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The Relationship Between School Mobility and Gifted Identification in Connecticut Public Schools

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Educators and policy makers are interested in understanding the impact of school mobility, which is often associated with negative outcomes including declines in academic achievement and increases in behavioral and discipline problems. Changing schools also puts students at risk of not having their academic needs recognized and met. For high ability, academically gifted students, this means that moves involving school changes may be associated with barriers that limit access to gifted identification. Lack of identification for students with gifted education needs limits the ability to advocate for or gain access to gifted education services within or beyond the school, ultimately contributing to the ongoing underrepresentation of homeless and highly mobile (HHM) students in gifted education programs. In Connecticut, state law requires gifted identification in K-12 public schools. While gifted identification is required, services are not. Schools may, but are not required to, provide gifted programs. In the absence of strong accountability, schools that do not offer gifted services may not identify gifted students at the same rates as schools that do offer services, so the likelihood of a student being identified gifted may vary based on the characteristics of the school and district in which the student is enrolled. Findings of the study indicated that about 42% of districts in the state are minimal identifiers, reporting 0.5% or less of their students as gifted. For the more than 30% of HHM students enrolled in these districts, this means that these students have virtually no chance of gifted identification. While there was some evidence that these districts on average tend to have

slightly higher poverty and slightly lower reading and mathematics achievement than districts that identify gifted students, HHM students were not found to be disproportionately represented in districts that did not identify gifted students. Within districts that identify gifted students, no significant differences were found between the proportions of identified gifted students among HHM and non-HHM groups when those students were matched on district, race, English language proficiency, special education status, eligibility for lunch subsidies, and reading and mathematics achievement levels.

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The Relationship Between School Mobility and Gifted Identification in Connecticut Public Schools

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-Dan Rather

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CHAPTER 1: INTRODUCTION TO THE STUDY

Although currently at an all-time low, mobility rates in the United States remain among the highest in the world, with about 11% of the population changing residences in 2015 (U. S. Census Bureau, 2016). Despite the falling mobility rates, the subgroup of highly mobile students who are homeless has doubled in the last decade, soaring to over 1.3 million (National Center for Homeless Education, 2016). In Connecticut, residential mobility rates are similar to those of the nation, at about 12% (U. S. Census Bureau, 2015). For students, changing residences often means changing schools. Educators and policymakers are interested in understanding the impact of homelessness and school mobility, which are often associated with negative academic outcomes for students and schools.

One important challenge related to school mobility is that it disrupts the continuity of the school experience, particularly for students who are homeless or who experience frequent moves, thereby increasing the risk that students' academic needs will go unrecognized and unmet (Julianelle & Foscarinis, 2003; Kerbow, 1996; Mehana & Reynolds, 2004). For high ability, academically gifted students, this means that moves associated with school changes may introduce barriers that limit access to gifted education, contributing to the underrepresentation of homeless and highly mobile students in gifted education programs. In Connecticut, where identification procedures for gifted education use local, district-level norms, changing schools may also result in a change of identification status including possible loss of identification for previously identified students. Because of the risks school mobility may pose to students who have gifted education needs, it is important to examine the relationship between student mobility status and the likelihood of gifted identification in Connecticut schools.

Statement of the Problem

A large body of research has examined the educational outcomes associated with student mobility as it relates to both changes of residence and changes of school. School mobility in particular is linked to declines in academic performance (Friedman-Krauss & Raver, 2015; Selya et al., 2016; Temple & Reynolds, 1995; Voight, Shinn, & Nation, 2012), increases in behavioral problems (Rumberger, 2003; Swanson & Schneider, 1999) and increased risk that a student’s educational needs will go unrecognized and remain unmet (Juliannelle & Foscarinis, 2003; Kerbow, 1996). Conditions related to school mobility can limit communication between schools and parents, as well as between school personnel who may fail to transfer and process school records in a timely manner. Changing schools disrupts the consistency of the student’s educational experiences and relationships, making it more difficult for educators to consistently follow patterns of behavior and achievement that might allow them to recognize and identify student needs (Scanlon & Devine, 2001). Limitations in knowledge and resources may also make it difficult for some parents to recognize their children’s needs or seek appropriate educational intervention (Juliannelle & Foscarinis, 2003).

The risk of unrecognized and unmet needs increases markedly for students who change schools due to unplanned residential mobility, such as that associated with homelessness, as well as for students who change schools frequently (Heinlein & Shinn, 2000; Herbers et al., 2012; Lash, & Kilpatrick, 1990; Obradović et al., 2009). These homeless and highly mobile (HHM) students are often from families of low socioeconomic status (SES). The combination of low-SES and high-mobility is associated with even larger academic achievement gaps for HHM students when compared with low-income peers who are continuously housed (Fantuzzo & Perlman, 2007; Miller, 2011; Obradović et al., 2009; Rubin et al., 1996).

Although many studies have examined outcomes associated with mobility for students who experience academic and social challenges (Selya et al., 2016; Temple & Reynolds, 1995; Voight, Shinn, & Nation, 2012), it is also important to consider the implications for academically gifted students who may show similar declines in performance after moving that may mask their actual ability and potential for high achievement. The McKinney-Vento Act, which specifically addresses the educational rights of students who are homeless or experiencing residential instability, requires that schools provide these students with access to all programs and services for which they are eligible, explicitly including gifted and talented programs. Because the gifted identification process is often triggered by teacher referrals based on observations of classroom behaviors and academic performance, it is reasonable to expect that students who experience declines in performance related to moving may therefore be less likely to be referred for identification, creating significant barriers limiting access to gifted education. This is especially true for HHM students who experience the cumulative effects of multiple moves (Kerbow, Azcoitia, & Buell, 2003; Rumberger, Larson, Ream, & Palardy, 1999). If HHM students are identified at different rates when compared to low-mobility students, this could suggest a need to identify opportunities, develop policies, and implement practices that improve access to gifted education for HHM students.

Few studies have examined school mobility in the context of gifted education. In most instances, data sets and mobility studies that provided some information about the mobility of gifted students did so through simple descriptive statistics on the mobility rates of students who are already identified gifted, rather than examining the potential relationship between mobility and the identification itself. For example, the Colorado Department of Education (2017) collected mobility/stability statistics by instructional programs or services, which included gifted

education, and provided information about the mobility rates, mobile student counts, and instances of mobility among gifted and talented students. While about 17% of students in the state were mobile, only about 6% of identified gifted and talented students were mobile. A Georgia study similarly described mobility rates among gifted education students (Beaudette, 2014). In this study, gifted students were 11.3% less likely to be mobile than non-gifted students, and schools with higher rates of mobility tended to have lower proportions of students identified gifted. Findings from both states could suggest that students who are mobile are less likely that their non-mobile peers to be identified as gifted. Beyond such studies, only a single study (Plucker &Yecke, 1999) specifically explored factors related to mobility in the context of gifted education. This study focused on the academic, social, and emotional outcomes for identified gifted students after moving. The researchers found that gifted students who frequently relocated experienced few long-term social, emotional, or academic impacts. However, they also found that some students experienced short-term social difficulties related to their relocations.

Given the paucity of research on the potential relationship between school mobility and gifted identification and the implications for HHM students who may need access to gifted education, the purpose of this study was to address this gap by exploring the possible relationship between mobility and the likelihood of being identified gifted.

CHAPTER 2: REVIEW OF THE LITERATURE

The purpose of this study was to examine the possible relationship between school mobility and gifted identification in Connecticut public schools. The purpose of this review of the literature is to contextualize the study by exploring gifted identification definitions, policies, and practices, and by summarizing past research findings about the nature of and outcomes associated with homelessness and high mobility. The conclusion of this literature review discusses the intersection of mobility with the context of gifted education, linking existing research to the focus of this study.

Rationale for Identifying Gifted Students

Recognizing students' abilities and capacity for achievement is an important prerequisite to providing gifted students with the appropriate opportunities and resources, both in and out of school, needed to develop their potential. Talent development not only benefits students themselves, but also shapes the contributions each gifted individual has the potential to make in his or her family, school, community, and society. Failure to identify gifted students contributes heavily to those students' potential going unrecognized and underdeveloped, contributing to the growing "excellence gap" in K-12 education (Plucker, Burroughs, & Song, 2010). Students with unrecognized gifts and talents often face a substantial lack of opportunity through limited access to advanced coursework, challenging content, and strategies to develop the skills and habits of mind to support high achievement (Olszewski-Kubilius & Clarenbach, 2014).

Definitions of Giftedness

Federal definition. There are currently no federal laws requiring identification of gifted students. However, the Every Student Succeeds Act of 2015, like other reauthorizations of the

Elementary and Secondary Education Act of 1965 before it, provides a federal definition of gifted and talented students that has been adopted, in whole or in part, by the majority of states:

> The term "gifted and talented," when used with respect to students, children, or youth means students, children, or youth who give evidence of high achievement capability in areas such as intellectual, creative, artistic, or leadership capacity, or in specific academic fields, and who need services or activities not ordinarily provided by the school in order to fully develop those capabilities. (P.L. 114-95, 20 U.S.C. § 8101, 2015)

Intentionally broad, the federal definition reflects the range of diversity among a number of research-based conceptions and models of giftedness, allowing for a great deal of flexibility in how individual states define and operationalize it (Johnsen, 2004a). For instance, it recognizes both general intellectual (Cattell, 1963; Spearman, 1924; Warne, 2016) and domain-specific (Feldhusen, 1998; Stanley, 1976; VanTassel-Baska, 2005; von Károlyi, Ramos-Ford, & Gardner, 2003) types of giftedness and talent, including areas such as creativity (Guilford & Christensen, 1973; Runco, 2005; Sternberg, 2000; Torrance, 1984), the arts (Piirto, 2008; Piechowski, Silverman, & Falk, 1985; Winner & Martino, 2002), and leadership (Renzulli, Hartman, & Callahan, 1971). Through its emphasis on students' *capabilities* for achievement, the federal definition promotes a talent development approach to gifted education, forwarding the notion that, although students may bring with them the potential to achieve at high levels, that potential must be developed through targeted services and activities to be fully realized (Dai, 2010; Feldhusen, 1998; Gagné, 2005; NAGC, 2010; Renzulli, 1994, 2012; Tannenbaum, 2003; Treffinger & Feldhusen, 1996).

Because the federal definition does not define giftedness in terms of specific test scores or percentages of the population, it leaves room for a spectrum of identification philosophies

ranging from conservative approaches that use only psychometric assessments to identify narrow percentages of highly intelligent students (Carroll, 1993; Galton, 1869; Robinson, 2005; Terman & Merrill, 1937), to more liberal, flexible, and inclusive approaches that consider larger pools of students, take a multidimensional range of characteristics and behaviors into account, and allow for use of multiple quantitative and qualitative sources of evidence (Gardner, 1985; Lohman, 2013; Moon, 2013; Renzulli, 1978, 1990, 2005; Sternberg, 1984; Worrell, 2013). While some conceptions of giftedness are so narrow as to include students in the top 1% or less of the population, others include much larger proportions of students. For example, the National Association for Gifted Children defines gifted individuals as those who demonstrate outstanding aptitude or competence in the top 10% (2010). Other popular definitions also define giftedness to include the top 10% or even larger proportions of students (Gagné, 2005; Renzulli, 1978). It is common practice in schools across the country to identify 5% or more of their students as gifted.

State definitions. The 2014-2015 *State of the States in Gifted Education* report by the National Association for Gifted Children in collaboration with the Council of State Directors of Programs for the Gifted revealed that, of 39 responding states, 37 had official state definitions of gifted/talented, many of them reflecting the language and spirit of the federal definition (NAGC & CSDPG, 2015). Most of the responding states reported definitions that included intellectually gifted (34), academically gifted (24), creatively gifted (21), giftedness in the arts (21), and giftedness in specific academic areas (20), while relatively few states included leadership in their definition of gifted/talented (13). Perhaps a contributing factor to the ongoing underrepresentation of certain populations in gifted education, very few states specifically included in their definitions students from families of low socioeconomic status (9), culturally and ethnically diverse students (8), English language learners (8), twice-exceptional students (6),

or underachieving gifted students (4). Furthermore, definitions of gifted/talented sometimes varied further within states, as policies in 7 states granted local control, meaning that districts in these states were not bound to their states' definitions.

Connecticut definition. Gifted education in Connecticut falls under state special education law, which requires schools to identify children who

> [have] extraordinary learning ability or outstanding talent in the creative arts, the development of which requires programs or services beyond those ordinarily provided in the regular school programs but which may be provided through special education as part of the public school program. (CGS Section 10-76/a(5))

According to state regulations, "gifted and talented" includes students who possess "demonstrated or potential abilities that give evidence of very superior intellectual, creative, or specific academic ability" (RCSA Section 10-76a-2). This includes students who demonstrate or show the potential for achievement and/or creativity, as measured through performance or through standardized measures. It also includes students who demonstrate or show potential for achievement in music, visual arts, or performing arts. In practice, when Connecticut schools report students' gifted education statuses, "gifted" generally refers to students identified on the basis of academic or intellectual abilities, and "talented" refers to students identified based on achievement or potential in the arts. Students may be identified as either gifted or talented, or as both gifted and talented. For the purpose of the present study, only students reported as "gifted" on the basis of academic or intellectual abilities were included in the analysis.

Gifted Identification Practices and Procedures

State laws, local policies, and funding for gifted education vary widely, ranging from a complete absence of mandates and funding for gifted education to fully funded mandates for

both gifted identification and service. It follows that, as with definitions of giftedness, gifted identification practices and procedures also vary widely. The connection between identification and services is important, as it addresses the important question: *Identified for what?* Notably, Connecticut is one of a small number of states in which there is a mandate for gifted identification, but not for gifted services. In Connecticut schools without the resources and support needed to provide the services that would answer the "for what?" question, it may be reasonable to assume that there is little motivation to invest the resources necessary to comply with the identification mandate.

In schools in which gifted identification occurs, it often involves a multi-stage process including nomination, screening, and selection/identification (Johnsen, 2004b). In the nomination phase, schools create large pools of students, in some cases consisting of entire student populations at particular grade levels, who exhibit characteristics of possible giftedness or are otherwise in need of additional screening to look for potential giftedness. While nomination instruments can include existing group test results, student work samples, and peer or self-nominations, they commonly come from teacher or parent referrals (Callahan, Moon, & Oh, 2013; McBee, Peters, & Miller, 2016).

Through nomination, schools can narrow the pool of students included in the screening phase, thus potentially reducing the resources invested to further assess students who may be unlikely to qualify. Given that funding to support gifted identification is generally limited when it exists at all (NAGC & CSDPG, 2015), it is often necessary for schools to limit assessment costs as much as possible. The need to reduce expenditures of resources contributes to the wide-spread use of short, inexpensive, and easy-to-administer instruments, such as parent and teacher checklists or observation forms, to further narrow the pool before administering formal

identification assessments (Qaseem et al., 2012). However, McBee et al. (2016) found that use of identification procedures that rely on such nominations often leads to “alarmingly large numbers of false negatives, which . . . results in large numbers of students failing to receive needed educational intervention” (p. 275). Increasingly, evidence supports the use of universal screening procedures in which all students at given grade levels are assessed, in lieu of or in addition to nominations, to more effectively identify gifted students, particularly those from underrepresented populations (Card & Giuliano, 2015; Ford, Grantham, & Whiting, 2008; McBee, 2016).

Identification practices in Connecticut. Although Connecticut state law requires gifted identification for students in grades K-12, procedures tend to vary by district. As previously discussed, the lack of mandate for gifted services may contribute heavily to the practices that may result in minimal identification rates. In general, formal screening and identification procedures for many students in Connecticut most commonly occur starting around grade 3, which is the first time most students are assessed using standardized measures of achievement, and in some cases, measures of ability. The identification process for a large proportion of gifted students in the state is triggered by their grade 3 achievement scores. Outside of grade 3, the identification process is generally dependent on individual teacher or parent referrals that are typically made based on observations of classroom performance and behaviors that suggest above-average achievement or potential.

Local control. A key feature of gifted identification in Connecticut is the emphasis on local control and use of local norms (RCSA Section 10-76a-2). With local control, districts have the discretion to develop their own practices and procedures for gifted identification while working within the state definition. Using local norms allows districts to identify students whose

potential or achievement is high relative to students within the same district, a strategy that has been shown to result in more proportional identification of students from diverse and frequently underrepresented populations (Callahan, 2005; Lohman, 2005, 2006; Siegle et al., 2016). However, using local norms also has implications for the persistence of identification of students who move between districts. Because the achievement and potential of a given student are considered relative to those of the other students in her district, a student who would be identified gifted in one district may not be in another. For students who change schools across districts, this may result in a loss of identification. In the reverse situation, when a student moves from a district in which he would not be identified to a district where a student with his scores generally would be identified, the student may or may not be referred or formally identified. In this case, even with existing scores that might indicate a need for identification, a number of factors could delay or prevent formal identification. For example, delays in receiving and reviewing complete school records could cause school personnel to miss information that would suggest a need for identification in the new school. Different testing and identification process timelines across districts may cause students to miss screening opportunities because of the timelines of their moves. Teachers in the new school, without the advantage of familiarity with the student's patterns of achievement and behaviors over time, may not recognize the need to refer such a student for gifted identification. This may be particularly true if the student exhibits the declines in achievement and behavior often associated with changing schools, even if those declines are temporary (Rumberger, 2003; Selya et al., 2016; Voight, Shinn, & Nation, 2012).

Underrepresented Gifted Populations

While gifted individuals exist in diverse populations, those from a number of groups have historically gone underidentified and underserved, contributing to large gaps in opportunity and

achievement among high ability students (Plucker, Hardesty, & Burroughs, 2013; Siegle et al., 2016). These include students from low-income backgrounds (Olszewski-Kubilius & Clarenbach, 2012; Stambaugh, 2007; Swanson, 2006), twice-exceptional students who are gifted and have disabilities (Brody & Mills, 1997; Foley Nicpon, Allmon, Sieck, & Stinson, 2011; Nielson, 2002), and students with limited English proficiency (Bernal, 2002; Harris, Rapp, Martinez, & Plucker, 2007). Gifted students from diverse racial and cultural backgrounds are often disproportionately represented in gifted education. For example, White students and some groups of Asian students tend to be proportionately represented, or even sometimes overrepresented, among identified gifted students (Kitano & DiJiosia, 2001; Yoon & Gentry, 2009). On the other hand, students who are Black, Hispanic/Latino, Native American, or of two or more races tend to be underidentified (Ford & Grantham, 2003; Ford et al., 2008; Gentry, Hu, & Thomas, 2008; Omdal, Rude, Betts, & Toy, 2011; Worrell, 2014). Despite decades of attention to the problem of underserved gifted populations, it remains an ongoing challenge. For instance, recent studies have demonstrated that, even after controlling for race, FRL status, ELL status, student reading and math achievement, school and district SES, and district reading and math achievement, White non-FRL students were more than 2.5 times as likely to be identified gifted than Latino, FRL, and ELL students with the same achievement scores (Hamilton, McCoach, Tutweiler, & Estepar-Garcia, 2017; Siegle, McCoach, Gubbins, Callahan, & Knupp, 2015). These students from culturally, linguistically, and economically diverse groups often experience barriers such as limited opportunity to learn and lack of access to resources and activities to develop emerging talents. As discussed later, students from many of these underrepresented populations are also among those groups who are most likely to experience high mobility.

Characteristics of Homeless and Highly Mobile Students

A recent study by Cowen (2017) provided one of the largest systematic profiles of HHM students, using a rich, statewide administrative data set from Michigan. Findings of the study indicated that, although there was some variability in their characteristics, homeless and highly mobile students tended to be disproportionately Black and Hispanic/Latino, were twice as likely as low-mobility students to experience poverty as indicated by eligibility for lunch subsidies, and were more likely to have been diagnosed with special academic needs. However, there were few differences between HHM and non-HHM students who are Asian or ELL students. Similarly, HHM and non-HHM students tended to be similar on other background characteristics. However, the schools in which HHM students were enrolled often had higher overall proportions of Black and Hispanic/Latino students, high poverty, and average reading and mathematics achievement levels far below their statewide means. They also tended to be found primarily in urban and rural areas. These findings are consistent with earlier findings by Larson and Meehan (2011) who studied the attributes of HHM students in one Midwestern state, comparing students who were primarily homeless to those who were not homeless but who had moved within a single year (mobile), and to non-HHM students who did not move (non-mobile). They found that only 3.3% of homeless students and 9% of mobile students were identified gifted, compared to 20% of non-mobile students.

McKinney-Vento Act

In response to the significant needs of students experiencing homelessness and residential instability in the United States, Congress passed the Stewart B. McKinney Homeless Assistance Act in 1987. As reauthorized in 2016 by the Every Student Succeeds Act (ESSA), Section 725 of the McKinney-Vento Act defines homeless children and youth as “individuals who lack a fixed,

regular, and adequate nighttime residence." This includes those who share the housing of others due to economic hardship or loss of housing; those living in motels, hotels, trailer parks, campgrounds, or shelters; those whose nighttime residence is a place not normally used as a regular sleeping accommodation; those who live in cars, parks, public spaces, abandoned buildings, or substandard housing; and migratory children. Among other provisions, the McKinney-Vento Act attempts to reduce the school mobility of homeless children by ensuring that students are able to remain enrolled in the schools they attended prior to becoming homeless, except in cases where doing so is not in the best interest of the student. The Act further requires that homeless students must have access to all programs and services for which they are eligible, explicitly including gifted and talented programs.

