural sector (%)	Size of non-agricultural sector is measured as the share of population that do not live in rural area.
Tertiary education enrollment rate (%)	Tertiary education enrollment rate is derived from the World Bank.
Natural population increase rate (per 1,000 people)	Natural rate of population increase is calculated as the difference between crude birth rate and crude death rate. Both datasets are drawn from the World Bank.
Social Inequality Measures	
Income GINI coefficient	GINI coefficient of income inequality for each country. Data is derived from the World Bank.
Index of inequality of rural population distribution	Measured as Index of inequality/variation of rural population distribution. This index measures the inequality of the distribution of rural population (in percentage p). i.e. countries with a high or low percentage of the population in rural areas are less affected by the dichotomy between urban/suburban and rural life. Countries in the process of shifting from

	rural to urban residency have a higher degree of variation in residency. The index is calculated as $p * (1 - p)$.
Variance in Prior Achievement	
Variance in prior achievement	Calculated school-level variance in math std. achievement test scores, administered at the start of 8th grade from TIMSS datasets.
Educational Policy	
Academic-based promotion before 8th grade	National policy on the promotion/retention based on academic progress before the end of 8th grade. Dummy variable.
Sorting students before 8th grade	National policy using student achievement to assign students to classes before the end of 8th grade. Dummy variable.
High-stake exams before 8th grade	This variable measures whether a national educational authority administers examinations that have high-stakes consequence for *individual students* (such as entry to a higher school system, and/or exiting/graduating from school) before the end of 8th grade. Dummy variable.
Other School-level Controls	
Number of computers (deviation from country mean)	The variance of number of computers (in the unit of 10 computers)
Index of inequality/variation of concentrated economic disadvantage in schools	This index measures the inequality/variation of concentrated economic disadvantage in the percentage of schools having more than 50% of poor students. The index is calculated as $p * (1 - p)$ such that countries with a high or low proportion of poor schools have greater homogeneity in school poverty environment
Year Variable	
Year	The year in which TIMSS was conducted. 1-1995, 2- 1999, 3- 2003, 4-2007, 5-2011, 6-2015, 7-2019

4.3.2 Statistical Analyses

I run a series of Generalized Multilevel Linear Models (GMLM) with the Gamma distribution and logarithmic transformation of independent variable to estimate the school-to-school differences in OTL. I use the Gamma distribution and logarithm transformation to address the positively skewed distribution of the variance of school-mean Curricular Experience (CE) (Montt, 2011). The first model examines the relationship between socio-economic disparities within countries and school-to-school differences in OTL, controlling for internal-development factors (development of non-agricultural sector, educational expansion, population growth, and economic development). The stage 1 model has the general form,

$$\log(\sigma_{jt}^2) = \alpha_0 + \beta T_t + \gamma X_{jt} + \theta D_{jt} + \varepsilon_{jt} + \tau_j$$

Where σ_{jt}^2 are school-to-school differences in OTL measures (variance of school-mean MCE and SCE) for country j at year t. T_t is a year indicator. X_{jt} is a set of time-varying measures describing country j's developmental stage at year t. D_{jt} indicates a set of measures of social inequality measures for country j at year t. The estimation of coefficient θ explores the baseline sources of variation in school-level opportunity to learn adjusting for developmental stage.

The second model adds the key covariate related to functional explanations for variation in OTL, the variance of school-mean achievement (Z_{jt} is a time-varying variable indicating heterogeneity of school academic readiness for country j at year t). The stage 2 model has the form,

$$\log(\sigma_{jt}^2) = \alpha_0 + \beta T_t + \gamma X_{jt} + \theta D_{jt} + \delta Z_{jt} + \varepsilon_{jt} + \tau_j$$

δ explores the main functional source of variation in school-level opportunity to learn using a single indicator of functionalism. Finally, the third model considers the moderation effects of country-level stratification and standardization policies. It has the form (P_{jt} are education policy indicators at country j at year t.),

$$\log(\sigma_{jt}^2) = \alpha_0 + \beta T_t + \gamma X_{jt} + \theta D_{jt} + \delta Z_{jt} + \rho D_{jt} \times P_{jt} + P_j + \varepsilon_{jt} + \tau_j$$

The cross-product term $D_{jt} \times P_{jt}$ capture the interaction between social inequality measures and educational policy. ρ indicates whether the policies measured here moderate the effect of social stratification in producing school-to-school differences in Opportunity to Learn.

In addition to the multilevel modeling analysis, I consider a set of ancillary statistical analyses to support the results from the main analysis. I estimate a series of population-average models using the Generalized Estimating Equation (GEE) approach (Hubbard et al., 2010), emphasizing *country-to-country* differences in OTL inequality rather than differences within and between countries over time. Population-average models with GEE account for the within-country year-to-year correlation structure (i.e., the heterogeneity within each country due to year-to-year variation) but do not explicitly model the country-specific random effects over years. Instead, the model focuses on estimating the average country-level effects, with the assumption that the country-level independent variables have constant effects on dependent variables. Population-average models with GEE are useful here to support the main analysis because the vast majority of the overall variance in important predictors lies between countries and does not vary greatly between years.[36]

I also make some modifications to the analytic sample before running model estimations. First, I exclude countries that failed to capture the variation in dependent measure, curricular topics. Under this definition, Algeria, Austria, Bosnia and Herzegovina, Moldova,[37] and the Russian Federation,[38] are excluded from model estimations, yielding a new sample size of 278 observations across 67 counties.[39] Second, I use both simple imputation techniques and external data sources to deal with the missing data occurring among independent measures. For countries whose data are completely missing from the World Bank databases, I rely on statistics from each country's Bureau of Statistics. For example, I use data from the Directorate General of Budget, Accounting, and Statistics of Taiwan and Ministry of the Interior, ROC to acquire their economic and population data (e.g., GINI, birth and death rates, and rural population). I also visited the

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[36] In this analysis, I only consider population-average models with GEE approach as robustness check as this model greatly reduces the sample size.

[37] For example, Bosnia and Herzegovina, and Moldova surveyed STEM topics in teacher survey, but failed to capture any variation in school-mean MCD and SCD.

[38] Russian Federation did not include instructed math topics in teacher surveys.

[39] Czechoslovakia (only 1995) is also excluded from the model estimation, but both Slovak Republic and Czechia are included in this sample.

Palestinian Central Bureau of Statistics (PCBS) website for their complete developmental data. More commonly, countries only lack data for certain years. I use simple imputation to fill in year-missing data by calculating the mean of neighboring years. For example, Egypt is missing a tertiary education rate in 2019, but has the information for 2018 and 2021. I therefore use the mean of the 2018 rate and the 2021 rate as the best guess of the 2019 rate.

4.4 Results

4.4.1 Descriptive Statistics

To understand the baseline inequality in course taking, I first descriptively examine the country-to-country differences in inequality in Opportunity to Learn, including the variance of school-mean math and science Curricular Experience (CE) and the country-mean of average pairwise differences in school-mean MCE and SCE.[40] Using TIMSS 2019 as an example, Figures 4.4 and 4.5 report the average pairwise differences in school-mean MCE and SCE, respectively, for the 2019 cohort. As shown in Figure 4.4, among 39 sampled countries and regions from TIMSS 2019, Malaysia, France, Singapore, and Hong Kong have the lowest school-to-school differences

[40] Statistically speaking, the average pairwise differences perform similarly with the variance of Curricular Experience. Yet, later in this analysis, I choose to use the variance of school-mean Curricular Experience because (1) the variance functional regression fits better with the interpretation under logarithmic transformation and (2) the variance captures greater amount of variation in school-mean opportunity to learn provide than the pairwise differences.

in Math opportunity to learn with an approximately 10 percentage point difference in school-mean percentage of high-level math topics learned between two randomly selected schools. Schools from Turkiye, Chile, England, and South Africa, on the other hand, have the highest school-to-school differences in Math opportunity to learn with approximately a 30-percentage point difference in school-mean percentage of high-level math topics learned.[41] Figure 4.5 reports the pairwise analysis results of school-mean science Curricular Experience (CE) for the 2019 cohort. Among 39 sampled countries in TIMSS 2019, schools from Japan, Finland, Taiwan, Morocco have the lowest pairwise differences in school-mean science Curricular Experiences (around 10 percentage points differences) whereas schools from England, Chile, South Africa and Saudi Arabia experience the highest school-to-school differences in science OTL (around 25 to 30 percentage points differences). [42]

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[41] As a reference, the weighted grand-mean of school-mean percentage of high-level math topics learned across all sampled schools for the 2019 cohort is 60.2%. A 30 percentage-point difference in Math CE between two random selected schools is almost half of the grand-mean of school-mean MCE.

[42] The weighted grand-mean of school-mean percentage of high-level science topics learned across all sampled schools for the 2019 cohort is 69.9%.

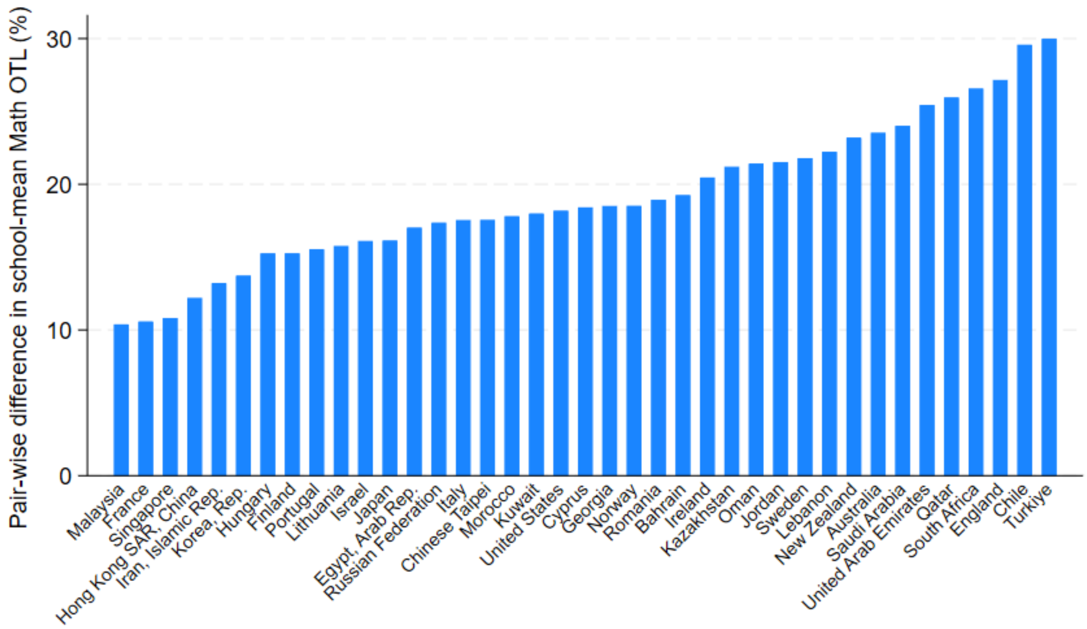

Figure 4.4 Pair-wise differences in school-mean percentage of Math topics learned (TIMSS 2019)

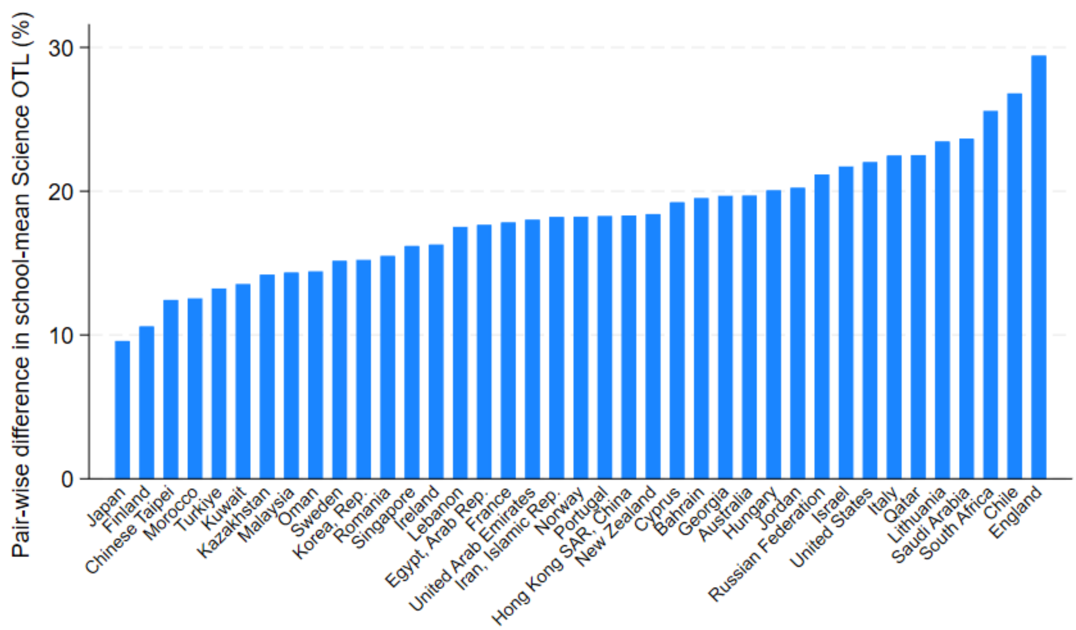

Figure 4.5 Pair-wise differences in school-mean percentage of Science topics learned (TIMSS 2019)

To further examine the amount of country-mean learning opportunities provided and inequality in OTL generated for each country, I plot the scatterplot of country-mean OTL against inequality in OTL for the 2019 cohort as an example. As shown in Figure 4.6, the vertical dashed line indicates the grand mean of inequality in Math OTL and horizontal dashed line represents the grand mean of country-mean Math learning opportunities. Among all sampled countries in TIMSS 2019, Malaysia, Singapore, Hungary, Indonesia, Israel, and the US, on average, provide students with rich learning opportunities while maintaining relatively low-level of inequality in school-mean Math OTL. France, Iran, Lithuania, and Finland maintain a low-level of inequality in OTL, but their mean Math OTL provided is below average. Note that no sampled country has high- or low-level country-mean Math OTL while exhibiting extremely great inequality in OTL. England, Armenia, and South Africa, to name a few, provide above-average Math OTL, but exhibit a moderate-to-high level of inequality in Math OTL. Figure 4.7 examines the country-mean and inequality in *Science* OTL. As shown in Figure 4.7, Finland, Turkiye, Romania, Kuwait, and Malaysia have high country-mean Science OTL, while maintaining low-level of inequality in OTL. Some other countries, such as Hungary, The US, Jordan, Lithuania, and Saudi Arabia, also have high-level Science OTL provided to students, but exhibiting moderate level inequality in Science OTL. The associations between level of inequality and country-mean level of Curricular Experience, however, do not appear to be significant in both figures.

