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Examining the association between neighborhood conditions and school readiness across low and highly segregated school attendance boundaries

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Neighborhood characteristics are well documented determinants of adolescent and adult health and well-being. One such neighborhood characteristic heavily explored in K-12 research is the role of residential segregation on educational outcomes. Surprisingly, little is known about how community conditions, as well as racial segregation, relate to children's early school readiness. This is a critical gap in the field as children's school readiness is a significant marker of school success, both in the short and long term. Thus, this study aimed to address this gap through examining statewide school readiness data and neighborhood opportunity resources related to early childhood development. Student-level readiness data from 84,720 kindergarteners collected through the 2019 Virginia Kindergarten Readiness Program were used to determine whether a student demonstrated school readiness skills. Community conditions surrounding a school were constructed using geospatial mapping of the 2015 School Attendance Boundary (SAB) Survey and Child Opportunity Index 2.0. This study then explored the role of neighborhood segregation in a SAB with student's school readiness with three separate approaches (entropy, exposure, and share of racial/ethnic groups). A series of logit regression models were used to examine the relationship between community resources and the likelihood a student was school-ready and whether this relationship varied across low and highly segregated SABs. Results indicated that a student in a higher resourced community was more likely to be school ready than a similar student in a lower resourced community. Distribution of students by race/ethnicity across neighborhood resource levels was uneven. Specifically, Black and Hispanic children are overrepresented in lower resourced communities, and White and Asian children overrepresented in higher resourced ones. Further, in two out of three measures of segregation, results show significant variation between neighborhood resources and school readiness likelihood across different levels of segregation. Consistently, students within a more segregated (and particularly Segregated Black or Hispanic) SAB were more sensitive to changes in community resources than those in less segregated SAB. Program and policy implications are discussed.

KEYWORDS

school readiness, early childhood, geospatial analyses, Virginia, neighborhood conditions, education, race, segregation

Introduction

The neighborhoods in which children grow up are linked with a host of short- and long-term outcomes, ranging from physical and mental health (Ross, 2000; Ross and Mirowsky, 2001; Kim, 2010) to earnings (Galster et al., 2007; Chetty et al., 2016) to school achievement and attainment (Dupéré et al., 2010; McCoy et al., 2015). However, relatively little is known about how neighborhood conditions, including neighborhood opportunity and racial segregation, contribute to or potentially remedy developmental inequities at the critical time before children enter school (Rimm-Kaufman et al., 2000; Minh et al., 2017). A recurrent challenge is the lack of generalizable neighborhood-level measures that provide a comprehensive picture of the myriad of factors that are important for young children's healthy development. The Child Opportunity Index (COI), a census tract-level index composed of neighborhood features associated with children's development, offers a potential solution to measure neighborhood opportunity. Emerging research suggests that the COI may be a useful tool to understand inequities in early childhood (Hardy et al., 2021), but the relationship between the COI and children's school readiness skills has not yet been explored. In addition, it is important to consider the role of the COI's developmentally-salient neighborhood resources in the context of racial segregation, which reflects another structural feature of communities with established links to child and adolescent school achievement and attainment (Wells and Crain, 1994; Sampson et al., 2008; Reardon, 2016). Little is known about how neighborhood segregation may affect children prior to school entry, despite evidence that young children experience racial segregation in preschool (Frankenberg, 2016). This study, then, aims to address this gap by examining the extent to which neighborhood opportunity is associated with a child's school readiness skills and how this association varies by community racial segregation levels.

Children's early school readiness skills are a key predictor of future development

The early childhood years are a critical developmental period, as children begin to experience the world and learn from families, teachers, and peers. It is during these years, from birth through kindergarten, that children learn and acquire skills that lay the foundation for the rest of their education (Shonkoff and Phillips, 2000; Annie E. Casey Foundation, 2013). These skills encompass various domains of child development and learning, such as cognitive skills (including literacy, language, math, and science skills, as well as approaches to learning), social–emotional skills (including self-regulation, interpersonal skills, and behavior), and other aspects of health and physical well-being (including fine and gross motor skills and physical fitness; Annie E. Casey Foundation, 2013; Latham, 2018). Importantly, these school readiness skills are linked to various academic, social, and adult outcomes (Hamre and Pianta, 2001; Heckman, 2006; Duncan et al., 2007; Galster et al., 2007; Chetty et al., 2011).