Mobility Patterns

Rumberger (2015) used data from the National Assessment of Education Progress (NAEP) to describe mobility patterns among fourth grade students in 2000. He found that 35% had changed schools at least once within the previous 2 years, with 19%, 7%, and 4% making one, two, or three moves, respectively (Rumberger, 2015). Similarly, Lee, Burkam, and Dwyer (2009), found that nationally, nearly 56% of students remain in the same school from the beginning of Kindergarten through the end of grade 3, while about 36% of students change schools once, about 8% change schools twice, and about 3% change schools three times within the same period. They also found that while a single move has relatively little impact on a student's achievement over time, students who experience two or more moves, particularly when those moves occur in the early grades, tended to show significant and lasting declines in achievement.

School Mobility in Connecticut

At least three times each year, school personnel in Connecticut report student enrollment information that includes dates of entry to and withdrawal from specific schools and districts. The Connecticut Department of Education assigns a unique identifier to each student enrolled in public, charter, or alternative programs, allowing tracking of students across schools and districts. A recent study of student mobility in Connecticut found a 6.4% school mobility rate among all Connecticut students (Apaloo, 2014). In this study, mobility rates indicated the number of students who transferred into or out of a Connecticut school, divided by the cumulative enrollment for the given academic year. Stability rates indicated the number of students who stayed in the same school, divided by the enrollment as of October 1 of the given academic year. Whereas White students had a mobility rate of 4.3%, mobility rates across non-White subgroups ranged from 8.4% to 11.2%. Mobility rates were also significantly above average for English language learners (ELL, 12.9%), students eligible for free or reduced lunch (FRL, 9.4%), and students identified for special education (SPED, 11.1%). The same study also examined stability rates within schools by District Reference Group (DRG) classifications, which are based on indicators of SES, need, and school enrollment. Schools with high SES and low need tended to have the lowest mobility and highest stability; those with low SES and high need tended to have the highest mobility and lowest stability.

Types of and Reasons for Moves

Student change schools for a number of reasons. For many HHM students, moves that lead to school changes may be associated with negative circumstances and tend to be largely involuntary. These include a wide variety of reasons such as personal conditions like job loss, eviction, homelessness, incarceration, divorce, or death of a parent/guardian; community issues

such as gang activity or violence; and environmental and safety issues, such as buildings closed due to lead or asbestos, as well as those damaged or destroyed due to events like floods, fire, or earthquakes. They also include school changes for disciplinary reasons, including suspensions and expulsions. These types of school moves, because they are often accompanied by other risk factors like poverty, stress, and disruptions, tend to be most strongly linked to negative student outcomes (Rumberger, 2015).

In contrast, other school changes may be the result of positive, often voluntary circumstances, and are frequently characterized as "moves to opportunity" (Scanlon & Devine, 2001). For example, families may relocate due to job promotions, students may change schools to take advantage of better environments or special programs, or families may take advantage of voucher programs designed to help them move to lower-poverty neighborhoods (Katz, Kling, & Liebman, 2001; Rosenbaum & Harris, 2010). Students who experience moves to opportunity may benefit from protective factors and more positive overall circumstances that outweigh the risks associated with moving (Masten, 2007; Militis, Sesma, & Masten, 1999).

Other moves tend to be more neutral in terms of potential risks and benefits. For example, most students experience structural or promotional types of school moves, such as those from elementary to middle school to high school. These can include other less common structural changes such as when school buildings open or close or when attendance zones are redrawn. Although these school changes require some adjustment, any risk associated with these changes is often minimized through structures and procedures implemented to smooth the transition between schools (Rumberger, 2015). Similarly, the military has put systems and procedures in place to reduce stress and facilitate smooth transitions for students who change schools due to military relocation. There is evidence that highly mobile students from military

families experience reduced risk and much smaller declines in achievement after moving than do those from civilian families (Lyle, 2006; Marchant & Medway, 1987).

Risks Associated With Mobility

School mobility has frequently been associated with poor academic performance and declines in achievement (Friedman-Krauss & Raver, 2015; Selya et al., 2016; Temple & Reynolds, 1995; Voight, Shinn, & Nation, 2012). In a meta-analysis of 26 mobility studies dated between 1975 and 1994, Mehana and Reynolds (2004) found that the average reading and mathematics achievement level of mobile students was equivalent to a 3-4 month performance disadvantage relative to non-mobile students. Mobility is often associated with poverty, and HHM students share many similarities with their low-SES but continuously housed peers. For instance, HHM students and low-SES students are more likely than their low-mobility and higher-SES peers to come from ethnic minority backgrounds, to have less access to adequate resources, to experience higher levels of adversity, and to suffer from mental or physical health problems (Rafferty, Shinn, & Weitzman, 2004; Samuels, Shinn, & Buckner, 2010). However, a number of studies have noted lower levels of achievement and greater declines in academic performance for HHM students, even when compared to their low-income peers (Fantuzzo & Perlman, 2007; Herbers, et al., 2012; Miller, 2011). Obradović et al. (2009) found gaps in achievement between HHM students and both their low-income and advantaged peers as early as second grade. These gaps persisted throughout elementary school, often widening considerably for students with multiple moves. This is consistent with earlier findings suggesting that students who move frequently experience the cumulative effects of multiple moves (Friedman-Krauss & Raver, 2015; Kerbow, Azcoitia, & Buell, 2003; Rumberger et al., 1999).

For some HHM students, mobility is also associated with social, psychological, and behavioral problems. The stress associated with moving has been found to impair self-regulation, which in turn leads to decreased attentional capacity and inhibitory control, ultimately contributing to lower academic performance (Lupien, King, Meaney, & McEwan, 2001). Friedman-Krauss and Raver (2015) found that students who frequently changed schools tended to have higher levels of teacher-reported cognitive dysregulation, including problems with memory, inattention, and a lack of inhibitory control in the classroom. Masten et al. (1997) found that behavior problems and lower adaptive functioning often co-occurred with low achievement among homeless students.

Protective Factors

Despite the association between mobility and various risk factors, some homeless and highly mobile students benefit from certain factors that promote resilience and help counter those risks. For example, Masten et al. (1997) found that some homeless students show resilience, defined as competence despite experiencing risk (Masten, Cutili, Herbers, & Reed, 2009), in both academic and behavioral domains. Several studies have provided evidence that some HHM students show resilience by achieving at or above national norms (Herbers et al., 2012; Huntington, Buckner, & Bassuk, 2008; Miller, 2001; Obradović et al., 2009). In one study, 58% and 63% of HHM students had achievement trajectories in reading and mathematics, respectively, within 1 SD of national test norms despite the risks they faced (Cutili et al., 2012).

Both the risks and protective factors each student experiences are a result of the complexity of various individual, family, and ecological contexts; therefore, even within the HHM population, there is wide variation in each individual's overall degree of risk and resilience. Students who show resilience may have access to relatively more resources, more

protective factors, or fewer total risk factors than other HHM students. For example, having good attendance, being female, not being an ELL student, and being of the majority racial group have all been recognized as protective factors for HHM students (Cutili et al., 2012). Other protective factors include strong general cognitive skills (Herbers et al., 2011), early literacy skills (Masten, 2012), self-regulation skills (Obradović, 2010), good health (Cutli, Herbers, Rinaldi, Masten, & Oberg, 2010), and factors related to parenting quality, family factors, and the child's broader ecology (Masten, 2007; Masten et al., 2009; Miliotis, Sesma, & Masten, 1999). While research on resilient HHM students remains somewhat limited, there is some evidence that early achievement, particularly in reading, may serve as a protective factor that can reduce declines in achievement after moving (Herbers et al., 2012).

Gifted Students Who Relocate

Transfer of gifted identification. Policies and practices vary widely with regard to how gifted identification is handled for students who relocate. For previously identified gifted students, the persistence of that identification across schools depends in part on whether students relocate within a state or transfer between states (NAGC & CSDPG, 2015). For example, although 12 of 39 responding states in the 2014-2015 *State of the States in Gifted Education* report indicated that gifted identification is transferrable within the same state, only 5 indicated that gifted identification may transfer from other states. Another 5 states specifically do *not* permit gifted identifications to transfer between states. In the remaining states, including Connecticut, and most often due to the absence of specific policy, decisions about whether gifted identification can transfer are left to the discretion of LEAs for students who move, whether those moves are between or within states.

Gifted children from military families. Although general guidance regarding gifted students who move is limited, a number of formal and informal resources about relocating with gifted students are aimed at a particular highly-mobile subgroup: military families. The Military Interstate Children's Compact (http://www.mic3.net/), developed in 2006 and since adopted by all 50 states and the District of Columbia, provides for consistent treatment of military children transferring between public schools, including provisions to facilitate timely transferal of complete educational records, to deal with redundant or missed testing opportunities, and to ensure appropriate placement of students in educational programs and services, explicitly including special services such as gifted education programs. Various state councils and education officials also provide guidance regarding gifted education. For example, the Commonwealth of Virginia Department of Education's Office of Mathematics and Governor's Schools (Poland, 2013) issued a briefing to the Virginia Council on the Interstate Compact on Educational Opportunity for Military Children to address how to navigate gifted education and Governor's School programs for military students. Military families themselves have also created a number of networks and resources to share information with each other. For example, gifted education is a frequent topic of discussion on a number of military blogs and websites, such as http://www.militarychild.org/ and http://familiesonthehomefront.com.

Conclusion

This review of literature provided insight into the issue of school mobility, discussing the characteristics of highly mobile students, types of and reasons for moves, and the risks and protective factors associated with mobility. It also illustrated the current landscape for gifted education in Connecticut, where state regulations provide a common definition of gifted but local control policies lead to widely varying district practices and procedures for gifted identification. Taken together, the literature on school mobility and gifted identification suggested that

changing schools may be associated with disruptions and declines that could contribute to lack of identification of the gifted education needs of highly mobile students. Furthermore, the literature suggested that many of the same populations that tend to be highly mobile are also among those who are historically underrepresented in gifted education programs, particularly students who are Black, Hispanic/Latino, or experiencing poverty. With little existing research on mobility in the context of gifted education, the information garnered from this review of literature supported the need to build understanding of the impact of school mobility on gifted identification, taking into account characteristics including race, socioeconomic status, English language learner status, special education status, and achievement levels.

CHAPTER 3: RESEARCH METHODS

In this chapter, I discuss the methods used in this research study. After providing an overview of the research questions and overall study design, I describe the sample, data sources, and participants. I also describe the procedures used to clean and organize data, create variables, and complete matching.

Research Questions

Using student, school, and district data provided by the Connecticut State Department of Education, this study examined the following research questions:

1. What were the rates of gifted identification in Connecticut public school districts?
    a. What were the characteristics of districts that did and did not identify gifted students?
    b. What was the relationship between district demographics and district gifted identification compliance?
2. For homeless and/or highly mobile (HHM) students in Connecticut public schools, what was the likelihood of attending school in a district that did not identify gifted students?
3. Among fourth graders attending Connecticut public schools in districts that identified gifted students, how do rates of gifted identification for HHM students compare to those of low-mobility students with similar achievement levels?

Research Study and Design

The primary goal of this study was to examine the possible relationship between school mobility and the likelihood of gifted identification for fourth grade students in Connecticut public schools. To accomplish this goal, given the variation in gifted identification practices

across districts, I first examined identification rates within each district to determine whether there were districts in which gifted identification generally did not take place. Next, I examined the overall demographics, including mobility rates, of districts that did and did not identify gifted students to determine the likelihood of a high mobility student attending a district in which there was virtually no gifted identification. Finally, for students in districts where gifted identification did take place, I compared gifted identification rates of HHM and low-mobility students using a weighted sample in which students were matched on district, race, ELL status, special education status, SES (as indicated by eligibility for lunch subsidies), reading achievement, and mathematics achievement. At each stage, I replicated the analyses across three cohorts of students to discern patterns of findings across different academic years.

Sample

This study was conducted using a statewide administrative dataset that included enrollment, demographic, and achievement data for students in Connecticut public schools who were in grades 1-4 during the academic years ranging from 2007-2008 through 2012-2013. These data were collected from all public schools in the state, including public charter schools, by the Connecticut State Department of Education (CSDE) through standard statewide accountability and reporting procedures. Students, schools, and districts were identified in the dataset using unique, state-assigned, numeric codes. The complete dataset contained 141,121 records for students who were enrolled at any point from the beginning of grade 1 through the end of grade 4 for the three most recent academic-year cohorts (students in grade 4 cohorts from 2010-2011 to 2012-2013). This study specifically focused on students who changed schools within Connecticut public schools, so 29,729 students with missing data in either grade 3 or 4, who likely represented moves to or from other states or moves to or from non-public schools,

were examined using descriptive statistics and compared to students with complete data (Appendix C, Table C.2) then excluded from further analysis. With the exception of reading achievement (cohort A, $t(3568.784) = 1.072$, $p = .284$, $d = 0.$, cohort B, $t(1070.387) = 2.021$, $p = .044$, $d = 0.$, and cohort C, $t(1118.791) = 1.922$, $p = .055$, $d = 0.475$), there were statistically significant differences at the $p < .001$ level between students with complete and missing data across all variables. Students with missing data were more likely to be Black, Asian, Hispanic/Latino, ELL, SPED, FRL, and homeless or highly mobile. They were less likely to be identified as gifted and had lower mathematics achievement scores. It is notable that about 10,000 students from each cohort were excluded due to missing data, yet these students included significantly higher proportions of HHM students than those retained for further analyses. The final analysis was performed using a sample drawn from records for 111,392 students with no missing data. Table 3.1 summarizes the sample sizes for each cohort before and after removing records with missing data.

Table 3.1

Sample Sizes by Cohort

Sample	A	B	C	Combined
Year	2010-2011	2011-2012	2012-2013	2010-2013
Total	47,706	46,424	46,991	141,121
Missing	10,158	9,829	9,742	29,729
No missing	37,548	36,595	37,249	111,392

Data Sources

The data used in this study were made available through the PARSACT memorandum of agreement between the Performance Office at the Connecticut State Department of Education and the Neag School of Education at the University of Connecticut. In exchange for service as a

graduate research intern at CSDE, I was granted access and permission to use the data provided for research and publication.

Public School Information System. CSDE uses the online Public School Information System (PSIS) to collect "timely and accurate" student-level enrollment and demographic data in October, January, and June of each academic year, as required by the Connecticut General Statute (C. G. S. 10-10a). Within each district, a designated PSIS contact person is responsible for coordinating with district personnel to collect and submit the required information. Data collected include school and district enrollment information, grade, gender, race/ethnicity, eligibility for free or reduced price lunch, special education status, English language learner status, homeless status, migrant status, and gifted/talented identification. These data include unique ID numbers for students, schools, and districts, which allow linking of data across PSIS and other CSDE data collection systems.

Connecticut Mastery Test. In addition to data collected through the PSIS, student data are also collected in connection with statewide standardized test administrations. Prior to 2015, all Connecticut public school students in grades 3-8, with the exception of those with very limited English proficiency, were required to take the Connecticut Mastery Test (CMT) each spring (Hendrawan & Wibowo, 2013). The CMT was designed to measure performance in reading and mathematics, as well as writing and science. It has been administered to Connecticut students since 1985. Each generation of the test was developed through a rigorous, 2- to 3-year process guided by staff members in CSDE's Bureau of Student Assessment and informed by a number of advisory committees made up of teachers, curriculum specialists, and content experts, as well as a Fairness Committee. Test items were carefully developed to align with the Connecticut Curriculum Frameworks for each content area, then were piloted and subjected to

extensive review to ensure their validity and fairness. Multiple test forms were then simultaneously constructed from the pool of test items, providing parallel forms with equivalent content and difficulty within each grade level.

CMT scores compare student performance against established standards, and are vertically scaled so a given score can be compared to other scores both within and across grades. The spring 2006 through spring 2015 test administrations used the fourth generation CMT (CMT4). CMT4 scores are interpreted relative to five levels of performance: Advanced, Goal, Proficient, Basic, and Below Basic (Hendrawan & Wibowo, 2013). Table 3.2 shows the range of scale scores in each performance category for grade 3 CMT4 reading and mathematics test.

Table 3.2

CMT4 Grade 3 Achievement Levels and Scale Score Ranges

Level	Reading	Mathematics
Advanced	279-400	288-400
Goal	235-278	242-287
Proficient	217-234	210-241
Basic	202-216	187-209
Below Basic	100-201	100-186

Along with students' achievement scores, CSDE's CMT files also included student enrollment and demographic data at the time of testing, providing a fourth collection point for these variables for students in tested grades.

Complete database. For this study, CSDE provided access to a database containing tables of PSIS data from October 2007 through June 2013. Together, the PSIS tables provided 12 collection points of data from the beginning of grade 1 through the end of grade 4 for three

complete academic year cohorts (grade 4 cohorts from 2010-2011 to 2012-2013). The database also contained CMT tables from test administrations in grades 3 and 4 from spring 2010 through spring 2013, providing two additional collection points for each group, for a total of 14 collection points over 4 years for each cohort. It is important to note that, at the time this archival data was collected, there was not a designated gifted education consultant at CSDE to provide guidance or oversight regarding gifted education practices and reporting.

Participant Demographics

Across the complete dataset, Connecticut public school students in the 2010-2011 to 2012-2013 cohorts included about 48.5% females and 51.5% males. These students were about 57% White, 5% Asian, 14% Black, 20% Hispanic/Latino, and 3% Other (including Alaskan Native, Pacific Islander, students of two or more races, and students for whom no race was reported). At some point during grades 1-4, 45% of these students had received free or reduced price lunch, 12% were English language learners, and 15% were identified for special education. The tables in Appendix A provide demographics by cohort for the total dataset (Table A.1), for the subset of students with complete data (Table A.2), and for the subset of students excluded from later analyses due to missing data in grades 3 or 4 (Table A.3). They also provide demographics for students in districts that identify gifted students (Table A.4), students in districts with minimal identification rates of 0.5% or fewer gifted students (Table A.5), and the subset of students who were matched within identifier districts as explained later in this chapter (Table A.6).

Procedures

I received the data for this study in a Microsoft Access database containing 24 tables of PSIS and CMT data. After cleaning and organizing the data in Access as detailed below, I

exported it to comma separated value files that could be imported into other software packages. I then used IBM SPSS Statistics, Version 24 to calculate descriptive statistics and other analyses, and I completed matching procedures in R, Version 3.3.3.

Cleaning and organizing data. Using unique student ID numbers to match records across files, I created a new table for each of the three cohorts, collecting all records for each student into the table for his or her cohort. Prior to merging data from each of the 14 collection points into the table for each cohort, I appended variable names with 3-character codes to indicate the cohort, grade level, and collection point for the data. For example, “B3D_Lunch” indicated the FRL status for a student in cohort B, in grade 3, at the fourth collection point of the academic year (June PSIS). This allowed me to organize data chronologically in a wide file with a single record for each unique student ID, providing a picture of each student’s status over time within each variable.

After merging data into the appropriate cohort files, it was necessary to recode several variables for consistency across collection points because data from the CMT collections were coded differently than those from the PSIS collections. The tables in Appendix D summarizes coding information for these variables. Table D.1 details the coding schemes for the original and recoded variables, and Table D.2 describes new variables from existing variables to summarize student status across collection points.

Determining mobility counts. To determine how many times each student changed schools, it was first necessary to create unique facility codes. Three codes in the original dataset indicated information about student enrollment: 2-digit institution codes indicated specific types of institutions; 3-digit district codes provided unique identifiers for each district in the state; and 2-digit school codes provided identifiers unique to each school within specific districts.

However, school codes were not unique across districts. Creating facility codes that combined the institution, district, and school codes into single, 7-digit strings resulted in unique identifiers for each school relative to others throughout the state.

Raw mobility counts. To calculate the raw mobility count, facility codes were organized chronologically from the beginning of grade 1 through the end of grade 4. Focusing on moves prior to the end of grade 4 provided a snapshot of each student's mobility around and including the time when initial gifted identification typically takes place (grades 3-4). Students with missing enrollment data at any given point were assigned a facility code of "9999999" to indicate that they were not enrolled in a Connecticut public school at that time. Then, each consecutive pair of facility codes were compared. At each possible transition point, "1" was recorded to indicate a change in facility codes, including entrance to or exit from Connecticut public schools, while "0" indicated no change. The raw mobility count comprised the sum of these transition values.

Structural mobility counts. Because promotional and structural school changes – those due to the organization of schools and districts and students' expected patterns of movement within them, rather than those due to individual student factors – tend not to be associated with the same risks and outcomes as other types of school changes, the next step was to adjust the raw mobility counts to account for these types of moves. There are a number of reasons for structural moves, including typical feeder patterns within a district (such as a district in which students attend a K-2 building, then move to a 3-4 building), redistricting (large numbers of students reassigned to one or more other schools at a given transition point), and school openings or closings. In the absence of specific information from each district to identify such structural moves, I closely examined the data to look for evidence indicating likely structural changes. For

instance, facility codes that newly appeared were assumed to be due to new buildings opening. Similarly, facility codes that disappeared were assumed to be due to school closings.

To identify other structural changes, I examined the number of students who had the same unmatched pair of facility codes at the same transition point. While it was not unusual to find small numbers of students with the same pair, these likely coincidental same-move patterns were rarely observed for more than about a dozen students per pair of schools. For school pairs with more than 20 same-move patterns, there were, in nearly all cases, one or more other signs that these were due to structural moves. For example, most of these occurred at the same relative point for students across all three cohorts (such as all students changing schools after grade 2). For others, the moves occurred at the same date, so were observed at different grade levels in each cohort (one-time redistricting in a particular year impacted students from cohorts A, B, and C in grades 3, 2, and 1, respectively). Though much less common, there were also some unique, one-time cases in which large groups of 60+ students made the same move that was not observed in other cohorts or at other points in time. Such cases were also assumed to be structural moves, due to the unlikelihood that so many students would make the same move at the same time due to individual factors alone.