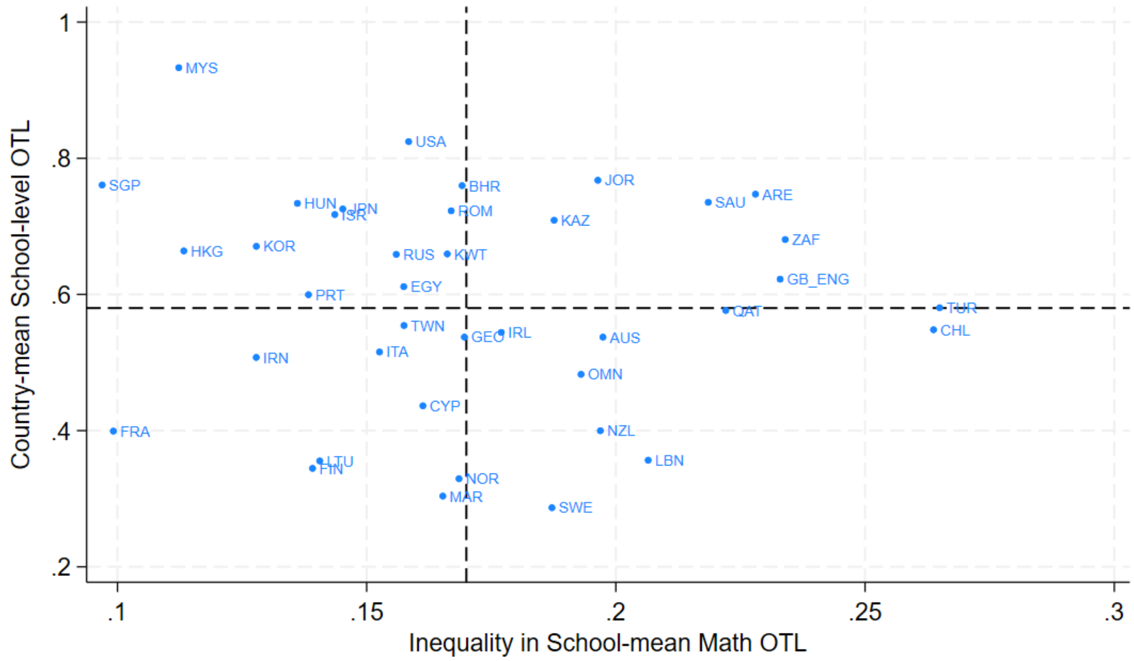

Figure 4.6 Inequality in School-mean Math OTL and Country-mean School-level OTL (TIMSS 2019)

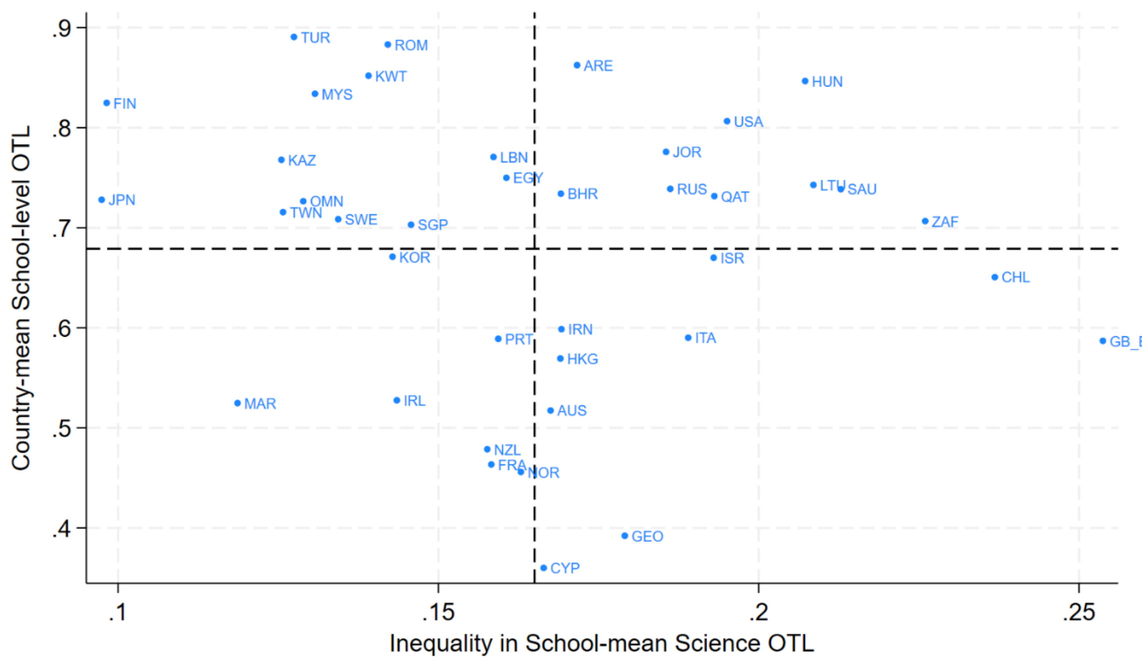

Figure 4.7 Inequality in School-mean Science OTL and Country-mean School-level OTL (TIMSS 2019)

Next, I descriptively examine the overall year-to-year and between-country variation in inequality in STEM OTL by plotting the side-by-side boxplot of the variance of school-mean math and science Curricular Experience (CE) over years. Examining the year-to-year variation, as shown in Figure 4.8, the variance of school-mean MCE is relatively stable across cohorts as most cohort-specific mean and median estimates are close to a .2 level. The within-year between country variation in dependent variables, on the other hand, is greater in early cohorts. This is likely due to greater variability involved in assigning students CE codes for the 1995 and 1999 cohorts.[43] Figure 4.9 reports the side-by-side boxplots of science DV. Looking at the year-to-year variation in cohort-specific median, the variances of school-mean SCE are stable across recent five cohorts, whereas the 1995 and 1999 cohorts show greater fluctuations across cohorts. The within-year between-country variation is also greater within the 1995 and 1999 cohorts than within the later five cohorts.

[43] There are more surveyed curricular topics in the TIMSS 1995 and 1999 studies than later studies, creating more variability across schools.

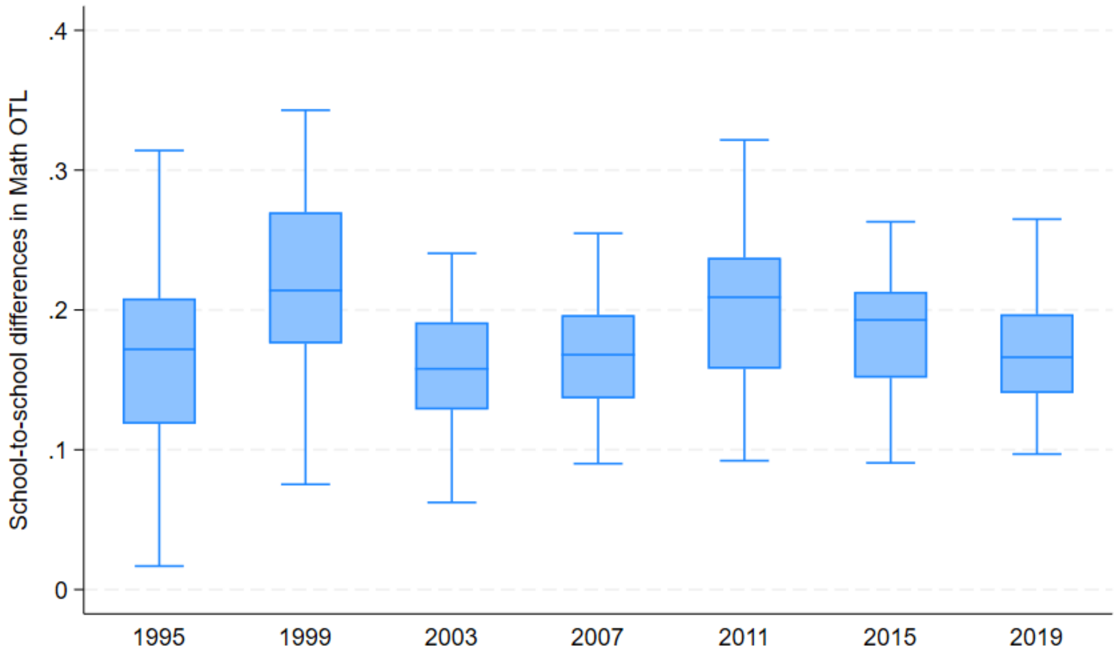

Figure 4.8 Side-by-Side Boxplot of School-to-school differences in Math OTL

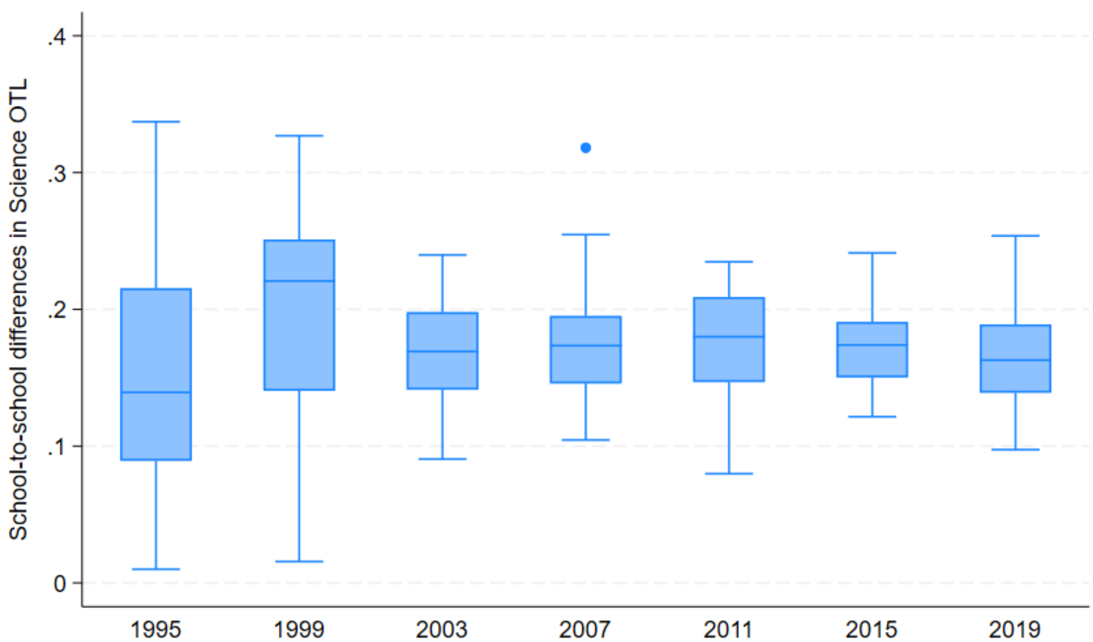

Figure 4.9 Side-by-Side Boxplot of School-to-school differences in Science OTL

4.4.2 Model Estimation Results

Tables 4.2 to 4.5 report the model estimation results concerning country-level inequality in math and science opportunity to learn, using Generalized Multilevel Linear Models and population-average models with GEE approaches. Tables 4.2 and 4.3 report generalized multilevel models exploring the sources of variation in Math and Science Curriculum Experiences (MCE and SCE), respectively, with the Gamma distribution and logarithmic transformation, using (1) country internal-development factors, (2) basic measures of social inequality, (3) school-to-school differences in average school readiness, and (4) country-level education policies concerning both stratification and standardization. Tables 4.4 and 4.5 then report results from population-average models which serve as robustness check in later analysis.

Table 4.2 Multilevel models: Country variance of school-mean Mathematics Curriculum Experience (MCE) as a function of internal development, social inequality, functionalism, and educational policy (Country-level covariates includes inequality in school resources, teacher quality, and geographic regions)

	Model 1	Model 2	Model 3	Model 4	Model 5
Year	-.001	-.003	-.006	-.015	.006
	(.009) [a]	(.008)	(.012)	(.011)	(.013)
Internal Development Factors					
Labor shift from agricultural sector (%)			-.005	-.005	.002
			(.004)	(.004)	(.008)
Size of non-agricultural sector (%)			.011~	.017*	.069**
			(.006)	(.008)	(.019)
Natural population increase rate (per 1,000 people)			.011**	.016**	.007
			(.004)	(.005)	(.005)
Tertiary education enrollment rate (%)			-.048**	-.033*	-.110**
			(.013)	(.012)	(.030)
GDP per capita (unit: 1000 US$)			.001	.002*	.002~
			(.001)	(001)	(.001)
Social Inequality Measures					
Index of inequality of rural population distribution (Standardized)		.028**	.140*	.177*	.110**
		(.007)	(.068)	(.078)	(.034)
Income GINI coefficient		.005	.020	.033	.007

		(.023)	(.023)	(.022)	(.022)
GINI Square		-.000	-.000	-.000	-.000
		(.000)	(.000)	(.000)	(.000)
Functionalism					
School-to-school differences in prior math achievement (standard deviation)				.092***	.101***
				(.017)	(.022)
Educational Policy					
Academic-based Promotion Policies					.031
					(.059)
Promotion × inequality of rural population distribution					-.013
					(.058)
Within-school sorting Policies					-.033*
					(.016)
Sorting × inequality of rural population distribution					.156**
					(.044)
High-stake Exam before 8th grade					.132
					(.112)
High-stake Exam × inequality of rural population distribution					-.058~
					(.033)
Country-level Covariates	No	No	Yes	Yes	Yes
σ_{ϵ}^{2}	.016	.015	.014	.012	.012
σ_{μ}^{2}	.015	.011	.010	.007	.007

a. Robust Standard errors in parentheses

*** p<.001, ** p<.01, * p<.05, ~ p<.1

Table 4.3 Multilevel models: Country variance of school-mean Science Curriculum Experience (SCE) as a function of internal development, social inequality, functionalism, and educational policy (Country-level covariates includes inequality in school resources, teacher quality, and geographic regions)