A wide body of research indicates that there are significant gaps in children's school readiness skills across racial/ethnic lines (Isaacs, 2012; Reardon and Portilla, 2016; Latham, 2018), and these gaps emerge due to learning opportunity disparities during early childhood (Rimm-Kaufman et al., 2000; Lee and Burkam, 2002; Magnuson et al., 2004; Pratt et al., 2016). Studies have also shown that racial gaps in school readiness exist, such that White children tend to score higher on various school readiness skills than Black and Hispanic children (Sonnenschein and Galindo, 2015; Reardon and Portilla, 2016; Latham, 2018). For instance, Latham (2018) found that Black children entered kindergarten half a grade behind White children in math, whereas Hispanic children entered two-thirds of a grade behind White students in math. Similarly, Black children were about one-fifth of a grade behind White children in literacy skills, and Hispanic children were about a third of a grade behind White children in literacy. While some research indicates school readiness gaps have narrowed over the past few decades, significant differences between student subgroups still exist (Reardon and Portilla, 2016; Latham, 2018).

When children enter school less ready for kindergarten, there are implications for kindergarten and later schooling. Children who start school less ready than their peers have to play catch up, and research indicates these gaps persist past kindergarten (Reardon and Portilla, 2016). The school readiness gaps can also lead to progressively bigger differences in children's educational outcomes, negatively affecting children much later in school and life (Belsky and MacKinnon, 1994; Hamre and Pianta, 2001; Sadowski, 2006; Duncan et al., 2007; Galindo and Sonnenschein, 2015). For example, in their meta-analysis of six longitudinal datasets, Duncan et al. (2007) found that math and literacy skills at the start of kindergarten were associated with learning outcomes later in elementary school. Similarly, Hamre and Pianta (2001) found an association between academic and behavioral outcomes through eighth grade for students with high levels of behavioral problems in kindergarten. Thus, if gaps are not addressed early, they can pose problems down the line.

Development happens in the context of neighborhoods

Understanding how and why school readiness gaps exist between children is a complicated yet crucial topic. Researchers are beginning to think more ecologically to explain differences beyond child and family characteristics (Bronfenbrenner, 1976). Neighborhoods are a critical context to consider, as they play an essential part in children's development and education and are potential targets for policy prevention and intervention efforts. Neighborhood conditions (e.g., availability of early childhood programs, neighborhood poverty and employment rates, access to healthy foods) are robust predictors of child and adolescent outcomes, including higher prosocial behaviors, cognitive skills, and school achievement and attainment (Kohen et al., 2008; Dupéré et al., 2010; Odgers et al., 2012; McCoy et al., 2015; Minh et al., 2017; Leventhal, 2018). Similarly, an extensive body of research indicates neighborhoods affect children into their adulthood, as seen through impacts on earnings potential, socioeconomic mobility, marriage status, and life expectancy (Sharkey and Faber, 2014; Acevedo-Garcia et al., 2016, 2020; Chetty et al., 2016; Chetty and Hendren, 2018). Thus, the neighborhoods where children grow up impact not only their current day-to-day experiences but also their experiences in later childhood, adolescence, and adulthood.

Previous neighborhood research has predominantly focused on the influence of communities on adolescent and adult outcomes (Minh et al., 2017). While there has been some research examining these connections in early childhood, evidence suggests this is a path worth exploring (McCoy et al., 2015). For example, McCoy et al. (2015) found that neighborhood poverty directly predicted children's pre-academic outcomes in Head Start. Similarly, Vaden-Kiernan et al. (2010) found direct links between school neighborhood disadvantage and Head Start students' math and language skills. Importantly, neighborhood structural characteristics, such as housing conditions and socioeconomic advantage, have been shown to shape child outcomes even when controlling for characteristics of families and schools, suggesting that children's neighborhoods represent a distinct and salient component of their ecologies (Klebanov et al., 1997; Leventhal and Brooks-Gunn, 2004; Kohen et al., 2008; Dupéré et al., 2010; Coulton et al., 2016). Recent research has also found that neighborhoods can provide protective factors for low-income preschoolers. For example, high-resource neighborhoods were associated with gains in children's executive function skills (McCoy et al., 2022), especially in lower income but higher-resourced neighborhoods (Wei et al., 2021). These findings suggest that neighborhoods are a key context to explore in considering children's developing school readiness skills.