Table 3.3

Students With Adjustments for Structural Moves

Cohort	1	2
A	7,169	147
B	6,893	191
C	7,658	262
Combined	21,720	600

Adjusted mobility counts. Altogether, I identified 298 unique pairs of facility codes at specific points in time that likely indicated structural moves. As might be expected, nearly all of these occurred during the transitions between school years. Only 2 pairs occurred within the school year, specifically between the October and January collections in grade 1 within a single district. For each student whose enrollment at the specific collection points matched the pairs identified, “1” was recorded to indicate a structural move at that transition point. As before, the total mobility adjustment needed comprised the sum of all transition points for structural moves. Table 3.3 indicates the number of students with mobility count adjustments in each cohort. Finally, the number of structural moves for each student was subtracted from the raw mobility count to arrive at the final mobility count.

***Categorizing mobility counts*.** After determining students’ final mobility counts, I examined the mobility count patterns and their associated demographics to determine how best to categorize student mobility (Table 3.4). One possibility was simply to differentiate between high and low mobility; another possibility was to add a third category to indicate moderate mobility. As expected, as mobility counts increased, the percentages of minority students, FRL students, and SPED students increased, and the percentage of gifted students decreased. While these changes were quite large at each step from 0-3 moves, they generally stabilized after three moves. The percentage of ELL students who moved one or more times was generally 2-3 times the percentage of ELL students among those who had not changed schools. Notably, among students with two or more moves, the percentages of minority, FRL, and ELL students was nearly twice that of the general population, while the percentage of gifted was only about a third of that for the general population. Based on these observations, I decided to proceed by categorizing based on two mobility categories: low and high mobility.

Table 3.4

Student Demographics by Mobility Count and Cohort

Moves	Cohort	*n*	Minority (%)	FRL (%)	ELL (%)	SPED (%)	Gifted (%)
0	A	28,175	25.74	29.87	7.63	14.30	5.79
	B	27,551	26.25	31.07	7.74	14.23	5.60
	C	27,751	27.60	32.78	7.98	14.45	5.11
1	A	13,507	49.03	56.42	16.93	15.53	2.52
	B	9,838	49.96	59.99	15.77	15.63	2.44
	C	13,374	47.90	57.31	16.76	15.40	2.13
2	A	4,127	64.50	77.51	21.61	16.31	1.55
	B	2,531	61.16	79.34	18.96	17.78	2.53
	C	4,126	59.33	71.40	18.61	15.73	1.79
3	A	1,206	72.39	85.28	22.89	19.40	1.49
	B	4,320	49.56	58.38	19.84	15.51	2.69
	C	1,125	64.71	84.18	20.53	21.24	0.53
4	A	432	73.38	89.35	17.82	29.86	0.46
	B	1,521	63.45	72.52	26.23	16.90	1.45
	C	358	75.14	87.15	18.44	35.75	0.56
5	A	174	66.67	85.63	17.24	44.83	1.15
	B	444	68.47	85.14	23.65	26.58	0.45
	C	182	66.48	84.07	10.99	42.31	2.20
6	A	63	84.13	84.13	14.29	61.90	0.00
	B	139	69.06	89.21	23.02	42.45	0.72
	C	50	78.00	94.00	16.00	54.00	2.00
7	A	19	78.95	94.74	26.32	57.89	0.00
	B	61	75.41	81.97	19.67	34.43	1.64
	C	19	78.95	100.00	10.53	52.63	0.00
8	A	1	100.00	100.00	0.00	100.00	0.00
	B	12	50.00	75.00	8.33	50.00	0.00
	C	6	83.33	83.33	0.00	50.00	0.00
9	A	2	100.00	100.00	50.00	50.00	0.00
	B	7	57.14	100.00	14.29	85.71	0.00
	C	0	--	--	--	--	--

Operationalizing high mobility. After deciding to use two mobility categories, the next step was to determine an appropriate threshold between low and high mobility. As previously noted, the differences in demographics for students with two or more moves relative to their lower mobility peers was striking, providing one piece of evidence to support defining high mobility as two or more moves. Previous studies on highly mobile students have defined high mobility relative to the number of moves and the span of time considered, as well as the general age range of the students. In their study using student data from grades K-3, Lee, Burkam, and Dwyer (2009) defined high mobility for students in the early grades as two or more moves, based on their finding of significant and lasting declines in achievement observed for these students. In addition to the observed demographic differences for students with two or more moves, the mobility count patterns observed in the present study were consistent with those observed by Lee et al. (2009). These studies also focused on moves for similar grades and spans of time. After taking these factors into consideration, I decided to define high mobility as two or more moves.

Table 3.5

Crosstabs of Homelessness and Mobility for Cohort A Students with Complete Data

		Mobility		
Homelessness		Low	High	Total
Non-Homeless	Count	34,047	3,131	37,178
	% of Total	90.7	8.3	99.0
Homeless	Count	195	175	370
	% of Total	0.5	0.5	1.0
Total	Count	34,242	3,306	37,548
	% of Total	91.2	8.8	100.0

Table 3.6

Crosstabs of Homelessness and Mobility for Cohort B Students with Complete Data

Homelessness		Mobility: Low	Mobility: High	Total
Non-Homeless	Count	31,248	4,966	36,214
	% of Total	85.4	13.6	99.0
Homeless	Count	194	187	381
	% of Total	0.5	0.5	1.0
Total	Count	31,442	5,153	36,595
	% of Total	85.9	14.1	100.0

Table 3.7

Crosstabs of Homelessness and Mobility for Cohort C Students with Complete Data

Homelessness		Mobility: Low	Mobility: High	Total
Non-Homeless	Count	33,679	3,160	36,839
	% of Total	90.4	8.5	98.9
Homeless	Count	218	192	410
	% of Total	0.6	0.5	1.1
Total	Count	33,897	3,352	37,249
	% of Total	91.0	9.0	100.0

Homeless and highly mobile. Next, I examined the characteristics of students who were homeless, highly mobile, or both. Tables 3.5-3.7 show the crosstabs for homelessness and mobility for students with complete data in each cohort, illustrating that there is a statistically significant association between homelessness and mobility (A: $X^2(1, 37{,}548) = 689.553$, $p < .001$; B: $X^2(1, 36{,}595) = 389.838$, $p < .001$; C: $X^2(1, 37{,}249) = 724.496$, $p < .001$). Across the cohorts, about 1% of students were homeless, about 10% were highly mobile, and about 0.5% were both homeless and highly mobile.

Table 3.8 shows the number of students in each category among all students in the dataset, while Table 3.9 details the demographics by mobility category for students with complete data. Notably, Table 3.9 illustrates that the characteristics of students who were homeless but not highly mobile closely resembled the characteristics of students who were highly mobile but not homeless. Furthermore, in all three cohorts, more than 50% of the homeless students were also highly mobile. Although I considered treating homelessness and high mobility as separate, distinct variables, the relatively small samples sizes and the high degree of similarity and overlap between them suggested that it made more sense to collapse these into a single, broad category encompassing both homeless and highly mobile students. This practice is consistent with a number of recent studies that have treated HHM students as a single category in this way (Cutili et al., 2013; Herbers et al., 2012; Larson & Meehan, 2011; Obradović et al., 2009; Selya et al., 2016). Table A.2 in Appendix A details the demographics for HHM and non-HHM students from the complete sample.

Table 3.8

Statewide Homeless and Highly Mobile Percentages (All Students)

		Homeless		Mobile		Both	
Cohort	*n*	Frequency	Percent	Frequency	Percent	Frequency	Percent
A	47,706	571	1.2	6,024	12.6	291	0.6
B	46,424	600	1.3	9,035	19.5	346	0.7
C	46,991	649	1.4	5,866	12.5	326	0.7

Table 3.9

Demographics of Students With Complete Data by Mobility Status

		Not Homeless, Not Mobile			Mobile, Not Homeless			Homeless, Not Mobile			Homeless and Mobile		
	Cohort	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*
White	A	34,047	0.65	0.48	3,131	0.28	0.45	195	0.22	0.41	175	0.25	0.44
	B	31,248	0.66	0.47	4,966	0.39	0.49	194	0.28	0.45	187	0.24	0.42
	C	33,679	0.64	0.48	3,160	0.39	0.49	218	0.30	0.46	192	0.27	0.44
Black	A	34,047	0.11	0.32	3,131	0.26	0.44	195	0.34	0.47	175	0.29	0.45
	B	31,248	0.11	0.31	4,966	0.21	0.41	194	0.30	0.46	187	0.29	0.45
	C	33,679	0.11	0.31	3,160	0.21	0.41	218	0.26	0.44	192	0.29	0.46
Asian	A	34,047	0.05	0.21	3,131	0.05	0.21	195	0.02	0.12	175	0.01	0.08
	B	31,248	0.05	0.22	4,966	0.06	0.24	194	0.02	0.14	187	0.01	0.10
	C	33,679	0.05	0.22	3,160	0.05	0.21	218	0.02	0.15	192	0.01	0.10
Hispanic/ Latino	A	34,047	0.16	0.37	3,131	0.37	0.48	195	0.38	0.49	175	0.43	0.50
	B	31,248	0.17	0.37	4,966	0.30	0.46	194	0.37	0.48	187	0.42	0.49
	C	33,679	0.18	0.38	3,160	0.32	0.47	218	0.36	0.48	192	0.40	0.49
Other Race	A	34,047	0.02	0.16	3,131	0.04	0.20	195	0.05	0.21	175	0.02	0.15
	B	31,248	0.02	0.14	4,966	0.03	0.17	194	0.03	0.17	187	0.04	0.20
	C	33,679	0.03	0.16	3,160	0.04	0.19	218	0.06	0.23	192	0.04	0.19
Lunch	A	34,047	0.35	0.48	3,131	0.83	0.38	195	0.97	0.17	175	0.98	0.15
	B	31,248	0.36	0.48	4,966	0.69	0.46	194	0.94	0.24	187	0.98	0.15
	C	33,679	0.38	0.48	3,160	0.76	0.43	218	0.95	0.23	192	1.00	0.00
ELL	A	34,047	0.09	0.28	3,131	0.18	0.39	195	0.18	0.38	175	0.14	0.35
	B	31,248	0.09	0.28	4,966	0.17	0.37	194	0.17	0.38	187	0.16	0.36
	C	33,679	0.09	0.29	3,160	0.15	0.36	218	0.19	0.39	192	0.15	0.36
SPED	A	34,047	0.11	0.31	3,131	0.14	0.35	195	0.16	0.37	175	0.12	0.33
	B	31,248	0.11	0.31	4,966	0.13	0.34	194	0.17	0.38	187	0.15	0.36
	C	33,679	0.11	0.31	3,160	0.14	0.35	218	0.14	0.35	192	0.18	0.38
Gifted	A	34,047	0.06	0.23	3,131	0.02	0.15	195	0.02	0.14	175	0.00	0.00
	B	31,248	0.06	0.23	4,966	0.04	0.19	194	0.01	0.07	187	0.00	0.00
	C	33,679	0.05	0.22	3,160	0.02	0.15	218	0.02	0.13	192	0.02	0.12
Reading (centered)	A	34,047	1.4	37.7	3,131	-12.3	38.9	195	-15.9	34.6	175	-12.8	35.8
	B	31,248	1.5	37.2	4,966	-7.9	39.3	194	-11.7	37.9	187	-15.2	38.9
	C	33,679	1.2	37.8	3,160	-10.1	38.2	218	-6.2	38.5	192	-15.1	35.9
Math (centered)	A	34,047	2.2	46.1	3,131	-13.7	47.7	195	-13.4	39.6	175	-15.3	46.9
	B	31,248	2.2	45.5	4,966	-7.4	47.2	194	-12.4	50.1	187	-25.4	42.8
	C	33,679	2.2	44.3	3,160	-12.2	45.4	218	-12.5	44.7	192	-20.4	46.1
Mobility Count	A	34,047	0.21	0.41	3,131	2.45	0.81	195	0.61	0.49	175	2.88	1.02
	B	31,248	0.16	0.36	4,966	2.94	0.88	194	0.49	0.50	187	3.39	1.37
	C	33,679	0.21	0.41	3,160	2.41	0.82	218	0.57	0.50	192	2.79	1.03

Matching. Mobility and giftedness are both relatively rare characteristics, so it follows that the sample for this study was dominated by low-mobility, non-gifted students. To avoid complications in interpretation due to overextrapolation, it was important to consider whether there was enough similarity between the HHM and non-HHM students to allow for reasonable comparison of these groups. To address this issue for analyses within districts that identify gifted students, I used coarsened exact matching procedures via the MatchIt package (Ho, Imai, King,

& Stuart, 2011) in R to match cases and achieve better balance between the HHM and non-HHM groups. Treating mobility as the treatment and using matching to balance the HHM (treatment) and non-HHM (control) groups provided justification for treating HHM and non-HHM students as if they were randomly assigned to treatment and control groups, ultimately allowing for inferences about the causal effects of mobility on the likelihood of gifted identification (Rubin, 1997).

Coarsened exact matching (CEM) is a member of a general class of matching techniques described by Iacus et al. (2011) as monotonic imbalance bounding (MIB), in which balance between treatment and control groups "is chosen [by the user] ex ante" (p. 346), and in which treatment and control subsets are produced "on the basis of a given vector or tuning parameters. . . one for each covariate" (p. 347). Iacus et al. (2011) demonstrated that the "tuning parameters" for each variable can be adjusted without impacting the balance on the remaining variables. CEM, like other MIB techniques, provides a way of pruning observations to provide better balance between groups who have similar distributions of covariates (Iacus et al., 2009). According to Iacus et al. (2009, 2011, 2012), when data are exactly balanced, causal effects can be estimated using a simple difference in means on the matched data. Furthermore, analyses using matched samples "are 'doubly robust' in that if *either* the matching analysis *or* the analysis model is correct (but not necessarily both) your inferences will be statistically consistent" (Ho et al., 2011, p. 6). CEM has a number of advantages relative to other matching methods. For example, it has been shown to better reduce imbalance, model dependence, and estimation error, and it often resulting in larger sample sizes after pruning the data (Ho et al., 2007; Iacus et al., 2009, 2012; King, Nielsen, Coberley, Pope, & Wells, 2011). It is both simple and extremely efficient computationally, producing matches in a single step without iteratively checking

balance and rematching, allowing it to work on large datasets without the need for expensive statistical software or modeling (Iacus et al., 2011; King et al., 2011).

The basic idea behind CEM is that variables are recoded so similar values are grouped and assigned the same value, and it is on this new value that individuals are exactly matched (Iacus et al., 2011). In essence, this is a process much like what one would use when creating the bars of a histogram. As Iacus et al. (2012) discussed, coarsening is already common practice when working with data, and is “almost intrinsic to the act of measurement” (p. 8). For example, they point out that recoding data collected on a 7-point Likert scale to reflect 3 categories could be considered a form of user coarsening of the data (p. 8). In this example, applying CEM would involve matching individuals based on the three categories rather than the seven possible responses. In CEM, all members of the treatment group for whom there are matches are retained, along with as many control cases as are matched, while unmatched members of the control group are discarded (Iacus et al., 2011). When analyzing matched data, any method that would have been appropriate with the unmatched data can still be used (Ho et al., 2011). However, because different numbers of controls are matched to each treatment unit, the analyses must use appropriate weightings to adjust for these differences (King et al., 2011). Furthermore, the coarsening used to create the matched subsets is somewhat temporary, as any analyses on the matched data still use individuals’ original values (Iacus et al., 2012).

In the present study, students were matched exactly on their grade 4 district and on all dichotomous covariates (dummy coded variables for race, FRL status, ELL status, and SPED status). For the continuous reading and mathematics achievement score variables, students were matched using coarsened exact matching (CEM) procedures (Iacus et al., 2009, 2012). I defined each of the strata by considering the state-defined achievement categories associated with CMT

reading and math scores, as well as examination of histograms showing the distributions of these scores for each cohort. I also took into account the assumption that most gifted students' scores would be concentrated within the range of Advanced scores, so created bins that split the Advanced score range into multiple sub-categories. I compared several different options for number and size of groupings to determine a combination that would help maximize the number of treatment cases matched while still making each range narrow enough to be meaningful, ultimately settling on using a total of 6 achievement score groupings. Table 3.10 describes the range of scores used for each strata.

After I recoded reading and math achievement scores to reflect the appropriate strata, individuals were then matched on these coarsened values rather than their actual scores. MatchIT retained all treatment (HHM) students for whom there were matches, as well as all control (non-HHM) students who matched to those treatment cases. It also assigned appropriate weighting to the non-HHM students, allowing estimation of the average treatment effect. Table 3.11 summarizes the results of the matching for each cohort.

Table 3.10

Score Ranges for Coarsening of Reading and Mathematics Achievement Scores

Strata	Achievement Level(s)	Reading	Mathematics
1	Below Basic, Basic	100-216	100-209
2	Proficient	217-234	210-241
3	Goal	235-278	242-287
4	Advanced	279-309	288-314
5	Advanced	310-329	315-339
6	Advanced	330-400	340-400

Table 3.11

Sample Sizes by Cohort After Matching in Districts That Identify Gifted Students

Cohort		Control	Treated
A	All	22,946	2,377
	Matched	7,209	1,933
	Unmatched	15,737	444
	Discarded	0	0
B	All	21,849	3,619
	Matched	10,007	2,916
	Unmatched	11,842	703
	Discarded	0	0
C	All	21,188	2,153
	Matched	6,085	1,480
	Unmatched	15,103	673
	Discarded	0	0

CHAPTER 4: FINDINGS

RQ1: What were the rates of gifted identification in Connecticut public school districts?

Examination of the overall dataset yielded important information about gifted identification throughout the state. For students with complete data, districts reported about 5% of students across the state as gifted, which is within the range of typical identification rates for public schools in the United States. However, when students with missing data were included, the statewide percentage of identified gifted students fell below that threshold for all three cohorts, to about 4% (Table 4.1). Among students with missing data, fewer than 1% were identified gifted in their Connecticut grade 4 districts, which may reflect the significant role that existing data, especially student achievement scores, play as a primary factor when districts determine a student's gifted identification status.

Table 4.1

Statewide Gifted Identification Percentages (All Students)

Cohort		*n*	Frequency	Percent
A	Total	47,706	2,057	4.3
	Missing	10,158	86	0.8
	No Missing	37,548	1,971	5.2
B	Total	46,424	1,990	4.3
	Missing	9,829	78	0.8
	No Missing	36,595	1,912	5.2
C	Total	46,991	1,996	3.8
	Missing	9,742	55	0.6
	No Missing	37,249	1,736	4.7
Combined	Total	141,121	6,043	4.3
	Missing	29,729	219	0.7
	No Missing	111,392	5,619	5.0

Although the overall statewide percentage of identified gifted students among those with complete data reflected the expected 5%, the same was not true across districts within the state. Figures 4.1-4.3 illustrate the distributions of gifted identification rates for districts in each cohort.

At the district level, more than 70 districts in each cohort – more than 40% – reported virtually no identified gifted students (0.0-0.5%). I refer to these districts as minimal identifiers. Of the remaining districts reporting more than 0.5% of their students as gifted, fewer than 30 districts reported gifted identification percentages at or near the expected 5% (Figure 4.4). Notably, there were also a number of districts whose percentages of identified gifted students far exceeded 5%, with a few outliers reporting a quarter to a half of their students as gifted (Figure 4.5). Given such extreme variation in gifted identification rates among districts, it was clear that students' districts of enrollment must be taken into account in any further analyses. Even before taking mobility or any other factors into account, the likelihood of a student being identified gifted changed drastically depending on whether or not his or her district complied with the mandate to identify gifted students. Students attending minimal identifier districts had virtually no chance of gifted identification.

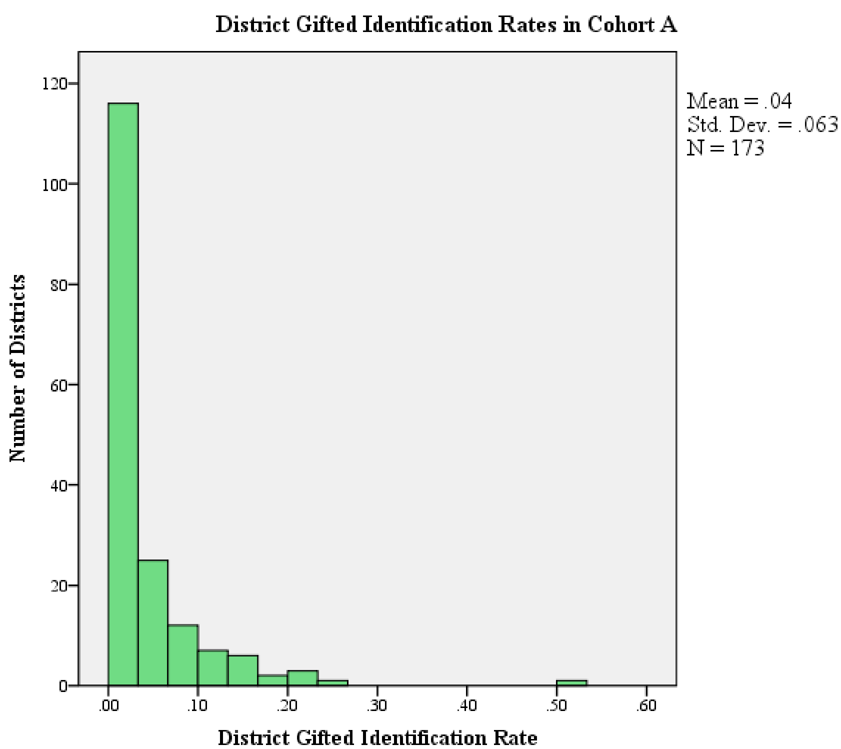

Figure 4.1. Histogram of district gifted identification rates in cohort A.