	Model 1	Model 2	Model 3	Model 4	Model 5
Year	.000	-.002	-.008	-.007	-.000
	(.001) [a]	(.011)	(.012)	(.013)	(.016)
Internal Development Factors					
Labor shift from agricultural sector (%)			-.002	-.002	.003
			(.006)	(.006)	(.009)
Size of non-agricultural sector (%)			-.016	-.016	-.017
			(.019)	(.018)	(.017)
Natural population increase rate (per 1,000 people)			.008*	.018*	.012**
			(.004)	(.008)	(.004)
Tertiary education enrollment rate (%)			.012	.001	.002
			(.012)	(.001)	(.002)

GDP per capita (unit: 1000 US$)			.000	.006*	.001
			(.001)	(.002)	(.001)
Social Inequality Measures					
Index of inequality of rural population distribution (Standardized)		.009	.085**	.088*	.104~
		(.006)	(.028)	(.038)	(.063)
Income GINI coefficient		.012	.022	.022	.007
		(.015)	(.020)	(.021)	(.011)
GINI Square		-.000	-.000	-.000	-.000
		(.000)	(.000)	(.000)	(.000)
Functionalism					
School-to-school differences in prior science achievement (standard deviation)				.053*	.052*
				(.021)	(.025)
Educational Policy					
Academic-based Promotion Policies					.038
					(.064)
Promotion × inequality of rural population distribution					-.015
					(.012)
Within-school sorting Policies					-.007
					(.012)
Sorting × inequality of rural population distribution					-.094
					(.087)
High-stake Exam before 8th grade					.043
					(.055)
High-stake Exam × inequality of rural population distribution					-.038
					(.031)
Country-level Covariates	No	No	Yes	Yes	Yes
σ_{ϵ}^2	.021	.021	.021	.021	.016
σ_{μ}^2	.007	.005	.005	.002	.001

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1

4.4.2.1 Hypothesis 4-1: The role of social inequality in generating educational inequality

I begin by examining the first Hypothesis of this chapter. Hypothesis 4-1 considers the intra-relationships among (1) a country's internal-development factors, (2) basic social inequalities, and (3) inequality in learning opportunities. In the baseline conceptual model depicted in Figure 4.1, a country's developmental stage produces the variation in basic social inequality, and social inequality in turn generates the inequality in opportunity to learn. After considering the generative processes of internal-development factors on social inequality (the evolution of social inequality), Hypothesis 4-1 states that the level of inequality in OTL should be responsive to basic forms of social inequality (Path A1 in Figure 4.1).

Models 2 and 3 from Tables 4.2 and 4.3 explicitly address this hypothesis. Model 2 only examines the extent to which variation in inequality in OTL is explained by basic social inequality, including urban/rural duality and income inequality, whereas Models 3 further considers all internal-development factors that are in the model. As shown in Table 4.2, Model 2, among two key elements of basic social inequality, the urban/rural duality is positively associated with the variance of school-mean MCE, whereas the partial effect of income inequality beyond urban/rural duality is not significant. Further in Model 3, I show that after considering internal-development factors, urban/rural duality remain positively associated with the variance of school-mean MCE, supporting that the level of inequality in OTL may be responsive to the basic social inequality, net of a country's development stage. Concerning the effect size in this baseline framework (Figure 4.1), Model 3 shows that a one standard deviation increase in urban/rural duality is related to a 15% increase in the variation in school-mean MCE ($e^{.140} - 1 = 15.02\%$), without considering the joint effect carried through income inequality. It is worthwhile to note that Model 3 also shows some direct effects of development stage on the level of inequality in OTL (Figure 4.1, Box 1 to Box 3). For example, the development of the non-agricultural sector and the increase of population are both positively associated with the level of inequality in OTL, while the expansion of tertiary education helps reduce the inequality in Math OTL as it has negative association with the DV.

Table 4.3, Models 2 and 3 report the results of the inequality of Science OTL using the same model specification. However, Model 2 fails to show the basic associations between social inequality and the variation of school-mean Science Curricular Experiences. Yet, after considering all internal-development factors in Model 3, I find a positive association between urban/rural duality and the science DV, providing some evidence that a country's level of inequality in STEM Opportunity to Learn is in fact responsive to basic social inequality, net of the evolution of social inequality due to development.

4.4.2.2 Hypothesis 4-2: Functional sources of school-to-school differences in OTL: Variation in school readiness

Next, I further explore the functional and conflict sources of inequality in OTL. Following the empirical work by Kelly and Price (2011), I argue that Path A1 in Figure 4.1 may ambiguously mix the technical-functional rationale and conflict forces of curriculum differentiation, and should be identified individually. Hypothesis 4-2 states that if the variation in school readiness/prior achievement in Box 4 can explain most of the relationship between social inequality and variation in school-level Opportunity to Learn (Path C), then the level of educational inequality is better characterized as reflecting technical-functional considerations. If, however, after controlling for this functional pathway, we can still observe significant relationships between social inequality and variation in school-level Opportunity to Learn, path A2 can be characterized as reflecting conflict processes.

Model 4 from Tables 4.2 and 4.3 explicitly address this empirical consideration by adding a key functional determinant of tracking, school-to-school differences in prior achievement, to Model 3. As shown in Table 4.2, Model 4, school-to-school differences in prior math achievement is positively associated with the variance of school-mean MCE, indicating an apparent technical-functional explanation of school-to-school differences in learning opportunities. Concerning the effect size, a one standard deviation increase in school-to-school differences in prior math achievement is related to a 9.6% increase in the school-to-school differences in math OTL. Yet, even considering this basic functional mechanism, Model 4 still shows a positive association between the basic social inequality and math DV, indicating some conflict forces that might motivate between-school curriculum tracking. While weaker in effect sizes, Table 4.3, Model 4 also shows a positive association between functionalism and inequality in Science OTL. The remaining relationship between social inequality and inequality in OTL is still positive, after considering the key functional factor. Overall, both math and science results provide some evidence that the between-school tracking may in fact be motivated by both technical-functional and conflict sources.

4.4.2.3 Hypothesis 4-3: Stratification and standardization policies as moderator

Lastly, this analysis explores *moderation* effects of major educational policies. Such moderation effects are often addressed in cross-national studies (e.g., Park, 2008) that consider how various educational stratification and standardization policies impact the basic relationship between social inequality and educational inequality (Figure 4.3). In Figure 4.2, I disentangle the relationship between social inequality and inequality in OTL into a technical-functional pathway (Path C) and a conflict pathway (Path A2). I thus argue that the test of moderation effect of educational policies should be conducted on the remaining relationship between social inequality and inequality in OTL (i.e., the conflict pathway), rather than the total association (i.e., Path A1). Hypothesis 4-3 states that practicing stratification policies (i.e., early sorting and gate-keeper courses) may exacerbate the effect of social inequality on inequality in OTL, while practicing standardization policies (i.e., national entrance examinations) may attenuate this effect instead.

Model 5 from Tables 4.2 and 4.3 explore Hypothesis 4-3 by adding the interaction terms between social inequality and dummy indicators of educational policies. As shown in Table 4.2, Model 5, the interaction term between urban/rural duality and the dummy indicator of national policy using student achievement to sort students before the end of 8th grade is positively associated with the variance of school-mean MCE, indicating an **exacerbation** effect of stratification policies on the relationship between social inequality and educational inequality. In particular, the effect of urban/rural duality on the variation in school-mean MCD among countries with national-level within-school sorting policies are 16.9% ($e^{.156} - 1 = 16.9\%$) higher than the effects among countries without such policies. On the other hand, the interaction term between urban/rural duality and the dummy indicator of national examinations that have high-stakes consequence for individual students before the end of 8th grade has a significant negative effect on the dependent variable, instead indicating an **attenuation** effect of country-level standardization policy on the relationship between urban/rural duality and the variation in STEM OTL. Referencing model-based calculations, a country with high-stake examinations, on average, has a 5.6% decrease in the effect of urban/rural duality on the variation in math OTL than a country without high-stake exams. The interaction terms between these policies and social inequality, however, shows no moderation effect on the Science DV. It's worthwhile to note that the measurement of educational policy in this analysis relies on country-level curriculum questionnaires, even as policy implementation may vary within countries in important ways. Therefore, the analysis in this sub-section is influenced by that measurement error.

4.4.3 Robustness Analysis

In this analysis, I consider two sets of robustness analysis to support the main analysis. First, to support the estimations of important country-to-country differences in the variation in STEM OTL, I explicitly model the country-specific effect of country-level composition by running a series of population-average models with GEE estimator. Population-average models explore average country-level effects, with the assumption that the country-level independent variables have constant effects on dependent variables across years. Table 4.4, Models 1 and 2 summarize the population-average model estimation of the variation in school-mean MCE and SCE, respectively, using the full model specification in Tables 4.2 and 4.3. In general, population-average model estimation results are similar to the results from multilevel modeling. First, in supporting Hypothesis 4-1, I find positive associations between urban/rural duality and the variance of school-mean MCE and SCE, net of internal-development factors. Considering Hypothesis 4-2, in this robustness analysis, I find evidence that supports both functionalism and conflict pathways of between-school curriculum tracking in this cross-national setting. While the evidence that support Hypothesis 4-3 may be less apparent, I find that education policies concerning early sorting and high-stake examination appear to moderate the associations between school-to-school differences and social inequality, net of a country's development stage and functional pathways of tracking.

Table 4.4 Robustness Check using Population Average Models: Country variance of school-mean Mathematics Curriculum Experience (MCE) and Science Curriculum Experience (SCE) as a function of internal development, social inequality, functionalism, and educational policy (Country-level covariates includes inequality in school resources, teacher quality, and geographic regions)

	Model 1: Math CE	Model 2: Science CE
Year	.005	.001
	(.013)	(.001)
Internal Development Factors		
Labor shift from agricultural sector (%)	.005	.003
	(.007)	(.010)
Size of non-agricultural sector (%)	.084*	-.006
	(.038)	(.008)
Natural population increase rate (per 1,000 people)	.007*	.013**
	(.003)	(.004)

Tertiary education enrollment rate (%)	-.131**	.002
	(.035)	(.001)
GDP per capita (unit: 1000 US$)	.002~	.001
	(.001)	(.001)
Social Inequality Measures		
Index of inequality of rural population distribution (Standardized)	.077**	.139**
	(.028)	(.024)
Income GINI coefficient	.015*	.009
	(.008)	(.012)
GINI Square	-.000	-.000
	(.000)	(.000)
Functionalism		
School-to-school differences in prior math/science achievement (standard deviation)	.104***	.049*
	(.022)	(.023)
Educational Policy		
Academic-based Promotion Policies	.026	.034
	(.060)	(.061)
Promotion × inequality of rural population distribution	.007	-.005
	(.005)	(.052)
Within-school sorting Policies	-.067**	-.026*
	(.013)	(.011)
Sorting × inequality of rural population distribution	.117*	.072
	(.054)	(.074)
High-stake Exam before 8^{th} grade	-.015	.044
	(.044)	(.052)
High-stake Exam × inequality of rural population distribution	-.059*	.042
	(.029)	(.047)
Country-level Covariates	Yes	Yes

Second, I model an alternative dependent measure concerning the percentage of high-level *Algebra* topics learned (as opposed to all math topics) as a function of internal-development stages, social inequality, functionalism, and education policies. Table 4.5, Model 2 shows that the country-level variance of school-mean percentage of high-level Algebra topics learned is positively associated with both measures of social inequality (income inequality and urban/rural duality), net of a country's development stage. Model 3 further examines the Hypothesis 4-2 and supports that the alternative math DV is also positively related to both functional and conflict sources of between-school tracking. Concerning Hypothesis 4-3, this alternative analysis only supports the **exacerbation** effect of early-sorting policies on the relationship between social inequality and educational inequality.

Table 4.5 Robustness Check using Multilevel Models: Alternative measures, country variance of school-mean percentage of high-level Algebra topics learned as a function of internal development, social inequality, functionalism, and educational policy (Country-level covariates includes inequality in school resources, teacher quality, and geographic regions)

	Model 1	Model 2	Model 3	Model 4
Year	.016	.015	.007	.012
	(.011)	(.013)	(.012)	(.012)
Internal Development Factors				
Labor shift from agricultural sector (%)		.006	.005	.006
		(.007)	(.007)	(.009)
Size of non-agricultural sector (%)		.017*	.017*	.061**
		(.008)	(.008)	(.018)
Natural population increase rate (per 1,000 people)		.016***	.016**	.009~
		(.004)	(.005)	(.005)
Tertiary education enrollment rate (%)		-.033*	-.020*	-.080***
		(.015)	(.008)	(.016)
GDP per capita (unit: 1000 US$)		.001	.002~	.004**
		(.001)	(.001)	(.001)
Social Inequality Measures				
Index of inequality of rural population distribution (Standardized)	.011	.040*	.081*	.111*
	(.013)	(.013)	(.041)	(.049)
Income GINI coefficient	.012	.038*	.032*	.024
	(.008)	(.013)	(.015)	(.026)
GINI Square	-.000	-.000	-.000	-.000
	(.000)	(.000)	(.000)	(.000)
Functionalism				
School-to-school differences in prior math achievement (standard deviation)			.079**	.103**
			(.028)	(.034)
Educational Policy				
Academic-based Promotion Policies				.083
				(.066)
Promotion × inequality of rural population distribution				-.024

				(.064)
Within-school sorting Policies				.138
				(.168)
Sorting × inequality of rural population distribution				.209*
				(.102)
High-stake Exam before 8th grade				.082
				(.059)
High-stake Exam × inequality of rural population distribution				-.030
				(.027)
Country-level Covariates	No	Yes	Yes	Yes

4.5 Discussion and Conclusions

Following a similar theorical paradigm of curriculum tracking considered in Chapter 3, this empirical chapter investigates the social determinants of school-to-school differences in math and science course-taking experiences, a key component of Opportunity to Learn (OTL), in a cross-national setting using a large cross-national sample with 278 observations across 67 countries, dating from 1995 to 2019. Drawing on basic theoretical perspectives of social inequality and educational stratification, this chapter proposes a conceptual framework that helps trace the fundamental sources of educational inequality. The framework incorporates traditional developmental theories of the evolution of inequality and social theories of curriculum tracking and advocates a comprehensive consideration of country-level development and social stratification processes in cross-national studies of educational inequality.