While most research exploring neighborhoods has used socioeconomic status (SES) of residents as the key distinguishing metric, recent research suggests that defining neighborhoods in this way falls short of capturing important variation in living conditions and resources (Wei et al., 2021). Thus, to better reflect the range of neighborhood conditions associated with children's development, Acevedo-Garcia et al. (2016, 2020) created the Child Opportunity Index (COI). The COI 2.0 is a census tract-level index, compiled across a range of publicly available data, and consists of 29 indicators measuring place-based resources such as access to and quality of early childhood education, access to healthy foods, and availability of green space, toxin-free environments, and socioeconomic resources (Diversitydatakids.org, 2022). The COI uses these various indicators and community resources to evaluate neighborhood opportunity. In addition to previous research linking the individual COI indicators to aspects of children's development, the overall COI composite measure has also been associated with life expectancy and intergenerational socioeconomic mobility (Acevedo-Garcia et al., 2020).

Research using the COI shows that neighborhood opportunity, or the community conditions that foster child development, varies considerably by race and ethnicity (Acevedo-Garcia et al., 2016, 2020; Hardy et al., 2021). For example, Hardy et al. (2021) found that nearly half of White children from low-income families live in moderate-, high- and very high-opportunity neighborhoods, whereas almost a quarter of White children from low-income households live in very low-opportunity neighborhoods. On the other hand, close to 70 percent of Black children from low-income families live in very low-opportunity neighborhoods. This means that Black children from low-income households are three times more likely than White children in similarly low-income households to live in neighborhoods with the lowest opportunity levels (Hardy et al., 2021). Thus, examining the relationship between the COI and children's school readiness, in the context of racial segregation, appears warranted.

Community segregation and children's development

Another important neighborhood condition, in addition to neighborhood opportunity is the racial segregation of neighborhoods and schools. After the *Brown v. Board of Education* ruling, school segregation began to decrease (Reardon and Owens, 2014; Fahle et al., 2020). Some research, however, indicates that school racial segregation has increased over the past few decades (Orfield et al., 2014; Ayscue and Orfield, 2015; Rothstein, 2015), especially once court-ordered integration policies came to an end (Liebowitz and Page, 2014). Further, housing policies, such as redlining, whereby banks denied loans and mortgages to Black families to prevent them from living in certain suburbs and neighborhoods, have added to ongoing neighborhood segregation (Rothstein, 2015). Despite the ending of the practice decades ago, research points to inequitable housing policies as leading to a wealth gap between White and Black families. This, along with continued gentrification of neighborhoods, has contributed to the ongoing segregation of families and schools (Rothstein, 2015; Pearman, 2019).

Residential segregation appears particularly salient for children's school achievement (Owens, 2017). For example, segregation was found to be a significant predictor of racial achievement gaps for math and English language arts assessments for students in grades three through eight (Reardon et al., 2019). Similarly, racial residential segregation was associated with lower rates of high school and college graduation for Black students (Quillian, 2014). Recent studies have also examined the relationship between racial segregation and school experiences. For example, Owens (2020) found that schools with larger populations of Black and Hispanic students tended to have harsher disciplinary measures, higher levels of chronic absenteeism, and less-experienced teachers. Additionally, a study of Chicago schools and neighborhoods found that segregation led to differences in school experiences, with Black students more likely to experience prison-like surveillance practices in their schools than White students (Shedd, 2015).

Segregation is not unique to school-aged children. A recent study found that preschools were more racially segregated than K-12 programs (Frankenberg, 2016). Specifically, Frankenberg (2016) discovered that over half of Black and Hispanic students attended public preschools, where children of color accounted for at least 90% of the student population. Further, White children were the most racially isolated ethnic group, relative to their own racial/ethnic group, with White students attending preschools that were 70% White on average (Frankenberg, 2016). However, how segregation affects young children and their emerging school readiness skills, particularly when considered alongside a robust measure of neighborhood resources like the COI, has not been studied. Further, it is unclear whether higher levels of segregation will amplify or mitigate any potential relationship between neighborhood opportunity and the development of school readiness skills when interacted with one another. Given that prior research has found positive associations for academic and social outcomes for children who experience diverse and integrated early childhood settings (Reid and Kagan, 2015; Wells et al., 2016; McArdle and Acevedo-Garcia, 2017), higher levels of segregation may diminish school readiness. Alternatively, for children of color, higher levels of segregation could have a positive impact on the relationship between neighborhood opportunity and children's school readiness skills. For instance, children of color in highly segregated areas may be more likely to have early childhood teachers and caregivers of their same race or from similar backgrounds (Paschall et al., 2020). Research has found that when early childhood educators and children are the same race, teachers are more likely to give students higher academic ratings (Downer et al., 2016; Redding, 2019) and may use fewer exclusionary discipline practices (Wymer et al., 2022). In this way, higher levels of segregation may have the potential to serve as a protective factor for children of color.