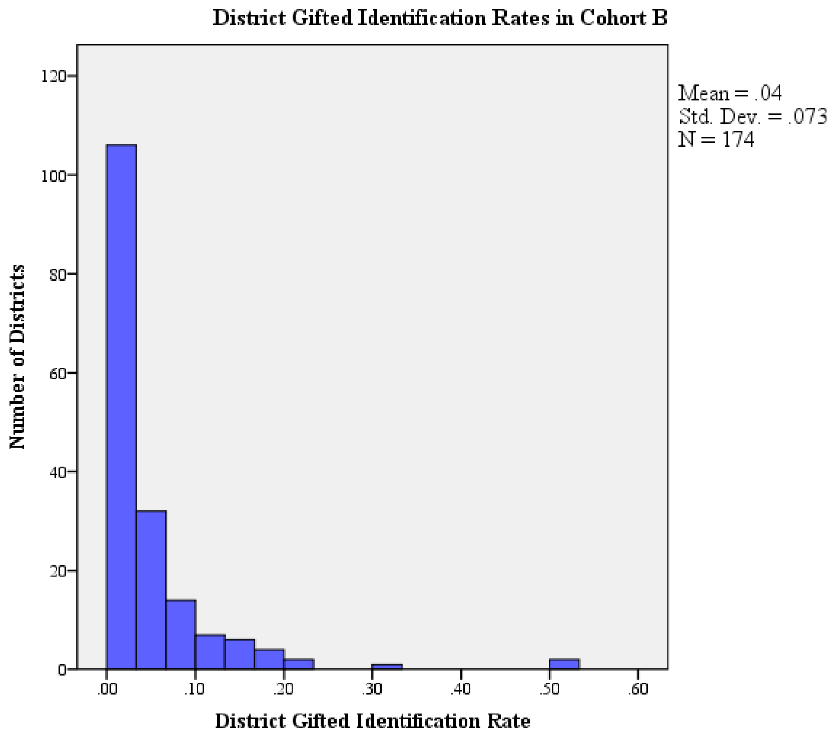

Figure 4.2. Histogram of district gifted identification rates in cohort B.

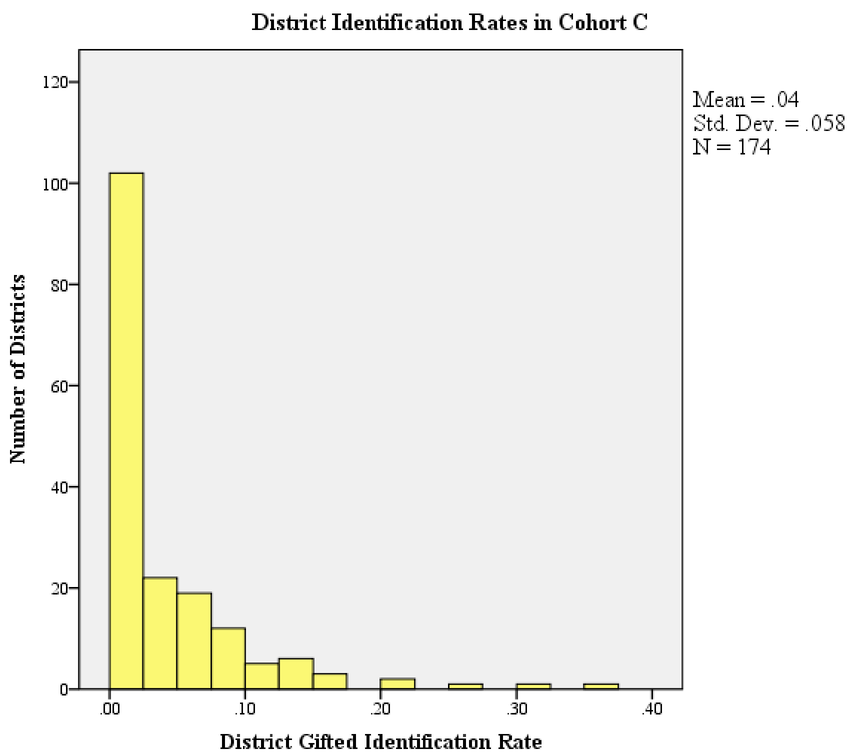

Figure 4.3. Histogram of district gifted identification rates in cohort C.

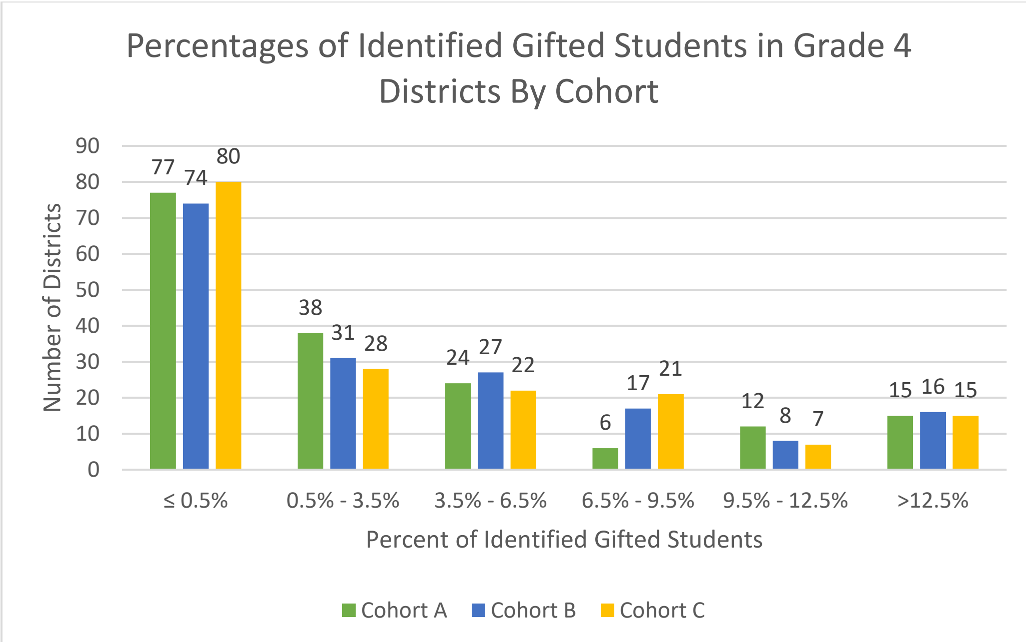

Figure 4.4. Bar chart of the number of districts reporting percentages of identified gifted students.

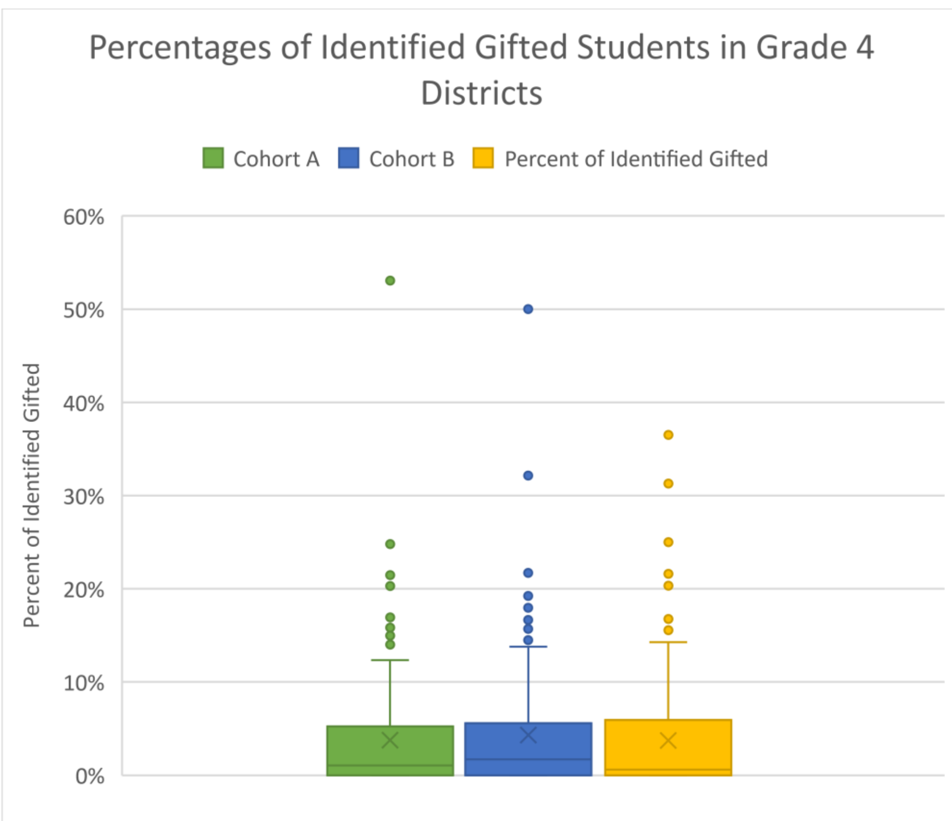

Figure 4.5. Box plots of district percentages of identified gifted students.

Table 4.2

Demographic Mean Differences Between Districts That Do and Do Not Identify Gifted Students

		Identifiers			Minimal Identifiers				
	Cohort	*n*	*M*	*SD*	*n*	*M*	*SD*	*t*-test	Cohen's *d*
Female	A	95	0.506	0.047	77	0.540	0.120	2.934*	0.414
	B	100	0.512	0.070	74	0.521	0.078	0.819	0.127
	C	94	0.516	0.044	80	0.502	0.111	0.993	0.172
White	A	95	0.738	0.250	77	0.718	.0290	0.496	0.146
	B	100	0.743	0.251	74	0.702	0.288	0.978	0.149
	C	94	0.766	0.200	80	0.661	0.314	2.677**	0.407
Black	A	95	0.089	0.148	77	0.099	0.198	-0.379	0.058
	B	100	0.073	0.127	74	0.131	0.229	1.964	0.325
	C	94	0.050	0.082	80	0.134	0.236	3.107**	0.529
Asian	A	95	0.042	0.032	77	0.033	0.042	1.540	0.234
	B	100	0.044	0.040	74	0.031	0.038	2.174*	0.335
	C	94	0.045	0.036	80	0.033	0.043	1.904	0.298
Hispanic/ Latino	A	95	0.106	0.126	77	0.117	0.167	0.522	0.079
	B	100	0.114	0.142	74	0.105	0.119	0.402	0.063
	C	94	0.109	0.127	80	0.132	0.167	1.137	0.160
Other Race	A	95	0.026	0.028	77	0.033	0.046	1.264	0.204
	B	100	0.027	0.029	74	0.030	0.032	0.721	0.109
	C	94	0.031	0.030	80	0.039	0.043	1.544	0.233
ELL	A	95	0.057	0.069	77	0.057	0.083	0.057	0.009
	B	100	0.064	0.079	74	0.054	0.065	0.866	0.136
	C	94	0.060	0.069	80	0.055	0.071	0.335	0.070
SPED	A	95	0.152	0.048	77	0.191	0.174	1.899	0.347
	B	100	0.161	0.059	74	0.180	0.155	1.026	0.182
	C	94	0.164	0.056	80	0.204	0.175	1.911	0.339
Lunch	A	95	0.283	0.247	77	0.344	0.272	1.555	0.237
	B	100	0.290	0.260	74	0.372	0.268	2.042*	0.312
	C	94	0.285	0.220	80	0.405	0.286	3.149**	0.475
HHM	A	95	0.075	0.072	77	0.118	0.193	1.838	0.320
	B	100	0.152	0.113	74	0.180	0.154	1.401	0.212
	C	94	0.083	0.112	80	0.125	0.187	1.853	0.281
Reading	A	95	246.630	14.800	77	241.950	19.761	1.775	0.271
	B	100	247.739	15.284	74	242.103	15.356	2.400*	0.368
	C	94	251.571	13.644	80	245.460	17.886	2.640**	0.388
Math	A	95	264.873	18.442	77	258.944	22.121	1.917	0.292
	B	100	266.115	18.776	74	258.383	20.967	2.555*	0.389
	C	94	269.346	17.744	80	261.047	23.441	2.733**	0.403

Identifiers: gifted identification rates >0.5%; minimal identifiers: gifted identification rates ≤0.5%.
*p < .05. **p < .01.

Research Question 1a. What are the characteristics of districts that did and did not identify gifted students? To better understand how minimal identifier districts compared to districts with higher identification rates, I examined district aggregates of student demographics and achievement levels. For the purpose of this study, districts reporting more than 0.5% of their students gifted are referred to as identifiers, while districts with gifted identification rates at or below 0.5% are referred to as minimal identifiers. Table 4.2 summarizes the mean demographics in districts that did and did not identify gifted students. Average proportions of HHM students were slightly higher in minimal identifier districts than in identifier districts, but these differences were not statistically significant. In cohort A, $t(172) = 1.838$, $p = .163$, $d = 0.320$; in cohort B, $t(94.390) = 1.401$, $p = .069$, $d = 0.212$; and in cohort C, $t(126.438) = 1.853$, $p = .066$, $d = 0.281$. While the proportions of students by race and by ELL status were similar across identifier and minimal identifier districts, percentages of special education students and students receiving lunch subsidies were generally higher, on average, in those districts that did not identify gifted students. Minimal identifiers also tended to have average reading and mathematics scores that were somewhat lower than in identifier districts. However, independent-samples *t* tests indicated that none of these differences were statistically significant across all three cohorts. Significant differences across two of the three cohorts were observed for three variables: the percentage of students receiving lunch subsidies in cohort A, $t(171) = 1.555$, $p = .122$, $d = 0.237$, cohort B, $t(172) = 2.042$, $p = .043$, $d = 0.312$, and cohort C, $t(171) = 3.149$, $p = .002$, $d = 0.475$; reading achievement scores for cohort A, $t(170) = 1.775$, $p = .078$, $d = 0.271$, cohort B, $t(172) = 2.400$, $p = .017$, $d = 0.368$, and cohort C, $t(171) = 2.640$, $p = .009$, $d = 0.388$; and mathematics achievement scores for cohort A, $t(170) = 1.917$, $p = .057$, $d = 0.292$, cohort B, $t(172) = 2.555$, $p = .011$, $d = 0.389$, and cohort C, $t(171) = 2.733$, $p = .007$, $d = 0.403$. In other

words, districts that did not identify gifted students tended to have higher percentages of students receiving lunch subsidies, and lower average reading and mathematics achievement scores. These differences, although statistically significant in only two of the three cohorts, generally had small to moderate effect sizes, so were not negligible. I also noted that there tended to be greater variation among minimal identifier districts, which generally had larger standard deviations than those in identifier districts across all three cohorts.

Research Question 1b. What was the relationship between district demographics and district gifted identification practice? Table 4.3 summarizes the correlations between demographic variables for districts within each cohort. General trends across the three cohorts revealed small but significant correlations between higher proportions of Black students (A: r = 0.029, n = 173, p = 705; B: r = 0.160, n = 174, p = 0.35; C: r = .243, n = 174, p < .001), students receiving special education services (A: r = 0.156, n = 173, p = .040; B: r = 0.087, n = 174, p = .252; C: r = 0.152, n = 174, p = .045), and students receiving lunch subsidies (A: r = 0.118, n = 173, p = .122; B: r = 0.154, n = 174, p = .043; C: r = 0.237, n = 174, p = .002) and minimal identification. The percentage of identified gifted students within districts also increased slightly as the percentage of Asian students increased (A: r = 0.170, n = 173, p = .025; B: r = 0.078, n = 174, p = .308; C: r = 0.178, n = 174, p = .019), but decreased slightly as the percentages of students receiving lunch subsidies increased (A: r = -0.179, n = 173, p = .019; B: r = -0.059, n = 174, p = .443; C: r = -0.213, n = 174, p = .005). The percentage of HHM students in districts was found to have small positive correlations with the percentages of Black students (A: r = 0.184, n = 173, p = .015; B: r = 0.326, n = 174, p < .001; C: r = 0.102, n = 174, p = .182) and English language learners (A: r = 0.171, n = 173, p = .025; B: r = 0.263, n = 174, p < .001; C: r = 0.081, n = 174, p = .291), moderate positive correlations with the percentages of Hispanic/Latino

students (A: $r = 0.621$, $n = 173$, $p < .001$; B: $r = 0.533$, $n = 174$, $p < .001$; C: $r = 0.406$, $n = 174$, $p < .001$) and students receiving lunch subsidies (A: $r = 0.536$, $n = 173$, $p < .001$; B: $r = 0.602$, $n = 174$, $p < .001$; C: $r = 0.363$, $n = 174$, $p < .001$), and a strong positive correlation with the percentage of students receiving special education services (A: $r = 0.843$, $n = 173$, $p < .001$; B: $r = 0.715$, $n = 174$, $p < .001$; C: $r = 0.715$, $n = 174$, $p < .001$). However, the correlation with special education percentages is misleading, as there were three outlier districts reporting 100% of their students in special education. When excluding these outliers, this correlation was no longer significant. Notably, across all three cohorts there were no significant correlations between the percentage of HHM students and the percentage of identified gifted students (A: $r = -0.143$, $n = 173$, $p = .060$; B: $r = 0.129$, $n = 174$, $p = .089$; C: $r = -0.122$, $n = 174$, $p = .108$).

With little difference between the characteristics of the identifier and minimal identifier districts, it is not surprising that few district-level demographics were significant predictors of district gifted identification compliance. Table 4.4 summarizes the results of the logistic regression analyses predicting minimal identification based on centered district-level characteristics. For each cohort, step 1 includes only district percentages of FRL, step 2 includes district mean reading and mathematics achievement scores, and step 3 includes interactions between FRL and achievement. Note that, in all logistic regressions in this study, the R^2 values reported are pseudo R^2 values using Cox and Snell's (1989) calculations. In cohort A, none of the district demographics significantly predicted district gifted identification practice, and the predictors in the models explained very little of the variance in gifted identification practice. The model predicting ID practice from FRL explained only about 1% of the variance, $R^2 = 0.011$, while the model also containing reading and mathematics achievement explained only 3% of the variance, $R^2 = 0.029$. In cohorts B and C, the only significant predictor of compliance was the

percentage of students receiving lunch subsidies. In cohort B, the model predicting ID practice from FRL explained only about 2% of the variance, R^2 = 0.023, while the model also containing reading and mathematics achievement explained about 4% of the variance, R^2 = 0.038. In cohort C, the model predicting ID practice from FRL explained about 6% of the variance, R^2 = 0.061, while the model also containing reading and mathematics achievement also explained about 6% of the variance, R^2 = 0.063. Interactions between FRL and achievement scores were not statistically significant, and accounted for only slight increases in the variance explained for each cohort (A3, R^2 = 0.040; B3, R^2 = 0.057, C3, R^2 = 0.066). Figure 4.6 illustrates how the predicted likelihood of minimal gifted identification increased as the district percentage of FRL students increased in each cohort.

Table 4.3

Correlation Matrix of District Aggregate Demographics by Cohort

	Cohort	1	2	3	4	5	6	7	8	9	10	11	12
	A												
1. Black	B												
	C												
	A	-.016											
2. Asian	B	-.083											
	C	-.122											
3. Hispanic/ Latino	A	.342**	-.026										
	B	.439**	.012										
	C	.327**	-.032										
	A	.119	.044	.029									
4. Other race	B	-.060	-.053	.007									
	C	-.068	.052	-.034									
	A	.262**	.389**	.648**	.175*								
5. ELL	B	.207**	.239**	.816**	.052								
	C	.224**	.265**	.669**	.024								
	A	-.098	-.148	.395**	-.075	-.066							
6. SPED	B	-.003	-.090	.212**	-.050	.095							
	C	-.098	-.193*	.217**	-.075	-.140							
	A	.656**	-.124	.694**	.216**	.542**	.216**						
7. Lunch	B	.708**	-0157*	.759**	.054	.560**	.260**						
	C	.651**	-.228**	.723**	.136	.520**	.146						
	A	-.118	.170*	-.082	-.064	-.005	-.108	-.179*					
8. Gifted	B	-.052	.078	.061	-.006	.004	.051	-.059					
	C	-.174*	.178*	-.060	-.050	.049	-.105	-.213**					
	A	.184*	-.117	.621**	.059	.171*	.843**	.536**	-.143				
9. HHM	B	.326**	-.089	.533**	-.040	.263**	.715**	.602**	.129				
	C	.102	-.144	.406**	.004	.081	.715**	.363**	-.122				
	A	.029	-.117	.040	.101	-.004	.156*	.118	-.534**	.150			
10. Non-comply	B	.160*	-.164*	-.031	.055	-.066	.087	.154*	-.509**	.106			
	C	.243**	-.144	.086	.120	-.026	.152*	.237**	-.596**	.145			
	A	-.433**	.094	-.630**	-.165*	-.421**	-.558**	-.752**	.173*	-.765**	-.135		
11. Reading	B	-.363**	.190*	-.542**	-.074	-.487**	-.345**	-.695**	.221**	-.439**	-.180*		
	C	-.368**	.209**	-.663**	-.055	-.340**	-.466**	-.776**	.221**	-.563**	-.198*		
	A	-.387**	.124	-.509**	-.204**	-.382**	-.428**	-.747**	.159*	-.616**	-.145	.883**	
12. Mathematics	B	-.291**	.213**	-.446**	-.073	-.407**	-.402**	-.620**	.255**	-.415**	-.191*	.919**	
	C	-.287**	.218**	-.618**	-.101	-.251**	-.532**	-.727**	.237**	-.579**	-.205**	.901**	

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Table 4.4

Logistic Regression Analysis Predicting District Minimal Gifted Identification by Cohort

Cohort	Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2
A	1	Constant	-0.208	0.154	1	.177		0.011
		Lunch	0.819	0.607	1	.177	(0.691, 7.445)	
	2	Constant	-0.213	0.155	1	.170		0.029
		Lunch	-0.174	0.962	1	.857	(0.128, 5.534)	
		Reading	-0.005	0.020	1	.824	(0.957, 1.036)	
		Math	-0.013	0.017	1	.443	(0.954, 1.021)	
	3	Constant	-0.117	0.187	1	.531		0.040
		Lunch	1.055	1.219	1	.387	(0.263, 31.317)	
		Reading	0.026	0.029	1	.365	(0.970, 1.087)	
		Math	-0.028	0.020	1	.161	(0.935, 1.011)	
		Lunch*Reading	0.198	0.117	1	.091	(0.969, 1.535)	
		Lunch*Math	-0.146	0.094	1	.122	(0.718, 1.040)	
B	1	Constant	-0.306	0.155	1	.045		0.023
		Lunch	1.174	0.586	1	.049	(1.026, 10.199)	
	2	Constant	-0.309	0.156	1	.048		0.038
		Lunch	0.461	0.834	1	.581	(0.309, 8.125)	
		Reading	0.003	0.028	1	.916	(0.949, 1.060)	
		Math	-0.018	0.020	1	.361	(0.944, 1.012)	
	3	Constant	-0.150	0.180	1	.405		0.057
		Lunch	0.776	0.852	1	.362	(0.409, 11.546)	
		Reading	-0.001	0.029	1	.967	(0.944, 1.057)	
		Math	-0.021	0.020	1	.301	(0.941, 1.019)	
		Lunch*Reading	0.120	0.097	1	.217	(0.932, 1.365)	
		Lunch*Math	-0.052	0.074	1	.476	(0.822, 1.096)	
C	1	Constant	-0.154	0.157	1	.329		0.061
		Lunch	2.019	0.640	1	.002	(2.148, 26.408)	
	2	Constant	-0.153	.158	1	.330		0.063
		Lunch	1.845	1.001	1	.065	(0.889, 45.044)	
		Reading	0.010	0.025	1	.689	(0.962, 1.061)	
		Math	-0.011	0.018	1	.527	(0.955, 1.024)	
	3	Constant	-0.141	0.188	1	.452		0.066
		Lunch	1.726	1.063	1	.104	(0.699, 45.102)	
		Reading	0.005	0.025	1	.750	(0.959, 1.059)	
		Math	-0.013	0.018	1	.484	(0.953, 1.023)	
		Lunch*Reading	-0.053	0.100	1	.598	(0.779, 1.155)	
		Lunch*Math	0.047	0.071	1	.507	(0.912, 1.204)	

Note: District lunch, reading, and mathematics aggregates are centered.