Concerning *Hypothesis 4-1*, this chapter first examines the association between basic social inequality and inequality in Opportunity to Learn. The internal-development framework describes the way in which the pattern of basic social inequality (i.e., unequal distribution of income and population) evolves as a country develops. This analysis then finds that the unequal distribution of learning opportunities at the country level follows a similar pattern of the basic social inequality, even after considering the generative effect of internal development on the basic social inequality. Specifically, this analysis explores two different forms of basic social inequality, income inequality and urban/rural duality, which both contribute to the overall conceptualization of basic social inequality. The main model estimation results reported in Table 4.2 and 4.3 indicate that urban/rural duality, as an important form of social inequality, is significantly positively associated with inequality in opportunity to learn. Yet, the remaining partial effect that is carried through income inequality is only positive but not significant in main models. Later in ancillary models reported in Table 4.5, I find that both forms of social inequality are significantly associated with inequality in math (mainly concerning algebra topic levels) opportunity to learn.

This Chapter further draws attention to social theories of curriculum tracking which speaks to both a fundamental technical-functional logic of tracking and conflict forces that are related to maintaining and producing more differentiated course-taking experiences. Theories of tracking help unpack the equivocal link between social inequality and inequality in learning opportunities; that is, the design and practices of school curriculum systems may bear the pedagogical consideration of teaching students with unequal distribution of school readiness, but school tracking systems may in fact favor high-SES and other advantaged social groups (see also discussion in Chapter 3).

Concerning the technical-functional sources of tracking, this chapter examines the way in which school-to-school differences in opportunity to learn is responsive to school-to-school differences in school readiness. *Hypothesis 4-2a* states that if a country's school tracking system relates to a functional logic, school-to-school differences of opportunity to learn may follow the distribution of academic readiness/prior achievement at the school level. Consistent with

Hypothesis 4-2a, this study finds a strong positive association between school-to-school differences in school-mean math and science opportunity to learn and between-school prior achievement disparity, which speaks to a clear technical-functional pathway of between-school tracking. Concerning the effect size, recall that a one standard deviation increase in school-to-school differences in prior math achievement is related to nearly a 10% increase in school-to-school differences in opportunity to learn.

However, this study finds a strong positive association between social inequality and school-to-school differences in opportunity to learn, even after considering the unequal distribution of school readiness. This result implies a set of conflict forces that are related to educational inequality in this cross-national setting. Previously in Chapter 3, I discussed a broad array of socio-political processes that both motivated high-SES families and exerted external pressures for schools to explicitly promote differentiated curricular systems. While a cross-national research setting may not enable a micro-level analysis of complicated organizational processes of curriculum differentiation, this analysis emphasizes likely conflict sources of school-to-school differences in opportunity to learn.

Relatedly, this study also examines the role of educational standardization and stratification policies in moderating the effect of conflict forces on school-to-school differences in OTL. While limited by data quality, this analysis finds evidence that, to some extent, supports *Hypothesis 4-3*. I find that policies concerning stratification, in the form of promoting early sorting, exacerbate the association between inequality in OTL and social inequality. Early sorting policies use students' measured achievement to determine school placements. Because students' school readiness is so tied to their family background, promoting early sorting based on academic achievement will exacerbate the role of family background in determining school placements. On the other hand, this analysis finds that standardization, in the form of high-stake examinations, attenuates the strong link between social inequality and inequality in OTL. High-stake examinations are used in many Asian countries, where country/province/state-level prescribed curriculum standards are in place. Standardized testing policies may push schools to implement a similar curricular system, regardless of students' average readiness and family background.

This chapter resonates with the 4th United Nations' Sustainable Development Goal (SDG) concerning inclusive and equitable education for all. This Sustainable Development Goal primarily focuses on ensuring that all children complete "free, equality and quality" primary and secondary education, with extended target of eliminating educational inequality due to between-group disparities (e.g., rural/urban and bottom/top wealth disparities, see also UN-SDG, Target 4.1 and 4.4). As documented by the United Nations, in 2019, only one third of and one sixth of countries or territories achieved urban/rural and bottom/top wealth parity in primary school completion, respectively. Regarding post-secondary enrollment, virtually no countries or territories achieved rural/urban and wealth parity (see also UN website, Goal 4 Progression). This analysis contributes to the examination of educational inequality globally by creating measures of and exploring inequality in opportunity to learn, an important component of education inequality. In particular, this analysis argues that the valuable STEM learning opportunities still disproportionately benefit students with advantaged backgrounds, with the consideration of developmental stages and functional considerations, an often-ignored conceptual source of differentiation in learning opportunities.

To interpret the findings, I should note that the results are derived from a cross-national sample with only 278 country-year observations, and the interpretation should not go beyond a country-level framework. For example, this analysis does not demonstrate the way in which individual schools create within-school between-classroom or even within-classroom curriculum differentiation. Limited by data quality, this analysis does not explicitly consider the actual level of learning opportunities that each student received during middle schools. The topic codes utilized in this analysis involve more measurement error compared to other commonly used measures of learning opportunities, such as transcript-based measures in previous chapters. The actual effect size of the associations examined in this analysis may be larger since the measurement error involved in DVs bias the estimation downwardly. The “unbiased” relationship between inequality in school-mean opportunity to learn and key predictors may be in fact even more positive than estimated in Tables 4.2 and 4.3. It’s also worth noting that, although I examine the moderation effects of policies, this analysis does not explicitly advocate that countries should implement any single educational policies solely in order to mitigate inequality in OTL, such as promoting high-stake exams to reduce the role of social inequality in generating inequality in OTL.

Future research that aims to examine inequality in opportunity to learn and to promote education equity globally may further explore the realized unequal distribution of learning opportunities at the school and student level. This may include collecting more nuanced course-taking data, creating more reliable measurement schemes of students’ course-taking and instruction experiences, and more explicit modeling strategies. Regarding future research that utilizes the theoretical framework in this study, they may extend the existing framework to explore more complex conceptual models. For example, this framework can be further applied to examine the role of inequality in opportunity to learn in creating inequality in educational attainment, with a more systematic consideration of developmental stages, social inequality, and functional logics. Future research that focuses on cross-national tracking may also further examine the role of policy trends and emphasis of equitable education and learning opportunities. Doing so may require intensive data collection processes of country-, state/province/district-, and school- level curriculum policy design and implementation.

Chapter 4 presents a conceptual framework that can be used to systematically understand the relationships among country development, social inequality, and curriculum tracking in cross-national research settings. While inferentially limited, this framework helps identify and conceptualize the technical-functional and conflict sources of between school tracking which are often less-emphasized in cross-national studies.

5.0 Chapter 5. Conclusion

Ever since the comprehensive school model was introduced in the early 1920s, US high school curriculum systems have started to arouse waves of debates and reforms that tackle the design of curriculum tracking. To systematically understand curriculum tracking, and the results of this dissertation study, it might be helpful here to pose two questions about tracking and the larger context of schooling. Fundamentally, tracked curriculum systems seek to provide students with an "appropriate" level of instruction that benefits their learning due to *technical* pedagogical considerations. In the aggregate or collectively, curriculum differentiation may also be *functionally* responsive to the development of a society, much as the early design of the US comprehensive high schools promoted differentiated programs to meet the society's needs of both vocational and academic education (Wraga, 2000). But *have school tracking systems gone too far away from the technical-functional considerations towards disproportionately benefiting a small group of students*? On the other hand, tracking occurs within the context of ongoing efforts to promote equal and high-quality education for all students, which has improved overall educational achievement and attainment and reduced overall educational inequality (e.g., Gamoran, 2004). But *might these efforts have promoted changes in curriculum tracking that ignore the instructional needs of different students and create too many or too little challenges for students with various levels of readiness*? Although I can't fully answer these questions about what an ideal tracking system *should* look like, or what caused the trends seen in the data, this dissertation study examines various social theories of tracking and hopes to draw attention to a more systematic understanding of curriculum tracking.

In this dissertation, I find much evidence of the *positive logic* of tracking and functionalism. First, the descriptive analysis of NCES datasets reveals that over the period of 1982-2013, US high schools increasingly provided STEM learning opportunities and promoted more students to higher-level STEM courses. For example, school-mean math sequence levels rose by almost 70% from 1982 to 2013, while math inclusiveness went up by 155% over the same period of time. Moreover, the standard deviation of school-mean math sequence level and inclusiveness have both become smaller in later decades. Thus, US high schools not only provide more opportunity to learn in math, but also vary less across schools in more recent decades. Levels of science course taking and inclusiveness have increased by 65% and 263%, respectively. Relatedly, descriptive analysis of the structure of tracking shows that US high school STEM curriculum systems have become less selective and more flexible. Collectively, although not directly investigated here, these results imply that US high schools, in general, are positioned to provide more STEM learning opportunities for students from diverse backgrounds.

Second, when the relationship between level-related measures of tracking and school composition is examined, this dissertation study reveals more evidence of the positive logic of tracking. I find strong evidence that level-related measures of course taking have stable relationships with relevant measures of achievement, a rational and logical consideration affecting patterns of course taking. Under a functional logic, we would expect schools to provide higher-level courses for students with advanced readiness. This analysis also finds a stable association between various measures of school heterogeneity and level-related measures of course taking, indicating that diverse schools also tend to have higher school-mean course-taking levels. This result may speak to a general competition among all students, not just high-SES students, that may drives up the overall level of course taking. Moreover, although this analysis shows a positive association between school-mean SES and course taking levels, indicating that high-SES parents and students actively seek advanced courses, this relationship has become generally weaker in later decades.

Finally, analyses of how school composition affects the organizational dimensions (structure) of tracking also reveal a functional logic. I find a strong technical-functional logic in the relationship between measures of achievement and the variance of STEM course taking, as well as Math Selectivity. Moreover, the relationship between Math Selectivity and functional predictors has become even stronger in recent decades. This may indicate that schools are responsive to heterogeneity in student academic readiness when designing differentiated curriculum systems. Overall, considering all evidence of functionalism, this study reveals rational and logical means of providing students with rigorous instruction, and of exposing students to differentiated curricular settings, remain important in US high school curriculum systems.

However, this dissertation study also finds some evidence, reflecting negatively on tracking systems, that US high school tracking systems are not fully functional. First, although the mean level of STEM course taking has increased, I find larger school-to-school differences in science course taking and Inclusiveness in later decades. Second, this analysis shows that the variance of both student math sequences and STEM tracking Selectivity are related to measures of school composition that indicate processes of status competition may be at work. Furthermore, the compositional measures that likely generate status competition are increasingly associated with STEM tracking selectivity over the period of this analysis. In all, in higher-SES school contexts I find more rigorous course taking, but also more differentiated, and more selective course taking. If these associations reflect status competition processes, the result is both more inequality (in the form of increased differentiation/variation in course taking), but perhaps also more motivation in these school contexts for parents and students to actively seek advanced courses. As in prior research (Kelly & Price, 2011), I find very little evidence to support an opportunity hoarding view of tracking.

In addition to the positive and negative trends, associations, and changes in associations summarized thus far, I find that much about how schools differentiate students' course taking remains unexplained. First, the correlational analysis shows that the various organizational dimensions of tracking considered in this study do not go tightly hand-in-hand with each other. This result departs from prior studies of tracking policies (Kelly, & Price, 2011) that found much higher inter-dimensional correlations between dimensions of tracking and used the formative construct of "the overall elaboration of tracking" to describe school-to-school variation in tracking systems. This inconsistency may be due to the fact that the actual realized measures of tracking considered in this analysis reveal more variation across schools than curriculum policies and guidelines. Yet, the measures of realized tracking structure likely also involve more measurement error (including sampling error). Moreover, in the multivariate models , the amount of variation in tracking structures across schools that is explained is generally quite low, leaving a large amount of unexplained variation.

Finally, in Chapter 4, I extend the framework used in Chapter 3, to investigate another form of curriculum differentiation, between-school tracking, in a cross-national setting. In this chapter, I first model the generative effect of basic social inequality on tracking, net of internal-development processes. Similar to Chapter 3, Chapter 4 then considers between-school achievement heterogeneity as a key functional factor, identifying the remaining association between social inequality and tracking that can more narrowly be attributed to conflict forces. In this chapter, I find that both functional and conflict pathways are related to greater school-to-school differences in learning opportunity. The theoretical framework in Chapter 4, although limited inferentially by the lack of richer measures of opportunity to learn, serves as an important reference for future research that explicitly examines inequality in opportunity to learn.

Appendix A Coding Process for Course Sequence Codes used in NCES Chapter

The coding of Mathematic Course Sequence (MCS) codes starts with assigning ten-level individual math course code to each course. As shown in Appendix Table 1, 1 represents math courses whose difficulty or requirement were lower than algebra I. These could be some informal math course or introductory courses for math in general. 2 represents algebra I or other courses with equal difficulty or requirement. Any algebra I sequence course is coded as 2 as well (i.e. algebra I part 1 and part 2 are both coded with 2). 3 represents geometry or other equal courses. 4 represents courses that are harder than Algebra 1 or equal courses but are not at the same level as Algebra 2. This code also includes courses that apply knowledge from Algebra 1 or other equal courses but not knowledge from Algebra II or higher-level courses. Courses coded with 4 are courses that transit from 1-3 to 5 or higher. 5 represents Algebra II or other equal courses. 6 represents applied math elective courses that include any course that may apply theories or knowledge from algebra II and/or geometry courses. Although these courses are based on prior courses, courses that are only based on pre-algebra or algebra I are not included. The intention for adding applied math elective code is to distinguish those students who finish algebra II and geometry and turn to other courses that apply knowledge they have learned from students who stop after finishing algebra II and geometry. 7 represents Algebra III and other higher-level algebra courses like number theory. 8 represents trigonometry and mathematic analysis courses. 9 represents Calculus and other equal courses that are based on pre-calculus, trigonometry, or algebra III. Finally, 10 represents courses that are harder than calculus. These may include higher level calculus courses, applied calculus courses that are based on calculus.