Important to note is that there are a variety of ways to operationalize segregation (Reardon and Owens, 2014). One way to measure segregation is to use Theil's entropy index, which looks at the relative distribution of racial groups in an area (Reardon and Firebaugh, 2002). In other words, the entropy index evaluates the distribution of race in one neighborhood relative to the distribution in other neighborhoods. The entropy measure is unique in that it measures segregation across multiple races, as opposed to more traditional methods of evaluating just two racial groups (Stroub and Richards, 2013). Another common measure of segregation is to evaluate the extent to which children of one racial group are exposed to children of other racial groups, called the exposure index (Stroub and Richards, 2013; Reardon and Owens, 2014; Frankenberg, 2016). For example, a neighborhood with a high proportion of children of color relative to White children would be considered a segregated neighborhood, as would a neighborhood with a high proportion of White children relative to other children of color. Finally, an additional method to measure segregation is to evaluate the share, or proportion, of different racial groups within a neighborhood (Stroub and Richards, 2013; Ayscue and Orfield, 2015). While the exposure measure analyzes the proportion of a racial group relative to another racial group, the share measure of segregation looks at the overall distribution of racial groups in a neighborhood.

Each of these three segregation measures provide unique contributions to conceptualizing children's neighborhood experiences. First, the exposure measure is an important contribution because it measures the probability that a child of one racial group may be exposed to a child of another racial group, thus capturing the potential interactions between different racial groups and allowing us to analyze the average or typical experience of a child from different racial groups (Frankenberg, 2016). Exposure is also unique because interaction probabilities are not symmetrical, meaning the probability that a White child may be exposed to a Black child is not necessarily the same probability that a Black child may be exposed to a White child (Forest, 2005). The share measure of segregation is also significant because it closely aligns with how people conceptualize segregation. Further, while the exposure measure evaluates probabilities, the share measure provides the actual racial composition of a neighborhood. Additionally, as entropy evaluates segregation across multiple racial groups, this allows for the measurement of "overall" segregation, as opposed to evaluating differences between racial groups. On the other hand, the exposure and share measures enable us to analyze both the influence of segregation and whether there was an association based on a racially dominant group in a segregated neighborhood. As all three of these segregation measures offer unique information about children's experiences in their neighborhoods, each of these were pursued in this study.

School attendance boundaries are a salient context for young children's development

As children age, schools become a central feature of their community, existing within neighborhoods defined by attendance boundary zones. While prior research has defined neighborhoods using census tracts (McCoy et al., 2015, 2022; Wei et al., 2021) or block groups (Dupéré et al., 2010), attendance boundaries provide a direct relationship between schools and the surrounding geographic area. School attendance boundary zones are drawn within school districts to determine which public school children attend based on where they live. For example, if there are three elementary schools in one school district, there will be boundary zones to delineate which neighborhoods will attend which elementary school. In some school districts, families may be able to choose which school their child goes to, but most attend their assigned schools. These boundary zones also only apply to public schools; families may choose to attend other school programs, such as private or charter schools (Bischoff and Tach, 2018), that are not subject to boundary zones.