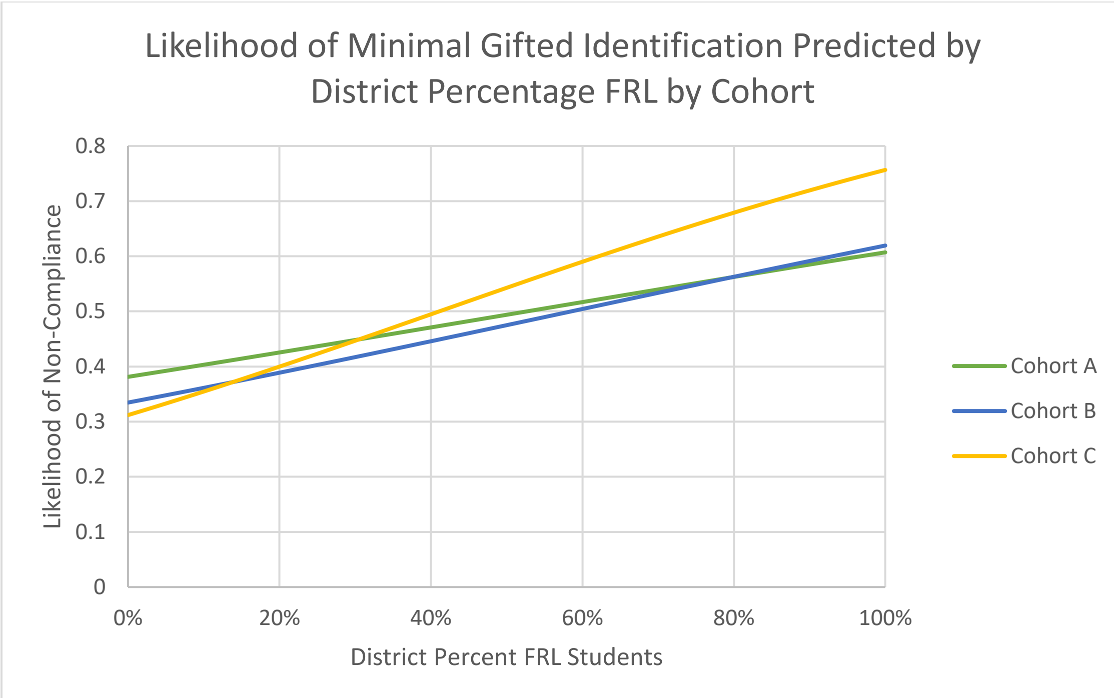

Figure 4.6. Plot of the likelihood of minimal gifted identification based on district percentage of FRL students.

Research Question 2: For homeless and/or highly mobile (HHM) students in Connecticut public schools, what was the likelihood of attending school in a minimal identifier district?

Overall, about one-third of all students were enrolled in districts that reported virtually no students as gifted. Examination of crosstabs of student mobility status and the gifted identification practice of each student's district (see Tables 4.5-4.7) indicated that there was a statistically significant association between student mobility status and enrollment in minimal identifier districts for student in two of the cohorts, A: $X^2(1, 37{,}548) = 0.361$, $p = .548$; B: $X^2(1, 36{,}595) = 10.811$, $p = .001$; C: $X^2(1, 37{,}249) = 9.351$, $p = .002$. About 32-40% of the HHM students in each cohort were enrolled in districts that reported virtually no identified gifted students. Similarly, about 30-37% of non-HHM students also attended school in minimal identifier districts.

Table 4.5

Crosstabs of Student Mobility Status and District Gifted Identification Practice for Cohort A

ID Practice		Mobility: Non-HHM	Mobility: HHM	Total
Identifier	Count	22,946	2,377	25,323
	% of Total	61.1	6.3	67.4
Minimal Identifier	Count	11,101	1,124	12,225
	% of Total	29.6	3.0	32.6
Total	Count	34,047	3,501	37,548
	% of Total	90.7	9.3	100.0

Table 4.6

Crosstabs of Student Mobility Status and District Gifted Identification Practice for Cohort B

ID Practice		Mobility: Non-HHM	Mobility: HHM	Total
Identifier	Count	21,849	3,619	25,468
	% of Total	59.7	9.9	69.6
Minimal Identifier	Count	9,399	1,728	11,127
	% of Total	25.7	4.7	30.4
Total	Count	31,248	5,347	36,595
	% of Total	85.4	14.6	100.0

Table 4.7

Crosstabs of Student Mobility Status and District Gifted Identification Practice for Cohort C

ID Practice		Mobility: Non-HHM	Mobility: HHM	Total
Identifier	Count	21,188	2,153	23,341
	% of Total	56.9	5.8	62.7
Minimal Identifier	Count	12,491	1,417	13,908
	% of Total	33.5	3.8	37.3
Total	Count	33,679	3,570	37,249
	% of Total	90.4	9.6	100.0

Additional crosstabs in Tables 4.8-4.10 indicated statistically significant associations between student HHM and FRL status (A: $X^2(1, 37{,}548) = 3211.643$, $p < .001$; B: $X^2(1, 36{,}595) = 2404.170$, $p < .001$; C: $X^2(1, 37{,}249) = 2181.439$, $p < .001$). About 40% of students received FRL, about 10% were HHM, and about 8% were HHM students receiving FRL.

Table 4.8

Crosstabs of HHM and FRL for Cohort A Students with Complete Data

		FRL		
HHM		Non-FRL	FRL	Total
Non-HHM	Count	22,134	11,913	34,047
	% of Total	58.9	31.7	90.7
HHM	Count	554	2,947	3,501
	% of Total	1.5	7.8	9.3
Total	Count	22,688	14,860	37,548
	% of Total	60.4	39.6	100.0

Table 4.9

Crosstabs of HHM and FRL for Cohort B Students with Complete Data

		FRL		
HHM		Non-FRL	FRL	Total
Non-HHM	Count	20,152	11,096	31,248
	% of Total	55.1	30.3	85.4
HHM	Count	1,542	3,805	5,347
	% of Total	4.2	10.4	14.6
Total	Count	21,694	14,901	36,595
	% of Total	59.3	40.7	100.0

Table 4.10

Crosstabs of HHM and FRL for Cohort C Students with Complete Data

HHM		FRL		Total
		Non-FRL	FRL	
Non-HHM	Count	21,051	12,628	33,679
	% of Total	56.5	33.9	90.4
HHM	Count	786	2,784	3,570
	% of Total	2.1	7.5	9.6
Total	Count	21,837	15,412	37,249
	% of Total	58.6	41.4	100.0

Table 4.11 summarizes correlations between student-level variables. Correlations between student characteristics and attendance in minimal identifier districts were generally very weak, even when statistically significant. FRL was among the strongest correlations with ID practice, (A: r = -0.011, n = 37,548, p = .040; B: r = 0.034, n = 36,595, p < .000; C: r = 0.124, n = 37,249, p < .000). ID practice had weak but statistically significant correlations with reading achievement (A: r = 0.012, n = 37,548, p = .020; B: r = -0.032, n = 36,595, p < .001; C: r = -0.075, n = 37,249, p < .001), and with mathematics achievement (A: r = 0.016, n = 37,548, p = .002; B: r = -0.025, n = 36,595, p < .001; C: r = -0.088, n = 37,249, p < .001). Weak but statistically significant correlations were also observed between HHM and ID practice in two of the cohorts, (A: r = -0.003, n = 37,548, p = .548; B: r = 0.017, n = 36,595, p = .001; C: r = 0.016, n = 37,249, p = .002).

Table 4.11

Correlation Matrix of Individual Demographics of Students with Complete Data by Cohort

	Cohort	1	2	3	4	5	6	7	8	9	10	11	12
1. Black	A												
	B												
	C												
2. Asian	A	-0.084**											
	B	-0.086**											
	C	-0.084**											
3. Hispanic/ Latino	A	-0.181**	-0.102**										
	B	-0.180**	-0.111**										
	C	-0.179**	-0.113**										
4. Other race	A	-0.063**	-0.036**	-0.077**									
	B	-0.057**	-0.035**	-0.073**									
	C	-0.061**	-0.039**	-0.082**									
5. ELL	A	-0.088**	0.168**	0.390**	-0.007								
	B	-0.084**	0.176**	0.373**	-0.029**								
	C	-0.079**	0.176**	0.356**	-0.032**								
6. SPED	A	-0.002	-0.040**	0.003	0.013*	-0.014**							
	B	0.004	-0.042**	0.005	-0.008	-0.010*							
	C	0.008	-0.041**	-0.004	0.002	-0.006							
7. Lunch	A	0.342**	-0.058**	0.413**	0.036**	0.262**	0.039**						
	B	0.323**	-0.055**	0.413**	0.010	0.269**	0.041**						
	C	0.327**	-0.051**	0.417**	0.014**	0.268**	0.032**						
8. Gifted	A	-0.047**	0.052**	-0.054**	0.005	-0.047**	-0.058**	-0.098**					
	B	-0.042**	0.057**	-0.063**	0.009	-0.052**	-0.059**	-0.107**					
	C	-0.057**	0.053**	-0.063**	0.008	-0.050**	-0.060**	-0.128**					
9. HHM	A	0.131**	-0.006	0.164**	0.029**	0.091**	0.027**	0.292**	-0.044**				
	B	0.119**	0.014*	0.130**	0.023**	0.095**	0.025**	0.256**	-0.036**				
	C	0.098**	-0.012*	0.111**	0.021**	0.060**	0.030**	0.242**	-0.038**				
10. Non-comply	A	-0.030**	-0.002	-0.028**	0.013*	-0.005	0.003	-0.011*	-0.160**	-0.003			
	B	-0.001	-0.009	0.000	0.013*	-0.012*	-0.008	0.034**	-0.153**	0.017**			
	C	0.085**	-0.002	0.037**	0.024**	0.024**	-0.002	0.124**	-0.169**	0.016**			
11. Reading	A	0.079**	0.052**	-0.126**	-0.005	-0.151**	-0.328**	-0.187**	0.276**	-0.106**	0.012*		
	B	-0.071**	0.052**	-0.130**	0.013*	-0.163**	-0.338**	-0.188**	0.279**	-0.092**	-0.032**		
	C	-0.088**	0.068**	-0.128**	0.012*	-0.171**	-0.321**	-0.196**	0.276**	-0.088**	-0.075**		
12. Mathematics	A	-0.118**	0.085**	-0.092**	-0.005	-0.087**	-0.269**	-0.166**	0.252**	-0.100**	0.016*	0.726**	
	B	-0.105**	0.109**	-0.103**	0.004	-0.087**	-0.275**	-0.174**	0.258**	-0.080**	-0.025**	0.730**	
	C	-0.124**	0.098**	-0.106**	0.002	-0.112**	-0.286**	-0.184**	0.254**	-0.098**	-0.088**	0.738**	

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

In cohort A, an independent-samples t test indicated that there was not a significant difference between the proportions of HHM (M = 0.321, SD = 0.467) and non-HHM (M = 0.326, SD = 0.469) students in districts that do not identify gifted students, t(37,546) = 0.601, p = 0.548, d = 0.010. In cohort B, there was a statistically significant but very small difference in the proportion of HHM (M = 0.323, SD = 0.468) and non-HHM (M = 0.301, SD = 0.459) students in districts that do not identify gifted students, t(7,216) = 3.242, p = .001, d = 0.047. Similarly, a statistically significant but very small difference in the proportion of HHM (M = 0.394, SD = 0.489) and non-HHM (M = 0.371, SD = 0.483) students in minimal identifier districts was observed for Cohort C, t(4,339) = 3.027, p = .002, d = 0.053. In cohorts B (F = 39.808, p < .001) and C (F = 31.364, p < .001), Levene's test indicated unequal variances. Taken together, patterns across the cohorts suggest that, while there are sometimes statistically significant differences between the relative proportions of HHM and non-HHM student in districts that do not identify gifted students, these differences are so small that they bear little practical significance. In other words, HHM students are essentially proportionately represented relative to their low-mobility peers in minimal identifier districts.

In models predicting student enrollment in a minimal identifier district from student characteristics, ELL status, SPED status, reading achievement, and mathematics achievement generally were not found to be significant predictors after controlling for mobility, race, FRL status, and their interactions. Tables 4.12-4.14 summarize the results of logistic regression analyses predicting enrollment in a minimal identifier district from student-level variables. In step 1, district ID status was predicted from student HHM status. Race/ethnicity was added to the model in step 2, FRL was added in step 3, interactions between race/ethnicity and FRL were added in step 4, and reading and mathematics achievement were added in step 5. Across all three

cohorts, student HHM status by itself accounted for none of the variance in attendance in minimal identification districts (A1, R^2 = 0.000; B1, R^2 = 0.000; C1, R^2 = 0.000). Although race/ethnicity, FRL, and their interactions were generally significant predictors, adding them to the model yielded little change in the amount of variance explained, which remained less than 1% in cohorts A and B, and approached 2% in cohort C (A2, R^2 = 0.002; B2, R^2 = 0.001; C2, R^2 = 0.011; A3, R^2 = 0.003; B3, R^2 = 0.002; C3, 0.018; A4, R^2 = 0.004, B4, R^2 = 0.004; C4, R^2 = 0.019). Adding achievement scores to the model did not increase the variance explained (A5, R^2 = 0.004; B5, R^2 = 0.004; C5, R^2 = 0.020).

Table 4.15 shows the likelihood of attending school in a minimal identifier district for students by race, FRL status, and mobility status. In Cohorts A and B, White students who were neither HHM nor FRL had about a 20% chance of attending a minimal identifier district. Across all racial groups, the chance of attending a minimal identifier district increased to about 30% for FRL students, whether or not those students were also highly mobile. Notably, HHM students who did not receive FRL were generally much less likely than FRL students to attend school in a minimal identifier district. These findings reflect the heavy influence of poverty on the likelihood of minimal gifted identification.

Table 4.12

Logistic Regression Predicting Student Enrollment in Minimal Identifier Districts in Cohort A

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
1	Constant	-0.726	0.012	1	<.001		0.000
	HHM	-0.023	0.038	1	.548	(0.907, 1.053)	
2	Constant	-1.111	0.104	1	<.001		0.002
	HHM	0.056	0.039	1	.154	(0.979, 1.142)	
	Black	0.246	0.035	1	<.001	(1.193, 1.370)	
	Asian	0.092	0.054	1	.089	(0.986, 1.218)	
	Hispanic/Latino	0.202	0.031	1	<.001	(1.153, 1.299)	
	Other	-0.093	0.068	1	.168	(0.798, 1.040)	
3	Constant	-1.186	0.107	1	<.001		0.003
	HHM	0.029	0.040	1	.473	(0.952, 1.113)	
	Black	0.307	0.039	1	<.001	(1.258, 1.467)	
	Asian	0.099	0.054	1	.068	(0.993, 1.227)	
	Hispanic/Latino	0.262	0.035	1	<.001	(1.214, 1.392)	
	Other	-0.064	0.068	1	.348	(0.821, 1.072)	
	Lunch	-0.101	0.029	1	<.001	(0.855, 0.957)	
4	Constant	-1.566	0.174	1	<.001		0.004
	HHM	0.031	0.040	1	.433	(0.954, 1.116)	
	Black	0.462	0.047	1	<.001	(1.447, 1.742)	
	Asian	0.410	0.109	1	<.001	(1.217, 1.864)	
	Hispanic/Latino	0.388	0.043	1	<.001	(1.354, 1.604)	
	Other	-0.186	0.096	1	.052	(0.688, 1.002)	
	Lunch	0.660	0.234	1	<.001	(1.223, 3.064)	
	Black*Lunch	-0.487	0.089	1	<.001	(0.516, 0.732)	
	Asian*Lunch	-0.411	0.125	1	.001	(0.519, 0.848)	
	HispLat*Lunch	-0.312	0.077	1	<.001	(0.629, 0.852)	
	Other*Lunch	0.337	0.138	1	.015	(1.068, 1.837)	
5	Constant	-1.570	0.174	1	<.001		0.004
	HHM	0.029	0.040	1	.463	(0.952, 1.114)	
	Black	0.464	0.047	1	<.001	(1.450, 1.745)	
	Asian	0.407	0.109	1	<.001	(1.214, 1.860)	
	Hispanic/Latino	0.389	0.043	1	<.001	(1.356, 1.606)	
	Other	-0.185	0.096	1	.054	(0.689, 1.003)	
	Lunch	0.664	0.234	1	.005	(1.227, 3.075)	
	Black*Lunch	-0.485	0.089	1	<.001	(0.517, 0.733)	
	Asian*Lunch	-0.411	0.125	1	.001	(0.519, 0.847)	
	HispLat*Lunch	-0.311	0.077	1	<.001	(0.629, 0.852)	
	Other*Lunch	0.335	0.138	1	.016	(1.066, 1.833)	
	Reading (centered)	0.000	0.00	1	.734	(0.999, 1.001)	
	Math (centered)	0.000	0.00	1	.694	(0.999, 1.001)	

**Note*: Cox and Snell pseudo R^2.

Table 4.13

Logistic Regression Predicting Student Enrollment in Minimal Identifier Districts in Cohort B

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
1	Constant	-0.844	0.012	1	<.001		0.000
	HHM	0.104	0.032	1	.001	(1.043, 1.181)	
2	Constant	-0.801	0.110	1	<.001		0.001
	HHM	0.108	0.032	1	.001	(1.046, 1.188)	
	Black	0.024	0.036	1	.510	(0.954, 1.099)	
	Asian	0.096	0.054	1	.074	(0.991, 1.223)	
	Hispanic/Latino	0.017	0.030	1	.581	(0.958, 1.079)	
	Other	-0.173	0.075	1	.021	(0.727, 0.974)	
3	Constant	-0.946	0.111	1	<.001		0.002
	HHM	0.065	0.033	1	.050	(1.000, 1.138)	
	Black	0.152	0.040	1	<.001	(1.077, 1.259)	
	Asian	0.112	0.054	1	.037	(1.007, 1.243)	
	Hispanic/Latino	0.146	0.035	1	<.001	(1.080, 1.238)	
	Other	-0.126	0.075	1	.094	(0.762, 1.021)	
	Lunch	-0.216	0.029	1	<.001	(0.761, 0.852)	
4	Constant	-1.298	0.176	1	<.001		0.004
	HHM	0.061	0.033	1	.063	(0.997, 1.134)	
	Black	0.321	0.047	1	<.001	(1.257, 1.512)	
	Asian	0.320	0.100	1	.001	(1.133, 1.674)	
	Hispanic/Latino	0.288	0.042	1	<.001	(1.228, 1.449)	
	Other	-0.192	0.111	1	.082	(0.664, 1.025)	
	Lunch	0.682	0.240	1	.004	(1.236, 3.164)	
	Black*Lunch	-0.540	0.092	1	<.001	(0.487, 0.697)	
	Asian*Lunch	-0.283	0.118	1	.017	(0.597, 0.950)	
	HispLat*Lunch	-0.389	0.078	1	<.001	(0.582, 0.789)	
	Other*Lunch	0.185	0.152	1	.221	(0.895, 1.620)	
5	Constant	-1.296	0.177	1	<.001		0.004
	HHM	0.063	0.033	1	.056	(0.999, 1.137)	
	Black	0.318	0.047	1	<.001	(1.252, 1.508)	
	Asian	0.326	0.100	1	.001	(1.140, 1.685)	
	Hispanic/Latino	0.286	0.042	1	<.001	(1.226, 1.446)	
	Other	-0.194	0.111	1	.079	(0.663, 1.023)	
	Lunch	0.674	0.240	1	.005	(1.227, 3.141)	
	Black*Lunch	-0.541	0.092	1	<.001	(0.486, 0.697)	
	Asian*Lunch	-0.283	0.118	1	.017	(0.598, 0.951)	
	HispLat*Lunch	-0.390	0.078	1	<.000	(0.582, 0.789)	
	Other*Lunch	0.189	0.152	1	.212	(0.898, 1.626)	
	Reading (centered)	0.000	0.000	1	.865	(0.999, 1.001)	
	Math (centered)	0.000	0.000	1	.324	(1.000, 1.001)	