NCES uses the Classification of Secondary School Courses (CSSC) to classify courses transcribed from the 1982 (HS&B), 1992 (NELS:88), and 2002 (ELS:2002) cohorts, and the School Courses for the Exchange of Data (SCED) to classify courses from the 2013 cohort (HSLS:09). See Appendix Table 2 for complete individual mathematic course codes with SCED codes and Appendix Table 3 for individual math course codes with CSSC codes. The Mathematic Course Sequence (MCS) codes capture cumulative course-taking experiences and start with 1–less than algebra I and end with 9–calculus or higher. Students with higher MCS values have deeper, and richer mathematic learning experiences than students with lower values. The full cumulative Mathematics Course Taking codes are shown in Table 2.1 from main text.

Appendix Table 1 Ten-level individual math course code

Individual math code	Description
1	less than Algebra 1
2	Algebra 1
3	Geometry
4	Transition
5	Algebra 2
6	Applied math elective
7	Algebra 3 and equal
8	Trigonometry and equal
9	Calculus and equal
10	Higher than "Calculus"

Appendix Table 2 Complete individual mathematic course codes using SCED codes

Course name	SCED code	Indiv. Code	Course name	SCED code	Indivi. Code
Informal Mathematics	02001	1	Mathematic Analysis/Analytic Geometry [1]	02108	8
General Mathematics	02002	1	Elementary Functions [2]	02109	8
Particular Topics in Foundation Mathematics	02003	1	Pre-Calculus	02110	8
Mathematics (early childhood education)	02028	no obs[3]	Linear Algebra [4]	02111	9
Mathematics (pre-kindergarten)	02029	no obs	Linear Programming [5]	02112	9

Mathematics (kindergarten)	02030	no obs	Abstract Algebra [6]	02113	9
Mathematics (grade 1)	02031	no obs	Calculus	02121	9
Mathematics (grade 2)	02032	no obs	Multivariate Calculus [7]	02122	10
Mathematics (grade 3)	02033	no obs	Differential Calculus [8]	02123	10
Mathematics (grade 4)	02034	no obs	AP Calculus AB [9]	02124	9
Mathematics (grade 5)	02035	no obs	AP Calculus BC [10]	02125	10
Mathematics (grade 6)	02036	no obs	Particular Topics in Calculus [11]	02126	9
Mathematics (grade 7)	02037	no obs	IB Mathematical Studies[12]	02131	8
Mathematics (grade 8)	02038	no obs	IB Mathematics [13]	02132	8
Mathematics—General	02039	no obs	IB Further Mathematics—HL [14]	02134	8
Foundation Mathematics—Independent Study	02047	1	IB Mathematics, Middle Years Program[15]	02135	7
Foundation Mathematics—Other	02049	1	Finite Mathematics	02136	no obs
Pre-Algebra	02051	1	Mathematical Modeling	02137	no obs
Algebra I	02052	2	College Mathematics Preparation	02138	no obs
Algebra I—Part 1	02053	2	Particular Topics in Analytic Mathematics	02141	7
Algebra I—Part 2	02054	2	Analytic Mathematics—Other	02149	7
Transition Algebra [16]	02055	4	General Applied Mathematics [17]	02151	4
Algebra II	02056	5	Occupationally Applied Mathematics [18]	02152	4
Algebra III	02057	7	Technical Mathematics [19]	02153	6
Particular Topics in Algebra[20]	02058	4	Business Mathematics [21]	02154	6
Integrated Mathematics I	02062	no obs	Business Mathematics with Algebra [22]	02155	6
Integrated Mathematics II	02063	no obs	Computer Mathematics with Algebra [23]	02156	4
Integrated Mathematics III	02064	no obs	Consumer Mathematics[24]	02157	1
Integrated Mathematics IV	02065	no obs	Probability and Statistics	02201	7
Algebra—Other [25]	02069	Dep.	Inferential Probability and Statistics	02202	7
Informal Geometry	02071	1	AP Statistics	02203	9
Geometry	02072	3	Particular Topics in Probability and Statistics [26]	02204	6
Analytic Geometry[27]	02073	6	Statistics	02205	no obs

Principles of Algebra and Geometry [28]	02074	6	Probability and Statistics—Independent Study	02207	no obs
Particular Topics in Geometry[29]	02075	3	Probability and Statistics—Other [30]	02209	Dep.
Geometry—Other [31]	02079	3	History of Mathematics	02991	1
Number Theory[32]	02101	7	Mathematics—Test Preparation[33]	02993	6
Discrete Mathematics[34]	02102	9	Mathematics Proficiency Development [35]	02994	Dep.
Trigonometry	02103	8	Mathematics—Aide [36]	02995	Dep.
Mathematic Analysis	02104	8	Mathematics—Supplemental[37]	02996	Dep.
Trigonometry/Mathematic Analysis	02105	8	Mathematics—Independent Study[38]	02997	6
Trigonometry/Algebra	02106	8	Mathematics—Workplace Experience [39]	02998	5
Trigonometry/Analytic Geometry	02107	7	Mathematics—Other	02999	Dep.
			Undefined	02061	Dep.

Foot Note:

1 Mathematic Analysis/Analytic Geometry prepares students eventually qualified in Calculus courses.

2 Elementary Functions prepares students eventually qualified in Calculus courses.

3 There is no observation on HSLS Transcript Students Course File.

4,5 Linear algebra and linear programming require students to finish pre-calculus or equal courses.

6 Abstract Algebra requires students to finish pre-calculus or equal courses.

7,8 Multivariate Calculus and Differential Calculus include topics that are based on calculus. In the meanwhile, to justify this coding level, I examined typical trajectories of students who took these two courses and found that students usually took Calculus and/or AP Calculus AB before these two courses if Multivariate Calculus or Differential Calculus was not the only calculus course they had ever taken.

9 Students usually took AP Calculus AB after Calculus if AP Calculus AB was not the only calculus course they had ever taken. However, according to course descriptions, AP Calculus AB shared the similar topics as Calculus including derivatives, differentiation, integration, the definite and indefinite integral, and applications of calculus.

10 Students usually took AP Calculus BC after Calculus and/or AP Calculus AB. In the meanwhile, in addition to topics covered by AP Calculus AB, AP Calculus BC covers parametric, polar, and vector functions; applications of integrals; and polynomial approximations and series, including series of constants and Taylor series.

11 To identify this coding level, I examined typical trajectory of students who took this course and found that students usually took Particular Topics in Calculus independently (i.e. Particular Topics in Calculus was usually the only calculus course students took if they chose to take Particular Topics in Calculus). I coded this course as equal as Calculus because, in some scenarios, Particular Topics in Calculus is the replacement course for Calculus.

12,13 These two IB courses prepare students to take IB math studies at standard level. Courses includes topics from algebra III, number theories, and trigonometry, but only introductory level calculus.

14 This IB course prepare students to take IB math studies at higher level. Course topics include Calculus and other high-level topics.

15 Instead of preparing student to take IB exam, IB Mathematics, Middle Years Program is built on a framework of five branches of mathematics: number, algebra, geometry and trigonometry, statistics and probability, and discrete mathematics. The program encourages students to develop an understanding of mathematical reasoning and

processes, the ability to apply mathematics. Students usually took this course on 9th grade and 10th grade (84.7% of students took Middle Year Program on 9th grade and/or 10th grade). As a contrast, students usually took IB Mathematics or IB Mathematics studies on 11th or 12th grade (78.4% and 89.3% of students took these two IB courses on 11th and/or 12th grade, respectively). Therefore, I coded Middle Year Program one level lower than IB Mathematics or IB Mathematics.

16 Transition Algebra courses review and extend algebra and geometry concepts for students who have already taken Algebra I and Geometry. Although, similar to Algebra II where students usually took it on 10th and/or 11th grade (77.8%), students usually took Transition Algebra after 9th grade (88.5%), Transition Algebra did not sufficiently apply knowledge harder than Algebra I series or Geometry. Therefore, I coded Transition Algebra as "4-transition".

17,18 General Applied Mathematics and Occupationally Applied Mathematics applied knowledge from Algebra I and used these skills in specific fields. However, similar to Transition Algebra, these two courses did not apply knowledge and skills from Algebra II or equal courses. Therefore, these two courses should belong to 4.

19,21,22 Technical Mathematics, Business Mathematics, and Business Mathematics with Algebra sufficiently applied basic principles from Algebra I, Algebra II and Geometry. I code these three courses as "applied math elective" because, although they combine principles of Algebra and geometry, they do not adequately provide solid theoretical background as pre-calculus does.

20 Particular Topics in Algebra built upon topics from pre-Algebra and Algebra I and examine specific topics such as linear equations or rational numbers. More than half of students usually took this course before 10th grade (56.8%). Compare to Algebra II where only less than 10% of students took Algebra II before 10th grade (7.8%), I coded Particular Topics in Algebra as "4-between Algebra I and Algebra II"

23 Intended for students who have attained the objectives of Algebra I, Computer Mathematics with Algebra courses include a study of computer systems and programming and use the computer to solve mathematics problems. However, this course did not applied knowledge higher than Algebra I.

24 Consumer Mathematics only applied knowledge from pre-Algebra such as arithmetic using rational numbers, measurement, ratio and proportion, and basic statistics to consumer problems and situations. Therefore, I coded this course as pre-Algebra.d

25 The level of Algebra-other depended on individual courses that students had taken. For example, Algebra Lab for ninth graders, or College Algebra and Intermediate Algebra for 12th graders both belonged to Algebra-Other.

26 Particular Topics in P&S usually covered topics such as elementary statistic and general statistic topics. Therefore, I coded this course one level lower than Statistic.

27,28 These courses apply basic principles from algebra I, and algebra II into studying of geometry. I code these two courses as "applied math elective" because, although they combine principles of Algebra and geometry, they do not adequately provide solid theoretical background as pre-calculus does.

29 Out of 680 students who took Particular Topics in Geometry, 490 students (72.0%) took this course as the only geometry course along four-year high school as the replacement of general Geometry and/or advanced level geometry courses. Therefore, I coded this course as a transition level course (4).

30 The category of P&S-Other contained courses for different levels of students. For example, there were introductory statistic courses for 10th grade, and advanced statistic, college statistic, and advanced mathematical decision making for 12th grade.

31 Unlike Algebra-Other with diversified content for students in different grades, student usually took Geometry-Other before 11th grade (70.3%). As a contrast, 80.2% of students took Geometry before 11th grade. Out of 370 students who took Geometry-Other, 250 students (67.4%) took this course as the only geometry course along their four-year high school as the replacement of general Geometry and/or advanced level geometry courses. Therefore, I coded this course as a transition level course (4).

32 This course reviews the properties and uses of integers and prime numbers which prepare students with higher level course, Discrete Mathematics. Part of theories in this course may be covered in Algebra III.

33 This course prepares students with test skills in PSAT, SAT and ACT. Topics include knowledge in algebra I and II and geometry.

34 Discrete Mathematics is built upon Algebra III and Number theory which is a higher-level course.

35-37 The level of these three courses are hard to be decided because the content of these courses depends on grade level.

38 Students usually took this independent study (70.1%) after 10th grade. The goal of this course was to expand their expertise in a particular application, to explore a topic in greater detail, or to develop more advanced skills based on courses they had taken on first two years. However, this independent study was not necessarily the subsequent course of Algebra III and other higher level courses. Therefore, I coded this course as an elective math course.

39 Mathematics—Workplace Experience was not usually part of math sequence (i.e. students might take calculus at 11th grade and then take Mathematics—Workplace Experience at 12th grade for other reasons). Therefore, although more than 60% of students took Mathematics—Workplace Experience after 10th grade, it's hard to decide the level of Mathematics—Workplace Experience based on trajectories. According to course description, there was not a solid math inquiry associated with this course, Mathematics—Workplace Experience set cooperatively by the student, teacher, and employer. Therefore, I coded this course as a transition level course.

Appendix Table 3 Complete individual mathematic course codes using CSSC codes

CSSC Code	Course Title	Individual Code
270101	Mathematics 7 [1]	1
270102	Mathematics 7, Accelerate [2]	1
270103	Mathematics 8 [1]	1
270104	Mathematics 8, Accelerated [2]	1
270105	Unused Code	Unused
270106	Mathematics 1, General [1]	1
270107	Mathematics 2, General 2 [2]	1
270108	Science Mathematics [3]	4
270109	Mathematics in the Arts	1
270110	Mathematics, Vocational [4]	4
270111	Technical Mathematics [5]	6
270112	Mathematics Review [6]	Manually
270113	Mathematics Tutoring [7]	1
270114	Consumer Mathematics [8]	1
270100	Mathematics, Other General	Manually
270200	Actuarial Sciences, Other	Manually
270300	Applied Mathematics, Other	Manually
270401	Pre-Algebra	1
270402	Algebra 1, Part 1	2
270403	Algebra 1, Part 2	2
270404	Algebra 1	2
270405	Algebra 2	5
270406	Geometry, Plane	3
270407	Geometry, Solid	3
270408	Geometry	3
270409	Geometry, Informal	1
270410	Algebra 3	7
270411	Trigonometry	8
270412	Analytic Geometry [9]	8

270413	Trigonometry and Solid Geometry	8
270414	Algebra and Trigonometry [10]	8
270415	Algebra and Analytic Geometry	8
270416	Analysis, Introductory [11]	8
270417	Linear Algebra [12]	9
270418	Calculus and Analytic Geometry	9
270419	Calculus	9
270420	Calculus	9
270421	Mathematics 1, Unified	Manually
270422	Mathematics 2, Unified	Manually
270423	Mathematics 3, Unified	Manually
270424	Mathematics, Independent Study [13]	7
270425	Geometry, Part 1	3
270426	Geometry, Part 2	3
270427	Unified Math 1, Part 1	Manually
270428	Unified Math 1, Part 2	Manually
270429	Pre-IB Geometry	3
270430	Pre-IB Algebra 2/Trigonomery	7
270431	IB Math Methods 1 [14]	8
270432	IB Math Studies 1 [15]	8
270433	IB Math Studies 2 [16]	8
270434	IB Math Studies/Calculus	9
270435	AP Calculus CD [17]	10
270436	Discrete Math [18]	8
270437	Finite Math [19]	8
270400	Pure Mathematics, Other	Manually
270511	Statistics	7
270521	Probability	7
270531	Probability and Statistics	7
270532	AP Statistics	8
270500	Statistics, Other	7
270601	Basic Math 1 [20]	2
270602	Basic Math 2 [21]	2
270603	Basic Math 3 [22]	2
270604	Basic Math 4 [23]	2
279900	Mathematics, Other	Manually

Foot Note:
1 These courses prepare students with basic knowledge of numbers and computational skills.
2 These courses prepare students to take high school Algebra I, serving as "pre-algebra"
3 Science Mathematics applies knowledge from Algebra I, but doesn't reach Algebra II level.
4 Vocational Mathematics applies knowledge from Algebra I and uses these skills in specific fields. However, this course doesn't apply knowledge and skills from Algebra II or equal courses. Therefore, this course should belong to level 4.