Hypothetically, attendance boundary zones should be drawn in consideration of the number of students and schools (with even proportionality in mind), as well as the distance between neighborhoods and schools, but this is not always the case. A study in 2015 found that school attendance boundary zones were not "accidents of geography" but instead were shaped in irregular ways (i.e., gerrymandered), perhaps to alter the composition of schools (Richards and Stroub, 2015). Studies have examined the effects of gerrymandered attendance boundary zones, especially related to racial segregation of schools (Richards, 2014; Saporito and Van Riper, 2016; Monarrez, 2021), but findings are mixed. Some studies found that gerrymandered boundary zones were related to increased racial segregation (Richards, 2014; Monarrez, 2021). A separate study, however, found that some irregularly shaped, gerrymandered districts had more racial *integration* than expected (Saporito and Van Riper, 2016). Districts, thus, may purposefully draw irregularly shaped boundary zones to achieve racial school integration in diverse neighborhoods (Saporito and Van Riper, 2016) or to fulfill court-ordered desegregation directives (Richards, 2014).

Additionally, it is important to note that attendance boundary zones are not a fixed entity, due to the continuously changing nature of neighborhoods and local populations. Typically, these changes occur over time to accommodate population growth or decline depending on the neighborhood. Schools in rapidly expanding neighborhoods may become overcrowded, whereas schools in less populous neighborhoods may be able to take in more students. School districts may also build new schools to address population growth or to replace aging buildings. However, these changes also present opportunities to racially gerrymander attendance boundary zones. For example, various studies found gerrymandering particularly evident in school districts that experienced rapid diversification (Siegel-Hawley, 2013; Richards, 2014; Richards and Stroub, 2015). Thus, school attendance boundaries serve as one compelling approach to defining neighborhoods, when considering children's community experiences of resources and segregation.

The current study

This study aimed to expand understanding of the intersection between children's school readiness and two types of neighborhood conditions: neighborhood opportunity and residential racial segregation. Using statewide kindergarten readiness data, this study examined how neighborhoods, defined by school attendance boundaries, varied in the conditions that foster children's development and whether this variation contributed to childrens' school readiness skills. In particular, this study utilized a novel application of the Children's Opportunity Index to represent neighborhood opportunity within school attendance boundaries and explores whether neighborhood racial segregation amplified or muted associations observed between neighborhood opportunity and children's school readiness skills. The specific research questions were:

1. Is a child's likelihood of being school ready associated with the neighborhood opportunity within their school attendance boundary?
2. Does the association between school readiness and neighborhood opportunity within a child's school attendance boundary vary by residential racial segregation?

Findings will better equip state and local policymakers to understand neighborhood conditions in relation to school readiness, which in turn could be used to inform decision making about community investments to support children's school readiness skills.

Materials and methods

Study context

This study leveraged student-level kindergarten readiness data collected through Virginia's statewide readiness assessment system. The assessments included measures of literacy, mathematics, self-regulation, and social skills which, when combined, establish a comprehensive, consistent statewide baseline of children's overall school readiness. The school readiness assessments were administered by teachers in both the fall and the spring. For this analysis, the Fall 2019 assessments were used for several reasons. First, these data represented the first-time assessments were completed statewide and included over 99% of the expected kindergarten population (Virginia Kindergarten Readiness Program, 2021). Second, the population reflects the Commonwealth's racial (20.4% Black), ethnic (17.2% Hispanic), and socioeconomic (37.6% economically disadvantaged) diversity. Third, these assessments predate the Covid-19 pandemic. Finally, the fall assessment captures students' school readiness skills as they enter kindergarten, minimizing skill variation attributed to kindergarten teacher and elementary school quality.

Student participants

In Fall 2019, 91,210 kindergartners across 1,106 schools completed the school readiness assessments (Virginia

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Kindergarten Readiness Program, 2021). This study utilized school attendance boundaries as the geographic organizer for neighborhoods (details to follow). Attendance boundary information was missing for 68 schools, and another four schools were dropped as they had less than half of their expected students' skills assessed (Virginia Department of Education, 2019). In addition, student characteristics were missing for 998 students and assessments were missing for 467 students. Thus, the final analytic sample included 84,720 students across 1,034 schools, 92.9% and 93.5% of the original sample, respectively. Difference-in-means *t*-tests revealed that the sampled students were not significantly different from the broader sample on any demographic or outcome variable except for the proportion of White students. The sample contained 0.61 percentage points fewer White students (47.8% and 47.2%, $p = 0.0058$).