**Note*: Cox and Snell pseudo R^2.

Table 4.14

Logistic Regression Predicting Student Enrollment in Minimal Identifier Districts in Cohort C

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
1	Constant	-0.528	0.011	1	<.001		0.000
	HHM	0.110	0.036	1	0.002	(1.040, 1.198)	
2	Constant	0.833	0.099	1	<.001		0.011
	HHM	-0.007	0.037	1	.853	(0.924, 1.067)	
	Black	-0.616	0.034	1	<.001	(0.506, 0.577)	
	Asian	-0.137	0.050	1	.006	(0.791, 0.961)	
	Hispanic/Latino	-0.311	0.028	1	<.001	(0.694, 0.774)	
	Other	-0.443	0.065	1	<.001	(0.566, 0.729)	
3	Constant	0.498	0.101	1	<.001		0.018
	HHM	-0.117	0.037	1	.002	(0.827, 0.958)	
	Black	-0.338	0.038	1	<.001	(0.662, 0.767)	
	Asian	-0.093	0.050	1	.064	(0.826, 1.005)	
	Hispanic/Latino	-0.039	0.033	1	.232	(0.902, 1.025)	
	Other	-0.340	0.065	1	<.001	(0.626, 0.810)	
	Lunch	-0.452	0.027	1	<.001	(0.603, 0.671)	
4	Constant	0.258	0.161	1	.109		0.019
	HHM	-0.120	0.037	1	.001	(0.824, 0.954)	
	Black	-0.287	0.044	1	<.001	(0.688, 0.818)	
	Asian	0.201	0.091	1	.027	(1.023, 1.462)	
	Hispanic/Latino	-0.004	0.040	1	.927	(0.922, 1.077)	
	Other	-0.446	0.098	1	<.001	(0.529, 0.776)	
	Lunch	-0.071	0.223	1	.751	(0.602, 1.441)	
	Black*Lunch	-0.167	0.093	1	0.73	(0.705, 1.015)	
	Asian*Lunch	-0.425	0.109	1	<.001	(0.528, 0.809)	
	HispLat*Lunch	-0.053	0.075	1	.479	(0.819, 1.098)	
	Other*Lunch	0.220	0.133	1	.098	(0.960, 1.617)	
5	Constant	0.280	0.161	1	.082		0.020
	HHM	-0.109	0.038	1	.004	(0.833, 0.965)	
	Black	-0.302	0.044	1	<.001	(0.678, 0.806)	
	Asian	0.213	0.091	1	.020	(1.034, 1.479)	
	Hispanic/Latino	-0.014	0.040	1	.716	(0.912, 1.065)	
	Other	-0.450	0.098	1	<.001	(0.526, 0.773)	
	Lunch	-0.107	0.223	1	.631	(0.581, 1.390)	
	Black*Lunch	-0.165	0.093	1	.076	(0.707, 1.017)	
	Asian*Lunch	-0.414	0.109	1	<.001	(0.534, 0.818)	
	HispLat*Lunch	-0.053	0.075	1	.479	(0.819, 1.098)	
	Other*Lunch	0.228	0.133	1	.086	(0.968, 1.630)	
	Reading (centered)	0.001	0.000	1	.083	(1.000, 1.001)	
	Math (centered)	0.001	0.000	1	.013	(1.000, 1.002)	

**Note:* Cox and Snell pseudo R^2.

Table 4.15

Probability of Enrollment in Minimal Identifier District by Student Race, Lunch, and Mobility Status

Race	Cohort	Non-HHM, Non-FRL	HHM, Non-FRL	Non-HHM, FRL	HHM and FRL
White	A	0.177	0.173	0.294	0.288
	B	0.225	0.215	0.365	0.351
	C	0.534	0.564	0.517	0.547
Black	A	0.255	0.249	0.289	0.283
	B	0.286	0.273	0.316	0.303
	C	0.463	0.493	0.404	0.434
Asian	A	0.245	0.239	0.294	0.288
	B	0.286	0.273	0.373	0.359
	C	0.584	0.613	0.461	0.491
Hispanic/ Latino	A	0.241	0.235	0.310	0.304
	B	0.279	0.267	0.342	0.328
	C	0.533	0.563	0.503	0.532
Other	A	0.152	0.148	0.327	0.320
	B	0.193	0.184	0.363	0.349
	C	0.424	0.453	0.460	0.490

Research Question 3: Among fourth graders attending Connecticut public schools in districts that identified gifted students, how did rates of gifted identification for HHM students compare to those of low-mobility students with similar achievement levels?

Using those students in identifier districts who were matched by district, race, ELL status, SPED status, FRL status, and reading and mathematics achievement, I examined a crosstabs of homelessness and mobility (Tables 4.16-4.18), as well as crosstabs of HHM and FRL (Tables 4.19-4.21). Homelessness had a statistically significant association with high mobility across the three cohorts, A: $X^2(1, 9{,}142) = 115.094$, $p < .001$; B: $X^2(1, 12{,}923) = 75.441$, $p < .001$; C: $X^2(1, 7{,}565) = 68.119$, $p < .001$. As expected given the matching, there were not statistically significant correlations between HHM and FRL, A: $X^2(1, 9{,}142) = 0.000$, $p = 1.000$; B: X^2(1,

12,923) = 0.000, p = .996; C: $X^2(1, 7,565) = 0.000$, p = .999. Of the matched students, about 2% were homeless, about 19% were highly mobile, and about 1% were homeless and highly mobile; about 60% received FRL, about 20% were HHM, and about 16% were HHM students who received FRL. Next, I compared means across HHM and non-HHM groups (Table 4.22). As expected, there were no statistically significant differences found between these groups for the matched background variables. As previously discussed, matching on these variables provided a way to treat the matched HHM and non-HHM groups as if there were randomly assigned, allowing for causal inferences about the relationship between mobility and gifted identification. Across all three cohorts, there were no statistically significant differences found in the percentage of identified gifted students between matched HHM and non-HHM groups (Cohort A, $t(9,140) = 0.921$, p = .357, $d < 0.000$; Cohort B, $t(1,227) = 1.227$, p = .220, $d = 0.049$; Cohort C, $t(7,563) = -0.815$, p = .415, $d < 0.000$).

Table 4.16

Crosstabs of Homelessness and Mobility for Matched Cohort A Students in Identifier Districts

Homelessness		Mobility: Low	Mobility: High	Total
Non-Homeless	Count	7,209	1,692	8,901
	% of Total	78.9	18.5	97.4
Homeless	Count	128	113	241
	% of Total	1.4	1.2	2.6
Total	Count	7,337	1,805	9,142
	% of Total	80.3	19.7	100.0

Table 4.17

Crosstabs of Homelessness and Mobility for Matched Cohort B Students in Identifier Districts

Homelessness		Mobility: Low	Mobility: High	Total
Non-Homeless	Count	10,007	2,706	12,713
	% of Total	77.4	20.9	98.4
Homeless	Count	113	97	210
	% of Total	0.9	0.8	1.6
Total	Count	10,120	2,803	12,923
	% of Total	78.3	21.7	100.0

Table 4.18

Crosstabs of Homelessness and Mobility for Matched Cohort C Students in Identifier Districts

Homelessness		Mobility: Low	Mobility: High	Total
Non-Homeless	Count	6,085	1,307	7,392
	% of Total	80.4	17.3	97.7
Homeless	Count	100	73	173
	% of Total	1.3	1.0	2.3
Total	Count	6,185	1,380	7,565
	% of Total	81.8	18.2	100.0

Table 4.19

Crosstabs of HHM and FRL for Matched Cohort A Students in Identifier Districts

HHM		FRL: Non-FRL	FRL: FRL	Total
Non-HHM	Count	951	3,258	7,209
	% of Total	10.4	68.5	78.9
HHM	Count	255	1,678	1,933
	% of Total	2.8	18.4	21.1
Total	Count	1,206	7,936	9,142
	% of Total	13.2	86.8	100.0

Table 4.20

Crosstabs of HHM and FRL for Matched Cohort B Students in Identifier Districts

HHM		FRL: Non-FRL	FRL: FRL	Total
Non-HHM	Count	2,944	7,063	10,007
	% of Total	22.8	54.7	77.4
HHM	Count	858	2,058	2,916
	% of Total	6.6	15.9	22.6
Total	Count	3,802	9,121	12,923
	% of Total	29.4	70.6	100.0

Table 4.21

Crosstabs of HHM and FRL for Matched Cohort C Students in Identifier Districts

HHM		FRL: Non-FRL	FRL: FRL	Total
Non-HHM	Count	1,073	5,012	6,085
	% of Total	14.2	66.3	80.4
HHM	Count	261	1,219	1,480
	% of Total	3.5	16.1	19.6
Total	Count	1,334	6,231	7,565
	% of Total	17.6	82.4	100.0

Table 4.22

Demographic Mean Differences Between Matched HHM and Non-HHM Students

		HHM			Non-HHM				
	Cohort	*n*	*M*	*SD*	*n*	*M*	*SD*	*t*-test	Cohen's *d*
White	A	1,933	0.25	0.435	7,209	0.25	0.435	.000	0.000
	B	2,916	0.40	0.489	10,007	0.40	0.489	.000	0.000
	C	1,480	0.35	0.476	6,085	0.35	0.475	.000	0.000
Black	A	1,933	0.30	0.457	7,209	0.30	0.457	.000	0.000
	B	2,916	0.25	0.431	10,007	0.25	0.431	.000	0.000
	C	1,480	0.24	0.427	6,085	0.24	0.427	.000	0.000
Asian	A	1,933	0.02	0.130	7,209	0.02	0.130	.000	0.000
	B	2,916	0.03	0.179	10,007	0.03	0.179	.000	0.000
	C	1,480	0.03	0.164	6,085	0.03	0.164	.000	0.000
Hispanic/ Latino	A	1,933	0.42	0.493	7,209	0.42	0.493	.000	0.000
	B	2,916	0.32	0.466	10,007	0.32	0.466	.000	0.000
	C	1,480	0.38	0.485	6,085	0.38	0.485	.000	0.000
Other Race	A	1,933	0.01	0.117	7,209	0.01	0.117	.000	0.000
	B	2,916	0.01	0.080	10,007	0.01	0.080	.000	0.000
	C	1,480	0.01	0.086	6,085	0.01	0.086	.000	0.000
ELL	A	1,933	0.16	0.3667	7,209	0.16	0.367	.000	0.000
	B	2,916	0.15	0.361	10,007	0.15	0.361	.000	0.000
	C	1,480	0.14	0.350	6,085	0.14	0.350	.000	0.000
SPED	A	1,933	0.12	0.321	7,209	0.12	0.321	.000	0.000
	B	2,916	0.10	0.302	10,007	0.10	0.302	.000	0.000
	C	1,480	0.11	0.311	6,085	0.11	0.311	.000	0.000
Lunch	A	1,933	0.87	0.338	7,209	0.87	0.338	.000	0.000
	B	2,916	0.71	0.456	10,007	0.71	0.456	.000	0.000
	C	1,480	0.82	0.381	6,085	0.82	0.391	.000	0.000
Gifted	A	1,933	0.03	0.166	7,209	0.03	0.178	0.921	0.000
	B	2,916	0.04	0.199	10,007	0.05	0.211	1.227	0.049
	C	1,480	0.03	0.170	6,085	0.03	0.159	0.815	0.000
Reading (centered)	A	1,933	-12.31	38.124	7,209	-10.86	36.691	1.488	0.039
	B	2,916	-7.64	37.030	10,007	-6.32	35.868	1.704	0.036
	C	1,480	-10.62	37.338	6,085	-9.38	36.538	1.164	0.034
Math (centered)	A	1,933	-14.41	45.895	7,209	-13.38	44.250	0.898	0.023
	B	2,916	-8.51	44.497	10,007	-7.49	44.688	1.093	0.023
	C	1,480	-13.66	44.719	6,085	-12.07	42.249	1.237	0.037

Note. None of the *t*-test results were significant at the $p < .05$ level.

To determine the average treatment effect of mobility for each cohort, I used logistic regression to estimate the likelihood of gifted identification based on mobility status, race, ELL status, SPED status, FRL status, and reading and mathematics achievement. Achievement scores were centered at the grand mean. For race/ethnicity, the reference group included students from the White and Other categories. Tables 4.23-4.25 show the results of stepwise analyses predicting gifted identification from 1) HHM, 2) FRL, 3) the interaction of HHM and FRL, 4) reading and mathematics achievement, 5) race/ethnicity, and 6) ELL and SPED. Across the three cohorts, in models using all of these covariates, mobility, race, ELL status, SPED status, and the interaction between HHM and FRL were generally not significant predictors of gifted identification after controlling for FRL status and achievement. In all three cohorts, FRL status and achievement levels consistently and significantly predicted gifted identification, with or without other predictors in the model. HHM accounted for none of the variance in gifted identification (A1, R^2 = 0.000; B1, R^2 = 0.000; C1, R^2 = 0.000). Achievement scores explained relatively larger portions of the variance than other predictors in the model after controlling for HHM and FRL (A4, R^2 = 0.074; B4, R^2 = 0.118; C1, R^2 = 0.079). Table 4.26 summarizes the results of the re-estimated models predicting gifted identification from mobility, FRL status, and reading and mathematics achievement in each cohort. These models accounted for about 7-12% of the variance (A, R^2 = 0.074; B, R^2 = 0.118; C1, R^2 = 0.078). The small but statistically insignificant coefficients for mobility after controlling for lunch status and achievement confirm that mobility status had virtually no effect on the likelihood of gifted identification for students in the matched sample.

Table 4.23

Logistic Regression Predicting Gifted Identification From Seven Variables in Cohort A

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	*R^2
1	Constant	-3.391	0.066	1	<.001		0.000
	HHM	-0.140	0.152	1	.358	(0.645, 1.171)	
2	Constant	-2.689	.0123	1	<.001		0.004
	HHM	-0.140	0.152	1	0.358	(0.645, 1.171)	
	Lunch	-0.864	0.138	1	<.001	(0.322, 0.553)	
3	Constant	-2.720	0.135	1	<.001		0.004
	HHM	0.017	0.291	1	.955	(0.574, 1.799)	
	Lunch	-0.821	0.155	1	<.001	(0.325, 0.596)	
	HHM*Lunch	-0.213	0.342	1	.533	(0.413, 1.579)	
4	Constant	-3.821	0.169	1	<.001		0.074
	HHM	-0.022	0.320	1	.944	(0.523, 1.829)	
	Lunch	-0.352	0.169	1	.038	(0.504, 0.980)	
	HHM*Lunch	-0.214	0.375	1	.568	(0.388, 1.683)	
	Reading	0.033	0.003	1	<.001	(1.028, 1.039)	
	Mathematics	0.014	0.002	1	<.001	(1.011, 1.018)	
5	Constant	-3.899	0.180	1	<.001		0.075
	HHM	-0.023	0.321	1	.944	(0.521, 1.834)	
	Lunch	-0.320	0.200	1	.110	(0.491, 1.075)	
	HHM*Lunch	-0.214	0.376	1	.569	(0.387, 1.686)	
	Reading	0.034	0.003	1	<.001	(1.029, 1.040)	
	Mathematics	0.014	0.002	1	<.001	(1.010, 1.018)	
	Black	-0.003	0.191	1	.989	(0.686, 1.450)	
	Asian	0.511	0.304	1	.092	(0.920, 3.025)	
	Hispanic/Latino	0.085	0.182	1	.643	(0.761, 1.556)	
6	Constant	-3.852	0.181	1	<.001		0.075
	HHM	-0.023	0.321	1	.944	(0.521, 1.834)	
	Lunch	-0.302	0.199	1	.129	(0.500, 1.092)	
	HHM*Lunch	-0.217	0.376	1	.563	(0.385, 1.680)	
	Reading	0.033	0.003	1	<.001	(1.028, 1.039)	
	Mathematics	0.014	0.002	1	<.001	(1.010, 1.018)	
	Black	-0.013	0.190	1	.944	(0.680, 1.433)	
	Asian	0.587	0.312	1	.060	(0.976, 3.313)	
	Hispanic/Latino	0.139	0.186	1	.455	(0.798, 1.654)	
	ELL	-0.348	0.257	1	.176	(0.427, 1.169)	
	SPED	-1.244	0.798	1	.119	(0.060, 1.377)	

**Note:* Cox and Snell pseudo R^2

Table 4.24

Logistic Regression Predicting Gifted Identification From Seven Variables in Cohort B

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
1	Constant	-3.016	0.047	1	<.001		0.000
	HHM	-0.124	0.104	1	.234	(0.720, 1.084)	
2	Constant	-2.120	0.057	1	<.001		0.029
	HHM	-0.128	0.106	1	.227	(0.715, 1.083)	
	Lunch	-1.696	0.090	1	<.001	(0.154, 0.219)	
3	Constant	-2.135	0.060	1	<.001		0.029
	HHM	-0.060	0.129	1	.642	(0.732, 1.212)	
	Lunch	-1.655	0.101	1	<.001	(0.157, 0.233)	
	HHM*Lunch	-0.208	0.228	1	.363	(0.519, 1.271)	
4	Constant	-3.487	0.098	1	<.001		0.118
	HHM	-0.053	0.149	1	.720	(0.708, 1.269)	
	Lunch	-1.120	0.112	1	<.001	(0.262, 0.406)	
	HHM*Lunch	-0.204	0.250	1	.415	(0.499, 1.332)	
	Reading	0.035	0.002	1	<.001	(1.031, 1.040)	
	Mathematics	0.018	0.001	1	<.001	(1.015, 1.021)	
5	Constant	-3.556	0.102	1	<.001		0.119
	HHM	-0.049	0.148	1	.740	(0.711, 1.273)	
	Lunch	-1.257	0.159	1	<.001	(0.208, 0.389)	
	HHM*Lunch	-0.206	0.251	1	.410	(0.498, 1.329)	
	Reading	0.035	0.002	1	<.001	(1.032, 1.040)	
	Mathematics	0.018	0.001	1	<.001	(1.015, 1.021)	
	Black	0.207	0.180	1	.249	(0.865, 1.749)	
	Asian	0.455	0.188	1	.016	(1.089, 20279)	
	Hispanic/Latino	0.270	0.175	1	.124	(0.929, 1.846)	
6	Constant	-3.521	0.103	1	<.001		0.119
	HHM	-0.048	0.148	1	.744	(0.713, 1.274)	
	Lunch	-1.219	0.160	1	<.001	(0.216, 0.404)	
	HHM*Lunch	-0.206	0.251	1	.411	(0.498, 1.330)	
	Reading	0.035	0.002	1	<.001	(1.031, 1.040)	
	Mathematics	0.018	0.001	1	<.001	(1.015, 1.021)	
	Black	0.186	0.179	1	.301	(0.847, 1.711)	
	Asian	0.468	0.189	1	.013	(1.103, 2.314)	
	Hispanic/Latino	0.331	0.178	1	.063	(0.982, 1.975)	
	ELL	-0.446	0.261	1	.087	(0.384, 1.068)	
	SPED	-0.701	0.580	1	.227	(0.159, 1.546)	

**Note:* Cox and Snell pseudo R^2.

Table 4.25

Logistic Regression Predicting Gifted Identification From Seven Variables in Cohort C

Step	Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
1	Constant	-3.626	0.081	1	<.001		0.000
	HHM	0.141	0.173	1	.416	(0.820, 1.616)	
2	Constant	-2.437	0.106	1	<.001		0.019
	HHM	0.145	0.175	1	.409	(0.819, 1.630)	
	Lunch	-1.798	0.145	1	<.001	(0.125, 0.220)	
3	Constant	-2.377	0.109	1	<.001		0.019
	HHM	-0.168	0.262	1	.522	(0.506, 1.413)	
	Lunch	-1.932	0.165	1	<.001	(0.105, 0.200)	
	HHM*Lunch	0.610	0.353	1	.084	(0.921, 3.678)	
4	Constant	-3.718	0.170	1	<.001		0.079
	HHM	-0.235	0.308	1	.447	(0.432, 1.447)	
	Lunch	-1.344	0.183	1	<.001	(0.182, 0.373)	
	HHM*Lunch	0.755	0.398	1	.058	(0.976, 4.644)	
	Reading	0.022	0.003	1	<.001	(1.016, 1.029)	
	Mathematics	0.028	0.003	1	<.001	(1.023, 1.034)	
5	Constant	-3.714	0.176	1	<.001		0.079
	HHM	-0.234	0.308	1	.447	(0.432, 1.448)	
	Lunch	-1.430	0.224	1	<.001	(0.154, 0.371)	
	HHM*Lunch	0.756	0.398	1	0.58	(0.975, 4.649)	
	Reading	0.022	0.003	1	<.001	(1.015, 1.028)	
	Mathematics	0.028	0.003	1	<.001	(1.024, 1.034)	
	Black	0.330	0.246	1	.181	(0.858, 2.254)	
	Asian	-0.040	0.293	1	.890	(0.541, 1.704)	
	Hispanic/Latino	-0.035	0.242	1	.885	(0.601, 1.552)	
6	Constant	-3.736	0.179	1	<.001		0.080
	HHM	-0.232	0.308	1	.451	(0.433, 1.451)	
	Lunch	-1.480	0.227	1	<.001	(0.146, 0.355)	
	HHM*Lunch	0.754	0.399	1	.058	(0.974, 4.645)	
	Reading	0.023	0.003	1	<.001	(1.016, 1.030)	
	Mathematics	0.028	0.003	1	<.001	(1.023, 1.034)	
	Black	0.361	0.248	1	.146	(0.882, 2.335)	
	Asian	-0.109	0.293	1	.709	(0.505, 1.592)	
	Hispanic/Latino	-0.141	0.252	1	.576	(0.530, 1.423)	
	ELL	0.681	0.332	1	.040	(1.032, 3.787)	
	SPED	-0.360	0.873	1	.680	(0.126, 3.863)	