5 Technical Mathematics applies basic principles from Algebra I, Algebra II (such as numerical trigonometry) and Geometry. I code this course as “applied math elective” because, although it combines principles of Algebra and geometry, it does not adequately provide solid theoretical background as pre-calculus does.

6 This course provides students with college entrance exam preparation. Since the college entrance exam varies across students, I will code this course manually.

7 Mathematics tutoring provides low-level of math knowledge tutoring.

8 Consumer Mathematics only applies knowledge from pre-Algebra such as arithmetic using rational numbers, measurement, ratio and proportion, and basic statistics to consumer problems and situations.

9 This course applies basic principles from Algebra III and trigonometry into studying of geometry.

10 Most topics covered in this course are in Algebra III (e.g., complex numbers and theory of equations).

11 This course is a pre-calculus level course.

12 Linear algebra requires students to finish pre-calculus or equal courses.

13 This independent study is an advanced course focusing on number theory. The number theory reviews the properties and uses of integers and prime numbers which prepare students with higher level course, Discrete Mathematics. Part of theories in this course may be covered in Algebra III.

14,15,16 These three IB courses prepare students to take IB math studies at standard level. Courses includes topics from algebra III, number theories, and trigonometry, but not introductory level calculus.

17 Students usually took AP Calculus CD after Calculus and/or AP Calculus AB. In the meanwhile, in addition to topics covered by AP Calculus AB, AP Calculus CD covers parametric, polar, and vector functions; applications of integrals; and polynomial approximations and series, including series of constants and Taylor series.

18 Discrete Mathematics is built upon Algebra III and Number theory which is a higher-level course, but not as high as Calculus

19 Finite Math applies knowledge of probability, and Algebra III, and is usually compared with pre-calculus.

20-23 These four courses cover the basic Algebra knowledge.

Different from individual math course codes, there are inherent categories associated with science courses, i.e., biology, chemistry, physics, or other science courses. Therefore, comparing the difficulties of courses, it’s equally important to count how many different types of science courses students have taken. For instance, students who have taken both physics and chemistry courses have more science learning experience than students who only take chemistry courses. Therefore, we added another individual code, apart from codes for difficulty level (code 2), to indicate the category of science courses (code 1). The description of two individual science courses code is shown in Appendix Table 4. Similar to individual math course code, I manually assign the two individual science course codes to each science course in HSLS transcript using SCED and science courses in HS&B, NELS, and ELS using CSSC. See Tables A5 and A6 for complete individual science codes.

To capture students' cumulative science course taking pattern, we assign each student a code according to their course-taking file. To consider the importance of both how many different types of science courses and how deep students have taken during their high school, we combine the two codes by counting how may "big-threes" (i.e. Biology, Chemistry, and Physics) student have taken and attaching "higher-level courses (higher than 3 on set 2 code) or not". The final five-level cumulative science course taking codes are shown in Table 2 in the main text.

Appendix Table 4 Individual science course codes

Code 1	
Science course category code	Description
1	Biology Category
2	Chemistry Category
3	Physics Category
4	Other Category, any combination course

Code 2	
Science course difficulty level code	Description
1	Course provides basic concepts on specific field
2	Course is based on level 1 course, providing a more detailed understanding on specific field, or introduction to a sub-field
3	Course provides an in-depth study on a specific sub-filed
4	Course provides a higher-level comprehensive study of specific field
5	In addition to level 4, course requires higher-level interdisciplinary knowledge to finish

Appendix Table 5 Individual science course codes

Course name	SCED Code	Code 1	Code 2
Earth Science	03001	4	1
Geology [1]	03002	4	2
Environmental Science	03003	4	1
Astronomy	03004	4	1
Marine Science	03005	4	1
Meteorology	03006	4	1
Physical Geography [2]	03007	4	2
Earth and Space Science	03008	4	1
Particular Topics in Earth Science	03009	4	1
Earth/Space Science (prior-to-secondary)	03010	4	1
Physical Science (prior-to-secondary)	03011	4	1
Energy and the Environment	03012	4	1

Earth Science—Independent Study	03047	4	1
Earth Science—Workplace Experience	03048	4	1
Earth Science—Other	03049	4	1
Biology	03051	1	1
Biology—Advanced Studies [3]	03052	1	2
Anatomy and Physiology [4]	03053	1	2
Anatomy [5]	03054	1	3
Physiology	03055	1	3
AP Biology [6]	03056	1	4
IB Biology [7]	03057	1	4
Botany [8]	03058	1	2
Genetics [9]	03059	1	2
Microbiology [10]	03060	1	2
Zoology [11]	03061	1	2
Conceptual Biology	03062	1	1
Particular Topics in Biology	03063	1	1
Regional Biology	03064	1	1
IB Sports, Exercise, and Health Science [12]	03065	1	2
PLTW Principles of Biomedical Science [13]	03066	1	3
PLTW Human Body Systems [14]	03067	1	3
PLTW Medical Interventions [15]	03068	1	3
Nutrition Science	03069	1	2
PLTW Biomedical Innovation	03070	1	3
Biology—Independent Study	03097	1	1
Biology—Workplace Experience	03098	1	1
Biology—Other	03099	1	1
Chemistry	03101	2	1
Chemistry—Advanced Studies [16]	03102	2	2
Organic Chemistry [17]	03103	2	3
Physical Chemistry [18]	03104	2	5
Conceptual Chemistry	03105	2	1
AP Chemistry [19]	03106	2	4
IB Chemistry [20]	03107	2	4
Particular Topics in Chemistry	03108	2	1
Chemistry—Independent Study	03147	2	1
Chemistry—Workplace Experience	03148	2	1
Chemistry—Other	03149	2	1
Physics	03151	3	1
Physics—Advanced Studies	03152	3	2
Principles of Technology	03153	3	2
AP Physics C [21]	03156	3	5
IB Physics [22]	03157	3	5
Life Science	03158	1	1

Physical Science	03159	3	1
Conceptual Physics	03161	3	1
Particular Topics in Physics	03162	3	1
AP Physics C: Electricity and Magnetism [23]	03163	3	5
AP Physics C: Mechanics [24]	03164	3	5
AP Physics 1 [25]	03165	3	4
AP Physics 2 [26]	03166	3	4
Physics—Independent Study	03197	3	1
Physics—Workplace Experience	03198	3	1
Physics—Other	03199	3	1
Integrated Science	03201	4	1
Unified Science	03202	4	1
Applied Biology/Chemistry	03203	4	1
Technological Inquiry	03204	4	1
Origins of Science	03205	4	1
IB Design Technology [27]	03206	4	3
AP Environmental Science [28]	03207	4	3
IB Environmental Systems and Societies [29]	03208	4	3
Aerospace	03209	4	2
Science, Technology and Society	03210	4	1
Technical Science	03211	4	1
Scientific Research and Design	03212	4	1
IB Sciences, Middle Years Program	03213	4	1
Forensic Laboratory Science	03214	no obs	
Science (early childhood education)	03228	no obs	
Science (pre-kindergarten)	03229	no obs	
Science (kindergarten)	03230	no obs	
Science (grade 1)	03231	no obs	
Science (grade 2)	03232	no obs	
Science (grade 3)	03233	no obs	
Science (grade 4)	03234	no obs	
Science (grade 5)	03235	no obs	
Science (grade 6)	03236	no obs	
Science (grade 7)	03237	no obs	
Science (grade 8)	03238	no obs	
Science—General	03239	no obs	
Life and Physical Sciences—Proficiency Development	03994	4	1
Life and Physical Sciences—Aide	03995	4	1
Life and Physical Sciences—Supplemental	03996	4	1
Life and Physical Sciences—Independent Study	03997	4	1
Life and Physical Sciences—Workplace Experience	03998	4	1

Life and Physical Sciences—Other	03999	4	1

Footnote:

1. Geology courses provide an in-depth study of the forces that formed and continue to affect the earth's surface.

2. Knowledge for Physical Geography is based on Earth science and Marine science that examine the physical environment place on human development.

3. This course usually taken after a comprehensive initial study of biology, Biology—Advanced Studies courses cover biological systems in more detail.

4. This course usually taken after a comprehensive initial study of biology, Anatomy and Physiology courses present the human body and biological systems in more detail.

5. Anatomy courses present an in-depth study of the human body and biological system. Students usually took this course after anatomy and physiology

6. Adhering to the curricula recommended by the College Board and designed to parallel college-level introductory biology courses, AP Biology courses emphasize four general concepts: evolution; cellular processes (energy and communication); genetics and information transfer; and interactions of biological systems.

7. IB Biology courses prepare students to take the International Baccalaureate Biology exams at either the standard or higher level.

8.9.10.11. These four courses provide students with a understanding of general concepts of specific sub-field

12. Although this is an IB course, this course provides students with standard level of understanding of this sub-field.

13.14.15. These three PLTW courses provide students with in-depth understanding of specific sub-field based on the knowledge from physiology and genetics.

16. This course usually taken after a comprehensive initial study of chemistry, Chemistry—Advanced Studies courses cover chemical properties and interactions in more detail.

17. Organic Chemistry courses involve the study of organic molecules and functional groups. Usually taken after advanced studies.

18. This is an interdisciplinary course. Usually taken after completing a calculus course, Physical Chemistry courses cover chemical kinetics, quantum mechanics, molecular structure, molecular spectroscopy, and statistical mechanics.

19. This AP course requires high school chemistry and algebra II.

20. This IB course provides students with higher level of understanding in Chemistry.

21. AP Physics C in a combination course of Physics C: Electricity and Magnetism and Physics C: Mechanics and requires calculus to resolve problems.

22. IB Physics requires calculus.

23.24. See note 21

25.26 Unlike AP C, these two AP courses are algebra-based physics, can't be coded as higher-level interdisciplinary course.

27.28.29 Although these three AP/IB courses provide comprehensive study of specific field, they don't provide a higher-level understanding of sub-field as AP chemistry or physics does.

Appendix Table 6 Complete individual science course codes using CSSC codes

CSSC Code	Course Title	Code 1	Code 2
260111	Science 7	1	1
260121	Biology, Basic 1	1	1
260122	Biology, Basic 2	1	1
260131	Biology, General 1	1	2
260132	Biology, General 2	1	3

260141	Biology, Honors 1	1	3
260142	Biology, Advanced	1	3
260143	Pre-IB Biology	1	3
260144	IB Biology 2	1	3
260145	IB Biology 3	1	4
260146	AP Biology	1	4
260151	Field Biology	1	2
260161	Genetics	1	3
260171	Biopsychology	1	3
260181	Biology Seminar	1	4
260100	Biology, Other General	1	Manually
260211	Biochemistry	1	5
260200	Biochemistry and Biophysics, Other	1	5
260311	Botany	1	2
260300	Botany, Other	1	2
260411	Cell Biology	1	4
260400	Cell and Molecular Biology, Other	1	5
260511	Microbiology	1	4
260500	Microbiology, Other	1	4
260611	Ecology	1	3
260621	Marine Biology	1	2
260622	Marine Biology, Advanced	1	3
260631	Anatomy	1	3
260600	Miscellaneous Specialized Areas, Life Sciences, Other	1	Manually
260711	Zoology	1	2
260721	Zoology, Vertebrate	1	2
260731	Zoology, Invertebrate	1	2
260741	Animal Behavior	1	2
260751	Physiology, Human	1	2
260752	Physiology, Advanced	1	3
260761	Pathology	1	2
260771	Comparative Embryology	1	2
260700	Zoology, Other	1	2
269900	Life Sciences, Other	1	Manually
300111	Science, Unified	4	Manually
300112	College Pre-Science Skills	4	1
300121	Science Study, Independent	4	1
300131	Outdoor Education	4	1
300100	Biological and Physical Sciences, Other	4	Manually
400111	Science 8	3	1
400121	Physical Science	3	2

400131	Chemistry and Physics Laboratory Techniques	3	2
400141	Physical Science, Applied	3	2
400100	Physical Sciences, Other General	3	2
400211	Astronomy	3	2
400200	Astronomy, Other	3	2
400300	Astrophysics, Other	3	2
400411	Meteorology	3	2
400400	Atmospheric Sciences and Meteorology, Other	3	2
400511	Chemistry, Introductory	2	1
400521	Chemistry 1	2	2
400522	Chemistry 2	2	3
400523	Pre-IB Chemistry 1	2	3
400524	IB Chemistry 2	2	3
400525	IB Chemistry 3	2	4
400526	AP Chemistry	2	4
400531	Geology (Organic Biochemistry)	2	4
400541	Physical Chemistry	2	5
400551	Consumer Chemistry	2	1
400561	Chemistry, Independent Study	2	2
400500	Chemistry, Other	2	Manually
400611	Earth Science	4	2
400621	Earth Science, College Preparatory	4	3
400622	AP Environmental Science	4	4
400631	AP Environmental Science	4	4
400632	Geology - Field Studies	4	2
400641	Mineralogy	4	2
400600	Geological Sciences, Other	4	2
400711	Oceanography	4	2
400700	Miscellaneous Physical Sciences, Other	3	Manually
400811	Physics, General	3	1
400821	Physics 1	3	2
400822	Physics 2	3	3
400823	IB Physics	3	4
400824	AP Physics B	3	4
400825	AP Physics C: Mechanics	3	5
400826	AP Physics C: Electricity/Magnetism	3	5
400831	Physics 2 without Calculus	3	4
400841	Electricity and Electronics Science	3	3
400851	Acoustics	3	3
400800	Physics, Other	3	Manually
400911	Rocketry and Space Science	3	2

400900	Planetary Science, Other	3	2
401011	Aerospace Science	3	2
409900	Physical Sciences, Other	3	Manually

Finally, ELA track placement is simply measured as the most rigorous ELA courses taken during high school. Students who completed at least one Enriched/advanced, Honors, or College level ELA course are labeled as high track; students who only completed Basic/remedial or General level ELA course are labeled as low track. This binary measure captures the basic variation in ELA course taking across students and is only used to calculate tracking scope. The individual course track placement is listed in Appendix Table 7. Appendix Table 7 also provides side-by-side comparison of course classification using both CSSC and SCED codes.