Measures

School readiness

Virginia's statewide assessment system includes assessments of students' skills across four domains: literacy, mathematics, self-regulation, and social skills. The Phonological Awareness Literacy Screening-K (PALS-K) assessed young children's knowledge of important fundamental literacy skills ranging from letter sounds and rhyme awareness to spelling and word recognition, which has shown adequate task and inter-rater reliability, as well as criterion-related validity, over time (Invernizzi et al., 2015). The Early Mathematics Assessment System (EMAS) measured children's mathematics knowledge and skills. EMAS is designed to measure children's skills across four areas: Geometry, Patterning, Numeracy, and Computation. Testing items were selected to represent a range of skills across the four subdomains and to target an appropriate level of difficulty. The EMAS has shown strong internal consistency ($\alpha = 0.905$) within the dataset (Ginsburg et al., 2010). Teachers' perceptions of students' self-regulation and social skills were assessed using the Child Behavior Rating Scale (CBRS; Bronson et al., 1990; Matthews et al., 2009). The CBRS is a teacher-report measure consisting of 17 items, 10 assessing self-regulation and seven assessing social skills, that measure teachers' perceptions of a student's behavioral regulation in both academic and social situations. After observing students' behaviors in the classroom, teachers completed the rating scale where each item asks them to rate the frequency with which a student exhibits a specific behavior from one (never) to five (always). The CBRS has shown strong reliability ($\alpha = 0.89$–0.95; Tindal et al., 2015; Moldovan and Bocos-Bintintan, 2016) as well as construct, concurrent, and predictive validity (Ponitz et al., 2009; Wanless et al., 2011; Gestsdottir et al., 2014; Schmitt et al., 2015).

Benchmarks for the mathematics (Early Mathematics Assessment System), self-regulation, and social skills (Child Behavior Rating Scale) assessments were established using developmental expectations in conjunction with data collected across the Commonwealth during the 2015–2019 pilot phase. Students scoring below these benchmarks are most likely not demonstrating the level of skills one would expect for a kindergarten student. The literacy assessment (PALS) uses benchmark scores to indicate whether a student has a heightened risk of long-term reading challenges (Phonological Awareness Literacy Screening, 2021). Students were considered overall "Ready" if they scored at or above the benchmark in all four readiness domains. Conversely, students were considered "Not Ready" if they scored below the benchmark in one or more of these four domains. This study uses this dichotomous overall readiness variable as the outcome in all models. While a binary outcome reduces the power of the analysis relative to a continuous outcome measure, this variable is consistent with the Virginia Department of Education's definition of school readiness (Altman and Royston, 2006). Using this dichotomous readiness variable allows for both a consistent measure to compare this study's results with previous research as well as a policy relevant definition useful for state and local policymakers. Overall readiness rates are shown below in Table 1.

School attendance boundary

School Attendance Boundaries (SAB), or school feeder zones, are the geographical area served by a school. The National Center for Education Statistics' (NCES) School Attendance Boundary Survey is one of the most complete and up-to-date sources of SABs available. Conducted between November 2015 and June 2016, the SAB Survey canvassed district superintendents and state officials across the country to collect the boundaries for their schools (Geverdt, 2018). As children age, schools become a central feature of their community, existing within neighborhoods that are defined by their SAB. SABs were chosen over other neighborhood definitions because of their direct relationship between schools and the surrounding geographic area. Without access to student addresses, SABs provided a way to group children and delineate neighborhoods around each elementary school. Thus, this study used these school boundaries as the geographical organizer for the neighborhoods where students live. A map of SABs across Virginia is shown below in Figure 1.

TABLE 1 Overall school readiness rates and by domain.

Readiness status	Overall
Ready	44,977
Not Ready	35,140
Total	80,117
% Ready	56.1
Missing	4,603
Total (missing included)	84,720
% Missing	5.43

*998 and 467 students dropped due to missing characteristic data and missing readiness data on any domain, respectively.

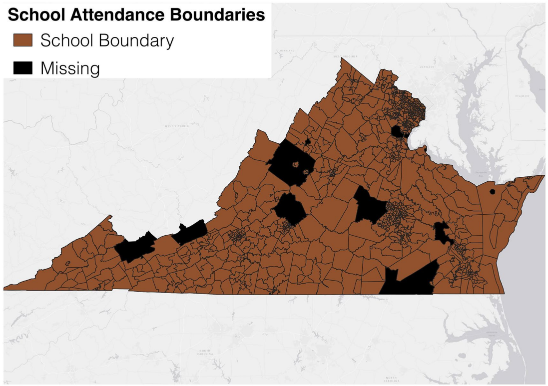

FIGURE 1
School attendance boundary map, Virginia 2015.