**Note:* Cox and Snell pseudo R^2.

Table 4.26

Logistic Regression Predicting Gifted Identification From Four Variables

Variable	*B*	*SE*	*df*	*p*	95% CI	R^2*
<u>*Cohort A*</u>						
Constant	-3.789	0.158	1	<.001		0.074
HHM	-0.180	0.166	1	.279	(0.603, 1.157)	
Lunch	-0.395	0.151	1	.009	(0.501, 0.906)	
Reading	0.033	0.003	1	<.001	(1.028, 1.039)	
Mathematics	0.014	0.002	1	<.001	(1.011, 1.018)	
<u>*Cohort B*</u>						
Constant	-3.471	0.096	1	<.001		0.118
HHM	-0.127	0.119	1	.286	(0.697, 1.112)	
Lunch	-1.161	0.100	1	<.001	(0.258, 0.381)	
Reading	0.035	0.002	1	<.001	(1.031, 1.040)	
Mathematics	0.018	0.001	1	<.001	(1.015. 1.021)	
<u>*Cohort C*</u>						
Constant	.3.795	0.168	1	<.001		0.078
HHM	0.194	0.196	1	.323	(0.827, 1.782)	
Lunch	-1.183	0.161	1	<.001	(0.223, 0.420)	
Reading	0.022	0.003	1	<.001	(1.016, 1.029)	
Mathematics	0.028	0.003	1	<.001	(1.023, 1.034)	

**Note:* Cox and Snell pseudo R^2.

Conclusion

This chapter detailed the results of the statistical analyses. Findings suggest that about one-third of HHM students attended schools in districts that did not identify gifted students. However, HHM students were no more likely than their non-HHM peers to attend minimal identifier districts. With the exception of the percentage of students receiving lunch subsidies, the differences in mean demographics between identifier and minimal identifier districts were not statistically significant. Regardless of race, students receiving lunch subsidies were much more likely to attend minimal identifier districts than students who did not receive lunch

subsidies. This was true for both HHM and non-HHM students. The high percentages of FRL students in the matched group reflect the strong link between poverty and mobility (see Appendix E, Table E.2). Among a matched sample of students in districts that complied with the gifted identification mandate, there were no significant difference found in the percentages of identified gifted HHM and non-HHM students after controlling for race, English language proficiency, special education status, receipt of lunch subsidies, reading achievement, and mathematics achievement.

CHAPTER 5: DISCUSSION

In this chapter, I discuss the findings detailed in Chapter 4, exploring their connections to previous research. I also discuss limitations of this study and implications for future research. Finally, I draw conclusions about the overall contribution of this study.

Discussion of Findings

To understand how mobility related to gifted identification in Connecticut public schools, I had to address two distinct issues. First, it was important to acknowledge that districts across the state did not provide equal access to gifted identification. Therefore, it was important to start by determining the likelihood that a highly mobile student was enrolled in a district in which gifted identification was even a possibility. Within districts that identified their gifted students, it was then possible to consider the likelihood of gifted identification after taking into account each student's race, ELL status, SPED status, FRL status, reading achievement, mathematics achievement, and mobility status.

Compliance With Gifted Identification Mandate

The data examined in this study paint a stark picture of overall gifted identification practices in Connecticut during the academic years 2010-2013. Despite a statewide mandate for gifted identification (RCSA Section 10-76a-2), over 40% of all districts reported virtually no identified gifted students, indicating widespread lack of compliance with state regulations. These districts include about one-third of all public school students in the state. The lack of a state gifted education consultant at that time is an important contextual factor that may have contributed to the problem of gifted under-identification in the state. Conventional wisdom in gifted education might suggest that districts that fail to identify their gifted students would likely be those with limited financial resources, higher proportions of traditionally underserved gifted

populations, and lower average achievement (Olszewski-Kubilius & Clarenbach, 2012; Siegle, McCoach, Gubbins, Callahan, & Knupp, 2015; Stambaugh, 2007; Swanson, 2006). In this study, comparison of district mean demographics provided evidence that, while there was somewhat more variation among minimal identifier districts as indicated by larger standard deviations, there was actually little difference in the mean demographics between identifier and minimal identifier districts. The only difference between identifiers and minimal identifiers with both statistical and practical significance was poverty. Overall, districts with higher proportions of FRL students were less likely to identify their gifted students.

Students in Minimal Identifier Districts

Findings of this study indicate that homeless and highly mobile students were generally enrolled in minimal identifier districts in the same proportions as their low-mobility peers. Overall, about a third of Connecticut students were in minimal identifier districts. This was reflected proportionately across both HHM and non-HHM students. However, because mobility is strongly associated with both poverty and race (Cowen, 2017; Larson & Meehan, 2011; Rumberger, 2015), the overall proportion of mobile students provides only part of the larger picture.

For students of any race, the probability of attending a minimal identifier district was nearly the same for HHM and non-HHM students of the same race when those students were not receiving lunch subsidies. However, across racial groups for non-FRL students, those who were Black, Hispanic/Latino, or Asian were more likely than White students to attend minimal identifier districts, generally by a difference of 5% or more. The differences in probabilities between races virtually disappeared among FRL students, for whom there was generally a 30% or greater chance of attendance in a minimal identifier district whether or not they were also

highly mobile. Relative to non-FRL students, this was an increase of about 12-15% for White students, and an increase of about 4-9% or more for Black, Hispanic/Latino, and Asian students.

In short, low-mobility, non-FRL, White students were least likely to attend minimal identifier districts. Within each race/ethnicity, HHM and non-HHM students who did not receive FRL had approximately equal likelihood of attending minimal identifiers. Non-White students were more likely than White students to attend minimal identifier districts. FRL students, almost universally across race and mobility status, were those with the greatest probability of enrollment in minimal identifier districts. After accounting for poverty and race, mobility had little effect on the likelihood of attending a minimal identifier. However, it is important to remember that many HHM students were indeed among those non-White, FRL students. Taken together, the characteristics of minimal identifier districts and the students likely to attend them demonstrate that those students most in need of access to resources and opportunity due to challenges related to poverty, race, or both, were also those who were most likely to attend districts with virtually no opportunity for gifted identification.

HHM Students in Connecticut

Across the total sample for the study, about 13% of Connecticut students were HHM students. Relative to low-mobility students, the HHM group included significantly higher percentages of Black, Hispanic/Latino, and FRL students, as well as somewhat higher percentages of English language learners and special education students (Appendix A, Table A.2). While about 60% of Connecticut students did not change schools in grades 1-4, about 27% changed schools once, and about 11% changed schools 2 or more times. These demographics and mobility patterns are consistent with previous findings (Cowen, 2017; Larson & Meehan, 2011; Lee, Burkam, & Dwyer, 2009; Rumberger, 2015).

The Impact of Mobility on Gifted Identification

The primary goal of this study was to explore the possible relationship between school mobility and gifted identification in Connecticut public schools. While previous studies described mobility rates and outcomes among students already identified as gifted, this study examined how mobility related to the likelihood that a student would be identified. For students attending school in districts that complied with the statewide mandate to identify gifted students, findings of the study suggest that, after matching on race, English language proficiency, special education status, socioeconomic status (as indicated by receipt of lunch subsidies), reading achievement, and mathematics achievement, there was not a significant difference between the gifted identification rates of highly mobile students and their low-mobility peers. This is a glimmer of good news for highly mobile students who attended identifier districts and who achieved at high levels, indicating that their mobility status had no impact on their likelihood of being identified gifted.

The finding that mobility did not decrease students' likelihood of gifted identification may be surprising in light of the evidence that mobility is often associated with declines in academic performance (Friedman-Krauss & Raver, 2015; Selya et al., 2016; Temple & Reynolds, 1995; Voight, Shinn, & Nation, 2012) and increased risk that a student's educational needs will go unrecognized and remain unmet (Juliannelle & Foscarinis, 2003; Kerbow, 1996). However, by nature of being gifted, these students likely benefit from a number of the same protective factors believed to protect against the risks associated with mobility, such as strong general cognitive skills (Herbers et al., 2011), early literacy skills (Masten, 2012), self-regulation skills (Obradović, 2010), and early reading achievement (Herbers et al., 2012). The presence of

these protective factors in gifted students could provide a possible explanation for why mobility was not associated with decreased likelihood of identification for highly mobile gifted students.

It is important to note that the finding of no differences between gifted identification rates of HHM and non-HHM students does not extend to students in minimal identifier districts or to the several hundred HHM students in each cohort without matches. Among these unmatched HHM students may be some potentially gifted students whose mobility has contributed to relatively low achievement and to limited opportunity for their potential to be nurtured and developed.

Limitations and Implications for Future Research

Gifted Education Practices

Although schools and districts in Connecticut are required to identify students for gifted education, the processes and procedures for doing so vary across the state. Schools are required to report each student's gifted education status each year, but information collected about the policies and procedures schools use when identifying students for gifted education is limited. Furthermore, although there is a mandate for identification, current Connecticut law does not require schools to provide gifted programs or services for identified students. Districts across the state vary widely with respect to the time, personnel, and resources devoted to gifted education services, when such services exist. In the absence of strong oversight and accountability to ensure that schools are actively identifying students for gifted education, many schools that do not offer formal gifted programs also do not identify gifted students at the same rates as schools that do offer gifted programs.

In this study, district identification practices were summarized by categorizing districts as identifiers or minimal identifiers. While this provided a baseline for understanding differences

between districts that did and did not identify gifted students, it did not take into account the wide range of differences in identification rates among the identifier districts. Future work could examine the differences among districts relative to the overall percentage of gifted students identified in those districts. This could provide a more nuanced picture of the relationship between mobility rates and gifted identification.

Understanding Gifted Under-Identification

The widespread under-identification of gifted students in many Connecticut schools could linked to a number of factors. These may include lack of adequate funding, personnel, time, and other resources; lack of local administrative support; resistance from teachers and staff; lack of demand for gifted identification by stakeholders such as parents and teachers; lack of adequate guidance regarding processes and procedures; or even the influence of local philosophical beliefs and values. A better understanding of the challenges and barriers that contribute to very low gifted identification rates would lend insight into the needs and opportunities to improve gifted identification in Connecticut public schools. State education officials and other education stakeholders could use this information to guide the development of both support systems and accountability procedures to ensure that all schools are providing their students with equitable opportunity for gifted identification. Conducting case studies of districts that successfully identify gifted students could help suggest best practices for gifted identification in the state, and may provide useful strategies and models to help other districts improve their identification practices. Given the link between poverty and compliance, it may be especially important to understand the practices implemented in high poverty districts that have found ways to identify their gifted students despite limitations in funding and resources.

Highly Mobile Gifted Students

That there was no significant difference found in the percentage of HHM and non-HHM students identified gifted could suggest that gifted students benefit from characteristics that serve as protective factors, countering the risks associated with mobility. Future studies could add to the body of knowledge about the impact of school mobility on gifted students by examining student characteristics and achievement trajectories before and after moving to better understand the short- and long-term effects of mobility on the achievement of gifted students. This work could build understanding of how characteristics often associated with giftedness, such as early high achievement, may influence outcomes for mobile gifted students.

For highly mobile gifted students, another important question relates to the persistence of the identification across settings. Inquiry into the practices and policies of Connecticut districts would shed light on the ways these schools handle gifted identification for mobile students. A better understanding of the ways districts handle previous identifications is needed to shed light on what happens as gifted students move between different local contexts, especially when moving between districts with dissimilar student achievement and demographics. As the state works to balance the implications of local control in districts with the need to provide equitable educational opportunity for students across the state, this information could help inform recommendations for practice.

Mobility Counts

Across the cohorts, mobility count patterns in cohort B were not consistent with those observed in cohorts A and C. Specifically, cohort B showed lower proportions of students with 1 and 2 moves, and higher proportions of students with 3, 4, 5, and 6 moves. This could suggest that some structural moves were not accounted for in cohort B, and warrants further examination.

Underrepresented Populations

The findings of this study illustrate that highly mobile gifted students, by virtue of their race and socioeconomic status, are often already members of underserved gifted populations. Therefore, research that yields information about how to better identify and serve gifted students from underrepresented populations, particularly those who are Black, Hispanic/Latino, and experiencing poverty, will also have implications relevant for many highly mobile students. There is a growing body of evidence that pre-identification and preparation programs designed to spot early signs of potential and provide promising young students from diverse populations with early intervention are often effective in increasing gifted identification rates among students from underrepresented populations (Brulles, Castellano, & Laing, 2011; Horn, 2015; Siegle et al., 2016). Studies that replicate implementation of such interventions in districts with high mobility rates could help determine whether these preparation programs could contribute to higher gifted identification rates of highly mobile students, particularly those who are also members of other underrepresented populations.

Missing Data

The very nature of school mobility – namely, the missing-ness of the students themselves from a given institution – contributes heavily to the problem of missing data that poses substantial challenges for understanding how school mobility relates to particular outcomes such as gifted education. When using methods that involve excluding participants with missing data, it is likely that a large proportion of those excluded are themselves members of the HHM population the study is designed to examine. In other words, the mobile nature of HHM students itself creates methodological challenges to studying that mobility. In this study, about 20% of the students from each cohort overall were excluded due to missing data. The excluded students

included a significantly larger proportion of HHM students than in the sample retained (see Appendix D, Table D.2). Furthermore, among students with complete data in identifier districts, matching procedures resulted in matches for about 70%-80% of the HHM students in the sample, while the remaining HHM students without matches were excluded from the analyses. This suggests that findings of this study should be interpreted with caution, as they may not provide a complete picture of the relationship between school mobility and gifted identification for those who were excluded from the analyses.

Future studies could examine current practices for transferal of records between schools and districts to identify opportunities to improve data management and sharing, and to determine the effectiveness of different practices. For example, the Military Interstate Children's Compact provides guidelines and suggests practices to facilitate transferal or educational records and to deal with redundant or missed testing opportunities. Future studies could examine whether implementation of these practices is related to more efficient transferal of student records and a reduction in missing data for military students who move. If shown to be effective with mobile military students, these practices could be expanded to other highly mobile populations.

Generalizability

The focus of this study is on understanding the relationship between mobility and gifted identification among students in traditional public school settings within Connecticut. Findings should not be generalized to students in nontraditional, alternative school programs, who were excluded from the analysis. Missing data for students in grade 3 or grade 4 likely indicate students who move into or out of Connecticut, or into or out of non-public schools, during these years. Because these students were excluded from the analyses, findings of this study should not be generalized to them. Furthermore, gifted identification practices and policies vary widely

from state to state, so findings from this study should not be generalized to other states. Future studies could be designed to focus specifically on other populations of students, such as students in other states, or those experiencing moves between different states.

Intra-and Inter-District Moves

In this study, analyses were conducted using mobility counts that reflected each change of school. However, no distinction was made between inter- and intra-district moves. Future work could differentiate between within- and between-district moves to better understand whether these different types of moves contribute to different outcomes. It may be reasonable to expect that student outcomes may be different when moving within a district than when moving between districts. As with structural and promotional moves, students changing schools within a district may experience smoother transitions and fewer disruptions in their educational experiences because of the shared characteristics and systems between schools within a district. Furthermore, while it is reasonable to expect that previously identified gifted students moving within Connecticut district would likely retain their gifted identification, the same may or may not be true for students moving between districts.

Reasons for School Mobility

Students may change schools for a number of different reasons, included those dictated by negative circumstances such as job loss or divorce, as well as those strategically taken in search of better educational opportunities (Rumberger et al., 1999). Although the majority of non-promotional school changes are due to residential moves, moves may also be associated with factors such as school safety concerns, suspension/expulsion, overcrowding, school closings, or availability of academic opportunities (Rumberger, 2003). It is reasonable to expect that the complex reasons underlying school changes may contribute to the outcomes related to

these moves; however, these explorations would require data beyond those which were available in the current data set, so were beyond the scope of this study. Future studies could focus specifically on students experiencing particular types of moves to better understand the patterns of risks and outcomes associated with them.

Mobility of military families. Although students from military families may resemble other highly mobile students, there is evidence that the students from military families experience much smaller declines in achievement after moving than do those from civilian families (Lyle, 2006; Marchant & Medway, 1987). Given that there are four military bases in the New London area, including one Navy base and three Coast Guard bases, it is reasonable to expect that a sizable proportion of students in and around New London come from military families. By nature of the moves from out of state that are common among military families, some of these students may already have been excluded from the analysis due to missing data in grade 3 or grade 4. However, a number of students from military families were likely included. Because the data did not include any variables that distinguish whether students come from military or civilian families, it was not possible to determine whether these groups experience differences in the relationship between mobility and gifted identification. For future studies, further data could be gathered to determine the percentage of students from military families in each district, which would allow comparisons in the gifted identification rates of mobile students in districts with relatively low and high proportions of students from military families.

Recommendations

Under-Identification of Gifted Students

The findings of this study revealed large-scale, systemic inequity in access to gifted identification throughout the state. More than 40% of districts, representing over 30% of the

students in the state, reported few to no gifted students, despite state statutes requiring gifted identification. Many possible factors may have contributed to the widespread under-identification of gifted students. The finding of higher poverty rates in minimal identifier districts suggests that access to resources may have been one contributing factor. Furthermore, the fact that the state required gifted identification but not gifted services is likely a powerful driving factor contributing to under-identification. Without a mandate to provide to identified services, districts may have seen no valid justification to invest the time and resources necessary to identify gifted students. As previously noted, during the time in which the data for this study was collected, there was not a gifted education consultant at CSDE. In the absence of such a position, districts lacked the benefit of the guidance, support, and accountability that a designated gifted education official could provide.

The following are recommendations that could help address the problem of gifted under-identification in Connecticut public schools:

- Conduct further research to identify the specific barriers and challenges that contribute to under-identification of gifted students in Connecticut public schools and to identify successful practices used in districts that identify gifted students, particularly in districts with limited resources.
- Provide professional development to address specific barriers to gifted identification, including information about how to identify gifted students from underrepresented populations (Callahan, 2005; CSDE, 2017; McBee, Peters, & Miller, 2016).
- Implement guidance, support, and accountability procedures to assist districts and ensure compliance with state gifted identification statutes.

- Consider legislation that would strengthen districts' responsibilities by mandating both identification and services for gifted students.
- Designate an employee at the Connecticut State Department of Education to serve as a gifted education consultant responsible for providing guidance, support, and accountability related to gifted education.

Homeless and Highly Mobile Students

Compared to their low-mobility peers, students who are homeless and highly mobile were found to include higher proportions of Black and Hispanic/Latino students, English language learners, and students receiving special education services. On average, they had lower reading and mathematics achievement. Perhaps more importantly, more than twice as many HHM students as non-HHM students received lunch subsidies, indicating widespread poverty. While most HHM students changed schools 2 or 3 times in grades 1-4, some experienced as many as 9 school changes in the same period. By nature of being highly mobile, HHM students are vulnerable to many potential risks. For the majority of HHM students, these are in addition to substantial risks they already may face related to their race/ethnicity and socioeconomic status. Notably, many HHM students are already members of traditionally underrepresented gifted populations, even before taking mobility into account. It is important that school personnel understand the risks associated with mobility, and that districts take steps to ensure access to gifted identification for students from underrepresented populations, including HHM students.

The following are recommendations that could help improve access to gifted identification for HHM students in Connecticut public schools:

- Utilize universal screening to identify potential giftedness among students from all populations (Card & Guiliano, 2015).

- Implement strategies to reduce the problem of missing data for homeless and highly mobile students, including assessment opportunities for student who have missed testing administrations, flexible timelines that allow rolling referrals, and provisions for timely screening of students who enter with missing data (CSDE, 2017; Lee, Burkam, & Dwyer, 2009; Rumberger, 2015).
- Provide school staff with professional development related to gifted identification, with specific emphasis on underrepresented gifted populations (Callahan, 2005; CSDE, 2017; Ford, Grantham, & Whiting, 2008; Siegle et al., 2016).
- Adopt, and intentionally include HHM students in, pre-identification and preparation programs to provide them with opportunities to develop potential giftedness (Brulles, Castellano, & Laing, 2011; Horn, 2015; McBee, 2016; Siegle et al., 2016).

Conclusions

The ultimate purpose of this study was to understand the potential impact of school mobility on gifted identification in Connecticut public schools. While a review of the literature suggested that students who were homeless and/or highly mobile may be less likely to be identified gifted, the findings of this study suggested that mobility has a complex relationship with gifted identification. First, more than a third of Connecticut students were enrolled in districts that do not identify gifted students. Non-White, FRL students – a group that included many highly mobile students – were among those most likely to attend these minimal identifier districts. Second, for those students in identifier districts, mobility was found to have no causal relationship with the likelihood of gifted identification after matching students on race, ELL status, SPED status, FRL status, and achievement. However, these findings cannot be extended

to the many highly mobile students excluded from the analyses due to missing data or lack of matches in the sample.