Appendix Table 7 Complete individual ELA track placement using both CSSC and SCED codes

CSSC Code	SCED Code	CSSC Course Title(s)	Rigor	Track Placement
230106	01001	English 1, Below Grade Level; English 9, Basic; Communication Skills, Non-College	B	Low
230107	01001	English 1; English 9, Average	G	Low
230108	01001	English 1, Honors; English 9, Honors	H	High
230161	01001	English Skills 1 for Visually Impaired	G	Low
230165	01001	Pre-IB English 1 (grade 9)	G	Low
230109	01002	English 2, Below Grade Level; English 10, Basic	B	Low
230110	01002	English 2; English 10, Average	G	Low
230111	01002	English 2, Honors; English 10, Honors	H	High
230162	01002	English Skills 2 for Visually Impaired	G	Low
230166	01002	Pre-IB English 2 (grade 10)	G	Low
230112	01003	English 3, Below Grade Level; English 11, Basic	B	Low
230113	01003	English 3; English 11, Average	G	Low
230114	01003	English 3, Honors; English 11, Honors	H	High
230163	01003	English Skills 3 for Visually Impaired	G	Low
230167	01003	Pre-IB English 3 (grade 11)	G	Low
230115	01004	English 4, Below Grade Level; English 12, Basic	B	Low
230116	01004	English 4; English 12, Average	G	Low
230117	01004	English 4, Honors; English 12, Honors	H	High
230164	01004	English Skills 4 for Visually Impaired	G	Low
230170	01005	AP English Language and Composition	E	High

230171	01006	AP English Literature and Composition	E	High
230168	01007	IB English 4 (grade 11 or 12)	E	High
230169	01007	IB English 5 (grade 12)	E	High
160121	01008	English as a Second Language 1; TESOL, Beginning	G	Low
160122	01008	English as a Second Language 2; TESOL, Intermediate	G	Low
160123	01008	English as a Second Language 3; TESOL,	G	Low
160124	01008	English as a Second Language, Skills Lab	B	Low
160125	01008	Transitional English	B	Low
520103	01009	English/Language Arts EMH	B	Low
520203	01009	English/Language Arts EH	B	Low
520301	01009	English/Language Arts Deaf	B	Low
542011	01009	Functional Language Arts 1	B	Low
542019	01009	Functional Language Arts 1, not for credit	B	Low
542021	01009	Functional Language Arts 2	B	Low
542029	01009	Functional Language Arts 2, not for credit	B	Low
542031	01009	Functional Language Arts 3	B	Low
542039	01009	Functional Language Arts 3, not for credit	B	Low
542041	01009	Functional Language Arts 4	B	Low
542049	01009	Functional Language Arts 4, not for credit	B	Low
562300	01009	Special Education Language Arts	B	Low
562322	01009	Resource Room English 2 (Special Education)	B	Low
562329	01009	Resource Writing, not for credit	B	Low
230101	01035	English 7 - Middle School Level	G	Low
230102	01035	English 7, Honors; English 7, Above Grade Level - Middle School Level	H	High
230103	01036	English 8, Below Grade Level - Middle School Level	B	Low
230104	01036	English 8; English 8, Average - Middle School Level	G	Low
230105	01036	English 8, Honors; English 8, Above Grade Level - Middle School Level	H	High
230152	01053	English, Real Life Problem Solving	G	Low
230700	01054	Literature, American, Other	G	Low
230711	01054	American Literature; Selected American	G	Low
230181	01055	Integrated English/History 1 (English)	G	Low
230182	01055	Integrated English/History 2 (English)	G	Low
230183	01055	Integrated English/History 3 (English)	G	Low
450881	01055	Integrated English/History 1 (History)	G	Low
450882	01055	Integrated English/History 2 (History)	G	Low
450883	01055	Integrated English/History 3 (History)	G	Low
230800	01056	Literature, English, Other	G	Low
230811	01056	British Literature Survey; Major British	G	Low

230821	01056	Shakespeare; Ages of Man; Political	G	Low
230831	01056	Modern British Writer	G	Low
230841	01056	Victorian Literature	G	Low
230851	01056	Satire, Modern British	G	Low
230861	01056	Arthurian Legend; Once and Future	G	Low
230871	01056	Medieval Literature	G	Low
230118	01058	World Literature; Modern Classical Literature	G	Low
230311	01058	Comparative Literature; Comparisons in	G	Low
230125	01059	Bible as Literature; Literature of the	G	Low
230151	01060	Seminar on an Author	G	Low
230127	01061	Drama, Introduction	G	Low
230128	01061	World Drama	G	Low
230129	01061	Plays, Modern Survey	G	Low
230130	01061	Novels	G	Low
230131	01061	Short Story; Short Narrative; Short	G	Low
230132	01061	Mysteries	G	Low
230133	01061	Poetry	G	Low
230134	01061	Rock Poetry	G	Low
230135	01061	Humor; Let's Laugh; American Humor	G	Low
230136	01061	Biography; Autobiography; Famous	G	Low
230137	01061	Non-Fiction	G	Low
230138	01061	Science Fiction; Literature of the Mysterious; Fiction and Fantasy	G	Low
230155	01061	Children's Literature & Fantasy	G	Low
230741	01061	Folklore, American	G	Low
230119	01062	Renaissance Literature; Man in a New World	G	Low
230120	01062	Romanticism; Man and Nature	G	Low
230121	01062	Realism	G	Low
230122	01062	Literature, Contemporary;	G	Low
230200	01062	Classics, Other	G	Low
230211	01062	Mythological Literature, Greek and	G	Low
230761	01063	State Writers; Regional Writers	G	Low
230771	01063	Western Literature; Frontier Literature	G	Low
230123	01064	Irish Literature	G	Low
230124	01064	Russian Literature	G	Low
230141	01064	Ethnic Literature; Minority Literature	G	Low
230142	01064	Women in Literature	G	Low
230150	01064	Nobel Prize Authors	G	Low
230321	01064	Latin American Authors/Literature	G	Low
230721	01064	Black Literature; Literature of Black America; Afro American Literature	G	Low
230751	01064	Indian Literature; American Indian	G	Low

230781	01064	Mexican American Literature	G	Low
300721	01064	Women's Studies in Literature	G	Low
230126	01065	Mythology and Fable; Mythology and	G	Low
230139	01065	Themes in Literature; War and Peace;	G	Low
230140	01065	Literature of Human Values	G	Low
230143	01065	Sports through Literature	G	Low
230144	01065	Occult Literature; Supernatural	G	Low
230145	01065	Protest Literature	G	Low
230146	01065	Youth and Literature; Adolescent	G	Low
230147	01065	Heroes	G	Low
230148	01065	Utopias	G	Low
230149	01065	Death	G	Low
230731	01065	American Dream in Literature; American	G	Low
380211	01065	Religion and Literature	G	Low
231215	01066	Speed Reading	G	Low
231216	01066	Advanced Reading and Study Skills;	G	Low
320111	01066	Speed Reading (Changed to 23.1215)	G	Low
231217	01067	Reading Improvement	G	Low
231212	01068	Reading Development 2	G	Low
231213	01068	Reading Development 3	G	Low
231214	01068	Reading Development 4	G	Low
320109	01068	Reading Development 1 (Changed to	G	Low
231211		23.1211)	G	Low
320110	01068	Reading Development 2 (Changed to	G	Low
542101	01068	Functional Reading	B	Low
542109	01068	Functional Reading, not for credit	B	Low
562310	01068	Special Education Reading	B	Low
562311	01068	Resource Reading	B	Low
562319	01068	Resource Reading, not taken for credit	B	Low
230153	01097	Reading, Independent Study	G	Low
230300	01099	Comparative Literature, Other	G	Low
230403	01099	Writing About Literature	G	Low
230401	01103	Composition, Expository; Writing	G	Low
230500	01104	Creative Writing, Other	G	Low
230511	01104	Creative Writing 10; Creative Writing 1	G	Low
230512	01104	Creative Writing 11; Creative Writing 2,	G	Low
230513	01104	Creative Writing 12	G	Low
230154	01105	Research Technique; Writing and	G	Low
231100	01105	Technical and Business Writing, Other	G	Low
231111	01105	Technical English	G	Low
562320	01139	Special Education Writing - Middle School Level	B	Low

230402	01147	Writing Laboratory; Writing Skills Workshop; Composition, Advanced Computer Assisted Writing Instruction	G	Low
230521	01147	Creative Writing, Independent Study	G	Low
230400	01149	Composition, Other	G	Low
230404	01149	Vocabulary; Fun With Words; College Vocabulary Skill Building; Word Power	G	Low
230405	01149	Spelling	G	Low
230531	01149	Journal Writing	G	Low
231011	01151	Public Speaking; Communications,	G	Low
231023	01152	Speech 3 (Changed to 23.1024)	G	Low
231024	01152	Advanced Speech	E	High
231025	01153	Debate	G	Low
231031	01153	Debate Practicum Contract	G	Low
230414	01155	Interpersonal Communication	G	Low
231311	01156	Functional English 1; Correlated	G	Low
231312	01156	Functional English 2; Correlated	G	Low
231313	01156	Functional English 3; Correlated	G	Low
231314	01156	Functional English 4; Correlated	G	Low
320118	01156	English, Functional (Changed to	B	Low
542051	01156	Functional Vocational English	B	Low
542059	01156	Functional Vocational English, not for	B	Low
542201	01156	Functional Oral Communication	B	Low
542209	01156	Functional Oral Communication, not for	B	Low
542301	01156	Functional Writing	B	Low
542309	01156	Functional Writing, not for credit	B	Low
230415	01199	Word Study - Remedial	G	Low
231000	01199	Speech, Debate, and Forensics, Other	G	Low
320115	01199	Word Study, Remedial (Changed to	G	Low
230406	01201	Grammar 7; Language Structure 7 -	G	Low
230407	01201	Grammar 8; Language Structure 8 -	G	Low
230408	01201	Grammar 9; Language Structure 9	G	Low
230409	01201	Grammar 10; Language Structure 10;	G	Low
230410	01201	Grammar 11; Language Structure 11; Grammar Review 11, College Preparation	G	Low
230411	01201	Grammar 12; Language Structure 12;	G	Low
230412	01202	Etymology; Wordsearch; Word Clues	G	Low
230611	01202	Linguistics; Language and Thought;	G	Low
231401	01997	English, Independent Study	G	Low
230100	01999	English, Other General	G	Low
230156	01999	Vocational English	G	Low
230413	01999	Handwriting; Penmanship	G	Low
230600	01999	Linguistics (includes Phonetics,	G	Low

230900	01999	Rhetoric, Other	G	Low
231315	01999	Transitional English	G	Low
239900	01999	Letters/English, Other	G	Low
320113	01999	Language, Developmental (Changed to 16.0125 for non-English speakers and 23.1311-23.1314 for English speakers)	G	Low

Appendix B Supplementary Tables from Chapter 3.0

Appendix Table 8 *Time-pooled Model* Estimation of School-level Variance of Math Sequence within the School using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Functional Factor						
1. Achievement Heterogeneity	.206***			.221***	.207***	.217***
	(.030) [a]			(.032)	(.032)	(.033)
2. School Size	.005			.001	.007	.001
	(.008)			(.008)	(.008)	(.009)
Status Competition						
3. School-mean Achievement		-.010		-.029~		-.026
		(.015)		(.015)		(.016)
4. School-mean SES		.093		.083		.064
		(.198)		(.200)		(.203)
5. Percentage of White		-.272		-.142		-.224
		(.353)		(.362)		(.381)
6. Percentage of non-free lunch		1.755***		1.838***		1.802***
		(.362)		(.365)		(.366)
Heterogeneity Measures						
7. SES Heterogeneity			.878*		.345	.373
			(.406)		(.407)	(.425)
8. Shannon Index of Race Diversity			-.006		-.287	-.195
			(.177)		(.185)	(.203)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.059	.057	.044	.077	.060	.074

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department

of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Appendix Table 9 *Cohort-Interaction Model* Estimation of the Trends of School-level Variance of Math Sequence within the School using functionally-related variables, status-competition related variables, and measures of heterogeneity, 1982-2013 (n = 3620 schools; School-level Covariates includes sample percentage of white students, school sectors, urbanicity, geographic region, student-teacher ratio, and average daily instruction hours)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Cohort (centered at 1992 cohort)	.300	1.425~	-.104	.908	.398	.824
	(.217) [a]	(.738)	(.219)	(.759)	(.277)	(.779)
Functional Factor						
1. Achievement Heterogeneity	.310***			.303***	.297***	.290***
	(.035)			(.037)	(.036)	(.038)
2. Achievement Heterogeneity × Cohort	-.083***			-.073**	-.082**	-.075**
	(.025)			(.027)	(.026)	(.027)
3. School Size	.005			.000	.003	-.002
	(.009)			(.009)	(.009)	(.009)
4. School Size × Cohort	-.003			-.003	-.007	-.006
	(.006)			(.006)	(.006)	(.006)
Status Competition						
5. School-mean Achievement		.026		.002		.000
		(.016)		(.017)		(.017)
6. School-mean Achievement × Cohort		-.042**		-.022		-.023
		(.015)		(.015)		(.015)
7. School-mean SES		.272		.383~		.402~
		(.205)		(.206)		(.208)
8. School-mean SES × Cohort		-.419*		-.550**		-.573**
		(.178)		(.176)		(.180)
9. Percentage of White		-.430		-.472		-.378
		(.370)		(.379)		(.395)
10. Percentage of White × Cohort		-.225		-.140		.037
		(.187)		(.195)		(.229)
11. Percentage of non-free lunch		1.171**		.919*		.908*
		(.439)		(.436)		(.439)
12. Percentage of non-free lunch × Cohort		.793**		.788**		.725*
		(.303)		(.300)		(.302)
Opportunity Hoarding						
13. SES Heterogeneity			1.154**		.474	.662
			(.425)		(.421)	(.437)
14. SES Heterogeneity × Cohort			-.574~		-.355	-.144

			(.327)		(.327)	(.341)
15. Shannon Index of Race Diversity			.347		.149	.049
			(.218)		(.221)	(.235)
16. Shannon Index of Race Diversity × Cohort			.193		.232	.254
			(.136)		(.146)	(.175)
School Covariates	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.085	.077	.060	.104	.088	.104

a. Robust Standard errors in parentheses
*** p<.001, ** p<.01, * p<.05, ~ p<.1
NOTE: Sample size is rounded to the nearest 10 as required by NCES.
SOURCE: U.S. Department of Education, National Center for Education Statistics, High School and Beyond Longitudinal Study of 1980 Sophomores (HS&B-So: 80/82), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, National Education Longitudinal Study of 1988 (NELS: 88/92), “Base-year Survey, First Follow-up Survey, High School Transcript Study, 1992.”; U.S. Department of Education, National Center for Education Statistics, Education Longitudinal Study of 2002 (ELS: 2002/2004), “Base-year Survey, First Follow-up Survey, High School Transcript Study”; U.S. Department of Education, National Center for Education Statistics, High School Longitudinal Study of 2009 (HSLS: 09/13), “Base-year Survey, First Follow-up Survey, 2013 Update Survey, High School Transcript Collection”.