Neighborhood conditions

Neighborhood opportunity

The *Child Opportunity Index* (COI) 2.0 was used to measure availability of resources and conditions that matter for children's healthy development (Noelke et al., 2020). The COI 2.0 is a census tract-level index of 29 indicators that measure place-based resources such as access and quality of early childhood education, green space, access to healthy foods, toxin-free environments, and socioeconomic resources. The 29 indicators are grouped into one overall state-normed composite score. This overall score ranges from 0 to 100 with higher scores indicating higher resourced neighborhoods (Diversitydatakids.org, 2022). The COI is strongly correlated with measures of intergenerational economic mobility from the Opportunity Atlas and measures of health and life expectancy (Acevedo-Garcia et al., 2020).

To join the COI at the census-tract level with the SABs, the geographical map of the 2015 SAB Survey was overlaid with the 2015 census tract map using geospatial analysis and calculated the percent, p, of each tract contained within an SAB (U.S. Census Bureau, 2016; National Center for Education Statistics, 2018). These percentages were then used to weight the overall COI score of each census tract t contained within an SAB, s, to calculate an SAB-wide weighted average COI score as shown in Equation 1.[1] A map of the weighted average COI across Virginia is shown below in Figure 2.

$$\text{SAB- wide weighted average COI for SAB, } s = \frac{\sum_{t=1}^{k} (p)_{st}{}^{*} (\text{COI})_{st}}{\sum_{t=1}^{k} (p)_{st}} \quad (1)$$

1 Excluded from these calculations were any tract with less than 0.2% of its area contained within the SAB. Further, 40 SABs were randomly selected to manually verify the number and weight of each tract within each SAB.

Neighborhood segregation

In addition to measures of neighborhood resources, the COI 2.0 contains data on the racial/ethnic composition of children ages 0–5 years living in a census tract. Applying the formula in Equation 1 to these data, the total number of children by race/ethnicity within an SAB was calculated. This weighted value was then used to generate three measures capturing the level (overall) and type (race-specific) of residential segregation present within the SAB. While all the measures capture residential racial segregation, each provide a unique lens through which to view it. In the following sections we both describe each measure and its unique advantage relative to the others.

The first segregation measure (*Entropy*) is an entropy index, or Theil's H, which calculates the relative distribution of races/ethnicities within an area. Entropy thus allows us to capture the effect of "overall" segregation irrespective of the dominant group. This index, shown in Equation 2, relied on the total population of an SAB and the share of five major racial groups (Asian, Black, Hispanic, White, and two or more races). The "Other" racial group was not included due its small share of the population

$$\text{SAB- wide entropy index for SAB, } s = -\sum_{j=1}^{5} h_{sj}{}^{*} \ln\left(h_{sj}\right) \quad (2)$$

In this case, h_{sj} is the share of ethnicity j in the SAB. Higher scores indicate the SAB has more equal representation of these racial/ethnic groups, while lower scores indicate more racially/ethnically homogenous SABs. To examine how the relationship between COI and school readiness varies with neighborhood segregation, SABs were divided into three levels of segregation according to their entropy index value: High Segregation (below the 25th percentile), Medium Segregation (25th–75th percentile), and Low Segregation (above the 75th percentile).

The second and third measures of segregation capture the level of segregation between marginalized (Black/Hispanic) and non-marginalized (White/Asian) students. Here we were interested in not only if segregation was impactful, but whether this effect varied depending on the racially dominant group in the segregated area. The existing literature shows a significant difference in other neighborhood conditions and effects on student outcomes from segregation across racial/ethnic lines. Consistently these studies found that segregated communities of color had on average worse living conditions that matter for child development and educational opportunities than segregated White areas (Quillian, 2014; Shedd, 2015; Frankenberg, 2016; Owens, 2020; Hardy et al., 2021). That is to say, a segregated area of marginalized children is systematically different from a segregated area of non-marginalized children. Thus, the second measure of segregation (*Exposure*) uses an exposure (or isolation) index to identify segregated SABs. The exposure index represents the probability that a child of one group was likely to interact with someone of another group

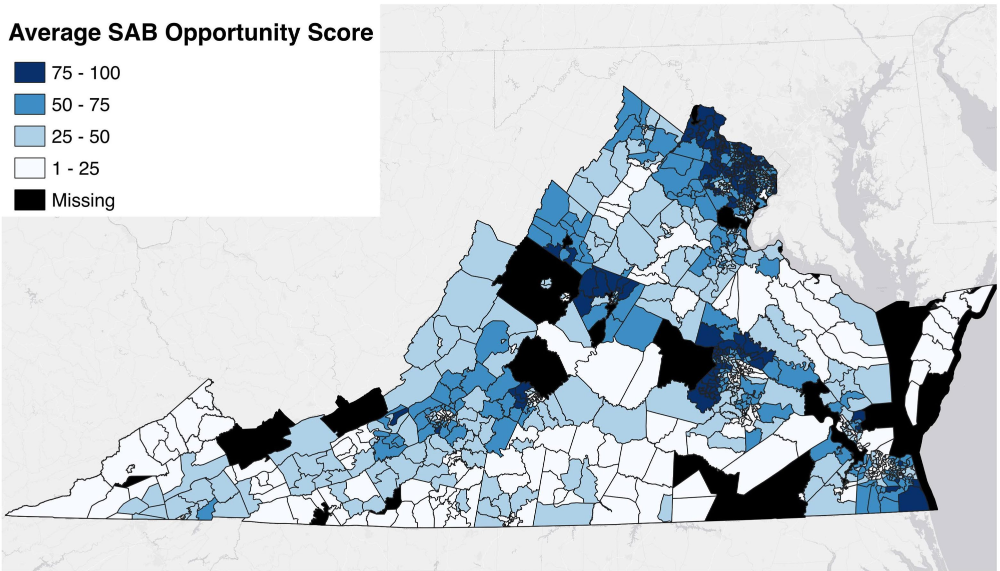

FIGURE 2
Weighted average COI score, by 2015 Virginia school attendance boundary.

within that tract prior to entering kindergarten (Forest, 2005). The Exposure measure is unique among our segregation metrics in that it is the only one we calculated at the tract level. This provides a more geospatially nuanced understanding of the level of cross-racial interactions expected in a community. The equation is shown in Equation 3.

$$\text{Tract - wide exposure index for Group 1 in SAB, } s = \sum_{t=1}^{k} \frac{n_{t1}}{n_{s1}} * \frac{n_{t2}}{n_t} \quad (3)$$

Where s_1 is the population of children in group 1 in SAB, s, and n_t is the total population of children in tract, t. n_{t1} is the number of children in group 1 and n_{t2} was the number of children in group 1 and group 2 in t. From this general equation, two indices were created. One where group 1 are Black and Hispanic children and group 2 are White and Asian children and another that reverses these groupings. Each index then captured the likelihood of group 1 being exposed to group 2. Each census tract was assigned an index score which was then averaged across the SAB to create a SAB-wide value using Equation 1. Again, to answer this study's research questions, SABs were categorized as being Segregated Black/Hispanic communities (Black/Hispanic exposure index values in the lowest 10th percentile, i.e., least likely to interact with a White or Asian child), Segregated White/Asian communities (White/Asian exposure index values in the lowest 10th percentile, i.e., least likely to interact with a Black or Hispanic child), or Not Segregated.

The third segregation measure (*Share*) identifies Segregated Black/Hispanic or White/Asian SABs based on the proportion of these groups within the SAB. Conceptually, this aligns the most with the general population's notion of what makes an area segregated. SABs with a share of Black and Hispanic or White and Asian children in the 90th percentile were categorized as Segregated Black/Hispanic or White/Asian, respectively. As shown in Table 2, these methods resulted in a comparable number of SABs and students identified in Segregated Black/Hispanic and White/Asian SAB. These numbers also corresponded to a roughly equal number of High Segregation SABs using the Entropy measure.

Student characteristics

Student demographic characteristics were collected by the Virginia Department of Education (VDOE) and drawn from Student Record Collection data entered and updated by school division personnel each fall (Virginia Kindergarten Readiness Program, 2019). The category race/ethnicity included Asian, Black or African American, Hispanic/Latino of any race, White, and two or more races, and Other (American Indian or Alaska Native, Native Hawaiian, or other Pacific Islander). Preschool experience was a state-assigned code