What began as a story about mobility has become a story about poverty and lack of opportunity. While examining gifted identification practices, this study revealed large discrepancies across districts throughout the state, revealing that a large number of districts did not identify their gifted students. Students in these minimal identifier districts, highly mobile students among them, have virtually no chance of gifted identification. This highlights an important need and opportunity to further examine gifted identification practices in the state to inform development of resources, practices, support systems, and accountability procedures to help ensure that schools fulfill their responsibility to provide equitable opportunity for gifted identification to all students, including those who are highly mobile and experiencing poverty.

Epilogue

Throughout the first half of 2017, as I was undertaking this study, gifted education advocates in Connecticut developed and supported legislation to strengthen gifted education in the state. Submitted by the Education Committee, and co-sponsored by Representatives Terrie E. Wood, Heather B. Somers, Kim Rose, Robert C. Sampson, and Kathleen M. McCarty, as well as Senators Toni Boucher and Steve Cassano, Substitute Senate Bill No. 911 was approved in June. Effective as of July 1, 2017, Public Act No. 17-82 is entititled *An Act Concerning Services for Gifted and Talented Students* (see Appendix G). This legislation now requires that an employee of the Department of Education be responsible for gifted education guidance, including providing boards of education and parents/guardians with information and assistance related to awareness about, identification of, and services to gifted and talented students. Furthermore, it requires that the Department of Education develop guidelines regarding best practices for serving

gifted and talented students, including practices for addressing the intellectual, social, and emotional needs of gifted students. Finally, it also requires that the Department of Education provide guidelines regarding best practices for providing professional development and teacher training related to gifted education. Though this legislation stops short of mandating gifted education services, it is an important step in that direction, providing a rich opportunity to support districts in their efforts to better identify and serve gifted students.

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Appendix A: Complete Sample

Table A.1

Descriptive Statistics for All Students

	Cohort A		Cohort B		Cohort C	
Variable	Frequency	Percent	Frequency	Percent	Frequency	Percent
n	47,706	100.0	46,242	100.0	46,991	100.0
Gender						
Female	23,070	48.4	22,461	48.4	22,772	48.5
Male	24,636	51.6	23,963	51.6	24,219	51.5
Race						
White	27,480	57.6	26,706	57.5	26,771	57.0
Asian	2,311	4.8	2,462	5.3	2,530	5.4
Black	6,886	14.4	6,358	13.7	6,107	13.0
Hispanic/Latino	9,844	20.6	9,809	21.1	10,059	21.4
Other	1,185	2.5	1,089	2.3	1,524	3.2
FRL	20,878	43.8	20,664	44.5	21,191	45.1
ELL	5,728	12.0	5,571	12.0	5,551	11.8
SPED	7,292	15.3	7,046	15.2	7,203	15.3
Gifted	2,057	4.3	1,990	4.3	1,791	3.8
HHM	6,304	13.2	9,289	20.0	6,189	13.2
Gifted*HHM	91	0.2	207	0.4	91	0.2

Table A.2

Demographic Mean Differences Between All HHM and Non-HHM Students

	Cohort	HHM *n*	HHM *M*	HHM *SD*	Non-HHM *n*	Non-HHM *M*	Non-HHM *SD*	*t*-test	Cohen's *d*
White	A	6,304	0.275	0.446	41,402	0.622	0.485	56.847*	0.745
	B	9,289	0.367	0.482	37,135	0.627	0.484	46.586*	0.538
	C	6,189	0.328	0.169	40,802	0.606	0.489	43.327*	0.845
Black	A	6,304	0.258	0.437	41,402	0.127	0.333	22.741*	0.340
	B	9,289	0.214	0.410	37,135	0.118	0.322	21.122*	0.262
	C	6,189	0.211	0.408	40,802	0.118	0.322	17.172*	0.255
Asian	A	6,304	0.049	0.216	41,402	0.048	0.215	0.228	0.005
	B	9,289	0.064	0.244	37,135	0.050	0.219	4.725*	0.060
	C	6,189	0.051	0.219	40,802	0.054	0.227	1.222	0.013
Hispanic/ Latino	A	6,304	0.380	0.486	41,402	0.180	0.384	31.337*	0.460
	B	9,289	0.319	0.466	37,135	0.184	0.388	25.749*	0.316
	C	6,189	0.329	0.470	40,802	0.197	0.397	21.044*	0.304
Other Race	A	6,304	0.038	0.191	41,402	0.023	0.149	6.051*	0.088
	B	9,289	0.036	0.187	37,135	0.020	0.141	7.731*	0.098
	C	6,189	0.082	0.275	40,802	0.025	0.156	16.001*	0.265
ELL	A	6,304	0.214	0.410	41,402	0.106	0.307	20.165*	0.301
	B	9,289	0.208	0.406	37,135	0.098	0.297	24.603*	0.313
	C	6,189	0.189	0.392	40,802	0.107	0.310	15.682*	0.234
SPED	A	6,304	0.196	0.397	41,402	0.146	0.353	9.342*	0.133
	B	9,289	0.177	0.382	37,135	0.145	0.353	7.254*	0.087
	C	6,189	0.196	0.397	40,802	0.147	0.354	9.143*	0.130
Lunch	A	6,304	0.811	0.391	41,402	0.381	0.486	78.552*	0.981
	B	9,289	0.693	0.461	37,135	0.383	0.486	57.330*	0.655
	C	6,189	0.765	0.424	40,802	0.403	0.491	61.196*	0.791
Gifted	A	6,304	0.014	0.119	41,402	0.048	0.213	18.058*	0.205
	B	9,289	0.022	0.148	37,135	0.048	0.214	13.605*	0.144
	C	6,189	0.015	0.120	40,802	0.042	0.200	14.797*	0.169
Reading (centered)	A	4,401	-10.996	39.213	36,273	1.334	37.884	19.770*	0.320
	B	5,751	-8.249	40.002	31,880	1.488	37.412	25.325*	0.252
	C	4,021	-10.291	39.416	34,310	1.206	38.021	17.563*	0.297
Math (centered)	A	4,558	-12.970	48.204	36,790	1.607	46.430	19.335*	0.308
	B	6,035	-9.834	48.704	32,177	1.844	45.869	14.156*	0.247
	C	4,170	-14.153	47.747	34,751	1.698	44.798	20.388*	0.343

* $p < .001$.

Appendix B: Students With Complete Data

Table B.1

Descriptive Statistics for Students With Complete Data

	Cohort A		Cohort B		Cohort C	
Variable	Frequency	Percent	Frequency	Percent	Frequency	Percent
n	37,548	100.0	36,595	100.0	37,249	100.0
Gender						
Female	18,580	49.5	18,167	49.6	18,524	49.7
Male	18,968	50.5	18,428	50.4	18,725	50.3
Race						
White	23,226	61.9	22,561	61.7	22,780	61.2
Asian	1,695	4.5	1,839	5.0	1,876	5.0
Black	4,827	12.9	4,497	12.3	4,387	11.8
Hispanic/Latino	6,810	18.1	6,868	18.8	7,191	19.3
Other	990	2.6	830	2.3	1,015	2.7
FRL	14,860	39.6	14,901	40.7	15,412	41.4
ELL	3,639	9.7	3,602	9.8	3,626	9.7
SPED	4,270	11.4	4,125	11.3	4,173	11.2
Gifted	1,971	5.2	1,912	5.2	1,736	4.7
HHM	3,501	9.3	5,347	14.6	3,570	9.6
Gifted*HHM	76	0.2	177	0.5	79	0.2

Appendix C: Students With Missing Data

Table C.1

Descriptive Statistics for Students With Missing Data

Variable	Cohort A		Cohort B		Cohort C	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
n	10,158	100.0	9,829	100.0	9,742	100.0
Gender						
Female	4,490	44.2	4,294	43.7	4,248	43.6
Male	5,668	55.8	5,535	56.3	5,494	56.4
Race						
White	4,254	41.9	4,145	42.2	3,991	41.0
Asian	616	6.1	623	6.3	654	6.7
Black	2,059	20.3	1,861	18.9	1720	17.7
Hispanic/Latino	3,034	29.9	2,941	29.9	2,868	29.4
Other	195	1.9	259	2.6	509	5.2
FRL	6,018	59.2	5,763	58.6	5,779	59.3
ELL	2,089	20.6	1,969	20.0	1,925	19.8
SPED	3,022	29.7	2,921	29.7	3,030	31.1
Gifted	86	0.8	78	0.8	55	0.6
HHM	2,803	27.6	3,942	40.1	2,619	26.9
Gifted*HHM	15	0.1	30	0.3	12	0.1

Table C.2

Demographic Mean Differences Between Students With Complete and Missing Data

	Cohort	Complete			Missing				
		n	*M*	*SD*	*n*	*M*	*SD*	*t*-test	Cohen's *d*
Black	A	37,548	0.129	0.335	10,158	0.203	0.402	17.057**	0.201
	B	36,595	0.129	0.328	9,829	0.189	0.392	15.424**	0.167
	C	37,249	0.118	0.322	9,742	0.177	0.381	13.966**	0.168
Asian	A	37,548	0.045	0.208	10,158	0.061	0.239	5.963**	0.072
	B	36,595	0.050	0.218	9,829	0.063	0.244	4.845**	0.056
	C	37,249	0.050	0.219	9,742	0.067	0.250	6.038**	0.072
Hispanic/ Latino	A	37,548	0.181	0.385	10,158	0.299	0.458	23.663**	0.280
	B	36,595	0.188	0.390	9,829	0.299	0.458	22.088**	0.262
	C	37,249	0.193	0.395	9,742	0.294	0.456	20.066**	0.237
Other	A	37,548	0.026	0.160	10,158	0.019	0.137	4.501**	0.047
	B	36,595	0.023	0.149	9,829	0.026	0.160	2.046**	0.019
	C	37,249	0.027	0.163	9,742	0.052	0.223	10.385**	0.130
ELL	A	37,548	0.097	0.296	10,158	0.206	0.404	25.339**	0.311
	B	36,595	0.098	0.298	9,829	0.200	0.400	23.548**	0.292
	C	37,249	0.097	0.296	9,742	0.198	0.398	23.223**	0.291
SPED	A	37,548	0.114	0.317	10,158	0.298	0.457	38.105**	0.475
	B	36,595	0.113	0.316	9,829	0.297	0.457	37.665**	0.476
	C	37,249	0.112	0.315	9,742	0.311	0.463	40.065**	0.512
Lunch	A	37,548	0.396	0.489	10,158	0.592	0.491	35.824**	0.400
	B	36,595	0.407	0.491	9,829	0.586	0.493	32.032**	0.364
	C	37,249	0.414	0.493	9,742	0.593	0.491	32.083**	0.364
Gifted	A	37,548	0.053	0.223	10,158	0.009	0.092	30.018**	-0.279
	B	36,595	0.052	0.223	9,829	0.008	0.089	30.191**	-0.282
	C	37,249	0.047	0.211	9,742	0.006	0.075	30.794**	-0.287
Homeless	A	37,548	0.010	0.099	10,158	0.020	0.139	6.744**	0.084
	B	36,595	0.010	0.102	9,829	0.022	0.148	7.510**	0.096
	C	37,249	0.011	0.104	9,742	0.025	0.155	8.158**	0.108
Mobile	A	37,548	0.088	0.283	10,158	0.268	0.443	38.778**	0.496
	B	36,595	0.141	0.348	9,829	0.395	0.489	48.357**	0.607
	C	37,249	0.090	0.286	9,742	0.258	0.438	35.952**	0.464
HHM	A	37,548	0.093	0.291	10,158	0.276	0.441	39.020**	0.500
	B	36,595	0.146	0.353	9,829	0.401	0.491	48.309**	0.604
	C	37,249	0.096	0.294	9,742	0.269	0.443	36.466**	0.469
Mobility Count	A	37,548	0.408	0.788	10,158	1.297	0.934	87.842**	1.033
	B	36,595	0.554	1.086	9,829	1.760	1.381	80.180**	0.978
	C	37,249	0.415	0.787	9,742	1.268	0.920	83.722**	0.999
Reading (centered)	A	37,548	0.063	37.985	3,126	-0.751	40.968	1.072	0.021
	B	36,595	0.085	37.633	1,036	-2.994	48.627	2.021	0.071
	C	37,249	0.082	37.969	1,082	-2.815	49.151	1.922	0.067
Math (centered)	A	37,548	0.706	46.444	3,800	-6.974	50.171	9.052**	0.159
	B	36,595	0.713	45.882	1,617	-16.127	56.869	11.739**	0.328
	C	37,249	0.782	44.612	1,672	-17.412	57.455	12.776**	0.357

* *p* <.01. ** *p* <.001.

Appendix D: Variables

Table D.1

Variable Codes

Variable	PSIS	CMT	Recoded
XXX_Race	1=American Indian 2=Asian American 3=Black 4=White 5=Hispanic	1=Hispanic/Latino 2=American Indian or Alaska Native 3=Black or African American 4=Asian 5=Native Hawaiian or Pacific Islander 6=White 7=Two or more races	White=White Asian=Asian Black=Black Hispanic/Latino=Hispanic/Latino Other=(American Indian, Pacific Islander, two or more races, or not reported)
XXX_ELL	Y=Yes N=No	1=Yes 2=No	Y=Yes N=No
XXX_SPED	Y=Yes N=No	1=Yes 2=No	Y=Yes N=No
XXX_Lunch	F=Free R=Reduced N=No	1=Free 2=Reduced 3=No	Y=Yes (Free or Reduced) N=No
XXX_Gifted	01=Not Gifted, not Talented 02=Gifted Identified 03=Gifted Served 04=Talented Identified 05=Talented Served 06=Gifted Identified, Talented Identified 07=Gifted Served, Talented Served 08=Gifted Identified, Talented Served 09=Gifted Served, Talented Identified	01=Not Gifted, not Talented 02=Gifted Identified 03=Gifted Served 04=Talented Identified 05=Talented Served 06=Gifted Identified, Talented Identified 07=Gifted Served, Talented Served 08=Gifted Identified, Talented Served 09=Gifted Served, Talented Identified	Y=Yes (02, 03, 06, 07, 08, or 09) N=No (01, 04, or 05)

Table D.2

Summary of Student Variables Created

New Variable	Description	Criteria	Coding
ELL	Ever ELL	If any XXX_ELL=Y	N=No Y=Yes
SPED	Ever SPED	If any XXX_SPED=Y	N=No Y=Yes
Lunch	Ever FRL	If any XXX_Lunch=Y	N=No Y=Yes
Gifted	Ever Gifted in Grade 4	If any X4X_Gifted=Y	N=No Y=Yes
Homeless	Ever Homeless or Migrant	If any XXX_Homeless=Y or any XXX_Migrant=Y	N=No Y=Yes
Mobile	Highly mobile (2+ moves)	Mobility count ≥2	N=No Y=Yes
HHM	Homeless and/or highly mobile	If Homeless=Y or Mobile=Y	N=No Y=Yes

Appendix E: Students in Identifier Districts

Table E.1

Descriptive Statistics for Students in Districts That Identify Gifted Students

Variable	Cohort A		Cohort B		Cohort C	
	Frequency	Percent	Frequency	Percent	Frequency	Percent
n	25,323	100.00	25,468	100.00	23,341	100.00
Gender						
Female	12,721	49.77	12,603	49.49	11,616	49.77
Male	12,602	50.23	12,865	50.51	11,725	50.23
Race						
White	15,328	60.53	15,698	61.64	15,090	64.65
Asian	1,152	4.55	1,313	5.16	1,184	5.07
Black	3,432	13.55	3,134	12.31	2,258	9.67
Hispanic/Latino	4,780	18.88	4,779	18.76	4,243	18.18
Other	631	2.49	544	2.14	566	2.42
FRL	10,113	39.94	10,086	39.60	8,554	36.65
ELL	2,478	9.79	2,569	10.09	2,146	9.19
SPED	2,862	11.30	2,911	11.43	2,625	11.25
Gifted	1,956	7.72	1,904	7.48	1,728	7.40
HHM	2,377	9.39	3,619	14.21	2,153	9.22
Gifted*HHM	73	0.29	173	0.68	79	0.34

Table E.2

Demographic Mean Differences Between Matched and Unmatched HHM Students in Identifier Districts

		Matched			Unmatched				
	Cohort	*n*	*M*	*SD*	*n*	*M*	*SD*	*t*-test	Cohen's *d*
White	A	1,933	0.25	0.435	444	0.24	0.428	0.525	0.023
	B	2,916	0.40	0.489	703	0.31	0.463	4.320**	0.189
	C	1,480	0.35	0.476	673	0.60	0.491	11.153**	0.517
Black	A	1,933	0.30	0.457	444	0.21	0.406	4.124**	0.209
	B	2,916	0.25	0.431	703	0.19	1.392	3.456**	0.066
	C	1,480	0.24	0.427	673	0.07	0.262	11.023**	0.493
Asian	A	1,933	0.02	0.130	444	0.14	0.349	7.413**	0.501
	B	2,916	0.03	0.179	703	0.15	0.357	8.378**	0.448
	C	1,480	0.03	0.164	673	0.08	0.272	4.643**	0.229
Hispanic/ Latino	A	1,933	0.42	0.493	444	0.28	0.451	5.572**	0.297
	B	2,916	0.32	0.466	703	0.24	0.427	4.322**	0.179
	C	1,480	0.38	0.485	673	0.17	0.374	11.055**	0.489
Other Race	A	1,933	0.01	0.117	444	0.13	0.332	7.011**	0.535
	B	2,916	0.01	0.080	703	0.11	0.316	8.812**	0.505
	C	1,480	0.01	0.086	673	0.08	0.272	6.795**	0.391
ELL	A	1,933	0.16	0.367	444	0.25	0.432	3.946**	0.225
	B	2,916	0.15	0.361	703	0.24	0.426	4.804**	0.229
	C	1,480	0.14	0.350	673	0.14	0.342	0.455	0.000
SPED	A	1,933	0.12	0.321	444	0.23	0.420	5.237**	0.297
	B	2,916	0.10	0.302	703	0.21	0.409	6.753**	0.309
	C	1,480	0.11	0.311	673	0.18	0.383	4.171**	0.202
Lunch	A	1,933	0.87	0.338	444	0.74	0.441	5.901**	0.334
	B	2,916	0.71	0.456	703	0.67	0.472	2.032*	0.086
	C	1,480	0.82	0.381	673	0.46	0.498	16.998**	0.819
Gifted	A	1,933	0.03	0.166	444	0.04	0.197	1.196	0.055
	B	2,916	0.04	0.199	703	0.07	0.262	3.079*	0.130
	C	1,480	0.03	0.170	673	0.05	0.222	2.312	0.102
Reading (centered)	A	1,933	-12.306	38.142	444	-10.891	44.222	0.623	0.034
	B	2,916	-7.636	37.030	703	-6.522	44.558	0.614	0.027
	C	1,480	-10.619	37.338	673	-6.202	41.028	2.380	0.113
Math (centered)	A	1,933	-14.140	45.895	444	-6.757	55.858	2.686*	0.145
	B	2,916	-8.514	44.497	703	-4.196	56.368	1.894	0.086
	C	1,480	-13.358	44.712	673	-6.527	48.347	3.247*	0.147

* $p < .01$. ** $p < .001$.

Appendix F: Students in Minimal Identifier Districts

Table F.1

Descriptive Statistics for Students in Districts That Do Not Identify Gifted Students

	Cohort A		Cohort B		Cohort C	
Variable	Frequency	Percent	Frequency	Percent	Frequency	Percent
n	12,225	100.00	11,127	100.00	13,908	100.00
Gender						
Female	5,978	48.90	5,534	50.00	6,908	49.67
Male	6,247	51.10	5,563	50.00	7,000	50.33
Race						
White	7,898	64.61	6,863	61.68	7,690	55.29
Asian	543	4.44	526	4.73	692	4.98
Black	1,395	11.41	1,363	12.25	2,129	15.31
Hispanic/Latino	2,030	16.61	2,089	18.77	2,948	21.20
Other	359	2.94	286	2.57	449	3.23
FRL	4,747	38.83	4,815	43.27	6,858	49.31
ELL	1,161	9.50	1,033	9.28	1,480	10.64
SPED	1,408	11.52	1,214	10.91	1,548	11.13
Gifted	15	0.12	8	0.07	8	0.06
HHM	1,124	9.19	1,728	15.53	1,417	10.19
Gifted*HHM	3	0.02	4	0.04	0	0.00

Appendix G: Public Act No. 17-82

Substitute Senate Bill No. 911

Public Act No. 17-82

AN ACT CONCERNING SERVICES FOR GIFTED AND TALENTED STUDENTS.

Be it enacted by the Senate and House of Representatives in General Assembly convened:

Section 1. (NEW) (*Effective July 1, 2017*) The Commissioner of Education shall designate an employee of the Department of Education, preferably an employee who has experience working with gifted and talented students, to be responsible for providing information and assistance to local and regional boards of education and the parents or guardians of students. Such information and assistance shall relate to awareness about, identification of and the provision of services to, gifted and talented students.

Sec. 2. (*Effective July 1, 2017*) The Department of Education shall develop guidelines regarding the provision of services to gifted and talented students in schools. Such guidelines shall include, but need not be limited to, best practices for (1) addressing the intellectual, social and emotional needs of gifted and talented students in schools, and (2) providing educator training and professional development relating to gifted and talented students. Not later than January 1, 2018, the department shall make such guidelines available to local and regional boards of education.