Appendix C Coding Process for Curricular Experience Codes used in TIMSS Chapter

Appendix Table 10 8th Grade Mathematics Topics Coding (TIMSS 2015, 2019)

Subject/Domain	Topic Taught	Equivalent Grade Level	Difficulty Code
Number			
BTBM21AA	Computing with whole numbers	5th Grade	1
BTBM21AB	Comparing and ordering rational numbers	7th Grade	2
BTBM21AC	Computing with rational numbers (fractions, decimals, and integers)	7th Grade	2
BTBM21AD	Concepts of irrational numbers	8th Grade	3
BTBM21AE	Problem solving involving percents or proportions	7th Grade	2
Algebra			
BTBM21BA	Simplifying and evaluating algebraic expressions	6h Grade	2
BTBM21BB	Simple linear equations and inequalities	6th Grade	2
BTBM21BC	Simultaneous (two variables) equations	8th Grade	3
BTBM21BD	Numeric, algebraic, and geometric patterns or sequences (extension, missing terms, generalization of patterns)	5th Grade	1
BTBM21BE	Representation of functions as ordered pairs, tables, graphs, words, or equations	8th Grade	3
BTBM21BF	Properties of functions (slopes, intercepts, etc.)	8th Grade	3
Geometry			
BTBM21CA	Geometric properties of angles and geometric shapes (triangles, quadrilaterals, and other common polygons)	5th Grade	1
BTBM21CB	Congruent figures and similar triangles	8th Grade	3
BTBM21CC	Relationship between three-dimensional shapes and their two-dimensional representations	7th Grade	2
BTBM21CD	Using appropriate measurement formulas for perimeters, circumferences, areas, surface areas, and volumes	7th Grade	2
BTBM21CE	Points on the Cartesian plane	5th Grade	1
BTBM21CF	Translation, reflection, and rotation	8th Grade	3
Data and Chance			
BTBM21DA	Characteristics of data sets (mean, median, mode, and shape of distributions)	6th Grade	2
BTBM21DB	Interpreting data sets (e.g., draw conclusions, make predictions, and estimate values between and beyond given data points)	7th Grade	2

BTBM21DC	Judging, predicting, and determining the chances of possible outcomes	7^{th} Grade	2

Appendix Table 11 8th Grade science topics coding (TIMSS 2015, 2019)

Subject	Topic Taught	Difficulty Code
Biology	Differences among major taxonomic groups of organisms (plants, animals, fungi, mammals, birds, reptiles, fish, amphibians)	1
	Major organs and organ systems in humans and other organisms (structure/function, life processes that maintain stable bodily conditions)	2
	Cells, their structure and functions, including respiration and photosynthesis as cellular processes	3
	Life cycles, sexual reproduction, and heredity (passing on of traits, inherited versus acquired/learned characteristics)	1
	Role of variation and adaptation in survival/extinction of species in a changing environment (including fossil evidence for changes in life on Earth over time)	1
	Interdependence of populations of organisms in an ecosystem (e.g., energy flow, food webs, competition, predation) and factors affecting population size in an ecosystem	3
	Human health (causes of infectious diseases, methods of infection, prevention, immunity) and the importance of diet and exercise in maintaining health	1
Chemistry		
	Classification, composition, and particulate structure of matter (elements, compounds, mixtures, molecules, atoms, protons, neutrons, electrons)	2
	Physical and chemical properties of matter	1
	Mixtures and solutions (solvent, solute, concentration/dilution, effect of temperature on solubility)	3
	Properties and uses of common acids and bases	2
	Chemical change (transformation of reactants, evidence of chemical change, conservation of matter, common oxidation reactions – combustion, rusting, tarnishing)	2
	The role of electrons in chemical bonds	4
Physics		
	Physical states and changes in matter (explanations of properties in terms of movement and distance between particles; phase change, thermal expansion, and changes in volume and/or pressure)	2
	Energy forms, transformations, heat, and temperature	1
	Basic properties/behaviors of light (reflection, refraction, light and color, simple ray diagrams) and sound (transmission through media, loudness, pitch, amplitude, frequency)	3

	Electric circuits (flow of current; types of circuits - parallel/series) and properties and uses of permanent magnets and electromagnets)	3
	Forces and motion (types of forces, basic description of motion, effects of density and pressure)	4
Earth Science		
	Earth's structure and physical features (Earth's crust, mantle, and core; composition and relative distribution of water, and composition of air)	1
	Earth's processes, cycles, and history (rock cycle; water cycle; weather versus climate; major geological events; formation of fossils and fossil fuels)	2
	Earth's resources, their use and conservation (e.g., renewable/nonrenewable resources, human use of land/soil, water resources)	1
	Earth in the solar system and the universe (phenomena on Earth - day/night, tides, phases of moon, eclipses, seasons; physical features of Earth compared to other bodies)	2

Appendix Table 12 8th Grade Mathematics Topics Coding (TIMSS 2003, 2007, 2011)

Subject/Domain	Topic Taught	Equivalent Grade Level	Difficulty Code
Number			
	Computing with whole numbers	5th Grade	1
	Concepts of fractions and computing with fractions	7th Grade	2
	Concepts of decimals and computing with decimals	7th Grade	2
	Representing, comparing, ordering, and computing with integers	6th Grade	2
	Problem solving involving percents or proportions	7th Grade	2
Algebra			
	Numeric, algebraic, and geometric patterns or sequences (extension, missing terms, generalization of patterns)	5th Grade	1
	Simplifying and evaluating algebraic expressions	6^{h} Grade	2
	Simple linear equations and inequalities	6th Grade	2
	Simultaneous (two variables) equations	8th Grade	3
	Representation of functions as ordered pairs, tables, graphs, words, or equations	8th Grade	3
Geometry			

	Geometric properties of angles and geometric shapes (triangles, quadrilaterals, and other common polygons)	5th Grade	1
	Congruent figures and similar triangles	8th Grade	3
	Relationship between three-dimensional shapes and their two-dimensional representations	7th Grade	2
	Using appropriate measurement formulas for perimeters, circumferences, areas, surface areas, and volumes	7th Grade	2
	Points on the Cartesian plane	5th Grade	1
	Translation, reflection, and rotation	8th Grade	3
Data and Chance			
	Reading and displaying data using tables, pictographs, bar graphs, pie charts, and line graphs	6th Grade	2
	Interpreting data sets (e.g., draw conclusions, make predictions, and estimate values between and beyond given data points)	7th Grade	2
	Judging, predicting, and determining the chances of possible outcomes	7th Grade	2

Appendix Table 13 8th Grade science topics coding (TIMSS 2003, 2007, 2011)

Subject	Topic Taught	Difficulty Code
Biology	Major organs and organ systems in humans and other organisms (structure/function, life processes that maintain stable bodily conditions)	2
	Cells and their functions, including respiration and photosynthesis as cellular processes	3
	Reproduction (sexual and asexual) and heredity (passing on of traits, inherited versus acquired/learned characteristics)	1
	Role of variation and adaptation in survival/extinction of species in a changing environment	1
	Interdependence of populations of organisms in an ecosystem (e.g., energy flow, food webs, competition, predation) and the impact of changes in the physical environment on populations (e.g., climate, water supply)	3
	Reasons for increase in world's human population (e.g., advances in medicine, sanitation), and the effects of population growth on the environment	2

	Human health (causes of infectious diseases, methods of infection, prevention, immunity) and the importance of diet and exercise in maintaining health	1
Chemistry		
	Classification, composition, and particulate structure of matter (elements, compounds, mixtures, molecules, atoms, protons, neutrons, electrons)	2
	Mixtures and solutions (solvent, solute, concentration/dilution, effect of temperature on solubility)	3
	Properties and uses of common acids and bases	2
	Chemical change (transformation of reactants, evidence of chemical change, conservation of matter, common oxidation reactions – combustion, rusting, tarnishing)	2
Physics		
	Physical states and changes in matter (explanations of properties in terms of movement and distance between particles; phase change, thermal expansion, and changes in volume and/or pressure)	2
	Energy forms, transformations, heat, and temperature	1
	Basic properties/behaviors of light (reflection, refraction, light and color, simple ray diagrams) and sound (transmission through media, loudness, pitch, amplitude, frequency)	3
	Electric circuits (flow of current; types of circuits - parallel/series) and properties and uses of permanent magnets and electromagnets)	3
	Forces and motion (types of forces, basic description of motion, effects of density and pressure)	4
Earth Science		
	Earth's structure and physical features (Earth's crust, mantle, and core; composition and relative distribution of water, and composition of air)	1
	Earth's processes, cycles, and history (rock cycle; water cycle; weather versus climate; major geological events; formation of fossils and fossil fuels)	2
	Earth's resources, their use and conservation (e.g., renewable/nonrenewable resources, human use of land/soil, water resources)	1
	Earth in the solar system and the universe (phenomena on Earth - day/night, tides, phases of moon, eclipses, seasons; physical features of Earth compared to other bodies)	2

Appendix Table 14 8th Grade Mathematics Topics Coding (TIMSS 1995, 1999)

Subject/Domain	Topic Taught	Equivalent Grade Level	Difficulty Code
Number			
BTBMTT01	Whole numbers – including place values, factorization and operations	5^{th} Grade	1

BTBMTT06	Relationships between common and decimal fractions, ordering of fractions	7th Grade	2
BTBMTT03	Computations with common fractions	7th Grade	2
BTBMTT11	Simple computations with negative numbers	7th Grade	2
BTBMTT10	Computations with percentages and problems involving percentages	7th Grade	2
Algebra			
BTBMTT28	Simple algebraic expressions	6h Grade	2
BTBMTT30	Solving simple equations	6th Grade	2
BTBMTT31	Solving simple inequalities	8th Grade	3
BTBMTT27	Number patterns and simple relations	5th Grade	1
BTBMTT20	Coordinates of points on a given straight line	8th Grade	3
Geometry			
BTBMTT21	Simple two dimensional geometry – angles on a straight line, parallel lines, triangles and quadrilaterals	5th Grade	1
BTBMTT22	Congruence and similarity	8th Grade	3
BTBMTT24	Visualization of three-dimensional shapes	7th Grade	2
BTBMTT18	Volume of rectangular solids – i.e., Volume = length × width × height	7th Grade	2
BTBMTT19	Cartesian coordinates of points in a plane	5th Grade	1
BTBMTT23	Symmetry and transformations (reflection and rotation)	8th Grade	3
Data and Chance			
BTBMTT32	Representation and interpretation of data in graphs, charts, and tables	6th Grade	2
BTBMTT33	Arithmetic mean	7th Grade	2
BTBMTT34	Simple probabilities – understanding and calculations	7th Grade	2

Appendix Table 15 8th Grade science topics coding (TIMSS 1995, 1999)

Subject	Topic Taught	Difficulty Code
Biology		
BTBSTT06	Human bodily processes (metabolism, respiration, digestion)	2
BTBSTT08	Biology of plant and animal life (diversity, structure, life processes, life cycles)	1
BTBSTT10	Reproduction, genetics, evolution, and speciation	2
BTBSTT09	Interactions of living things (biomes and ecosystems, interdependence)	3
BTBSTT07	Human nutrition, health, and disease	1
Chemistry		
BTBSTT11	Classification of matter (elements, compounds, solutions, mixtures)	2
BTBSTT12	Structure of matter (atoms, ions, molecules, crystals)	3
BTBSTT13	Chemical reactivity and transformations (definition of chemical change,	2

	oxidation, combustion)	
BTBSTT14	Energy and chemical change (exothermic and endothermic reactions, reaction rates)	4
Physics		
BTBSTT15	Physical properties and physical changes of matter (weight, mass, states of matter, boiling, freezing)	2
BTBSTT18	Heat and temperature	1
BTBSTT19	Wave phenomena, sound, and vibration	3
BTBSTT17	Energy types, sources, and conversions (chemical, kinetic, electric, light energy; work and efficiency)	4
BTBSTT16	Subatomic particles (protons, electrons, neutrons)	2
BTBSTT21	Electricity and magnetism	3
BTBSTT22	Forces and motion (types of forces, balanced/unbalanced forces, fluid behavior, speed, acceleration)	4
Earth Science		
BTBSTT01	Earth's physical features (layers, landforms, bodies of water, rocks, soil)	1
BTBSTT02	Earth's atmosphere (layers, composition, temperature, pressure)	2
BTBSTT03	Earth processes and history (weather and climate, physical cycles, plate tectonics, fossils)	1
BTBSTT04	Earth in the solar system and the universe (interactions between Earth, sun, and moon; relationship to planets and stars)	2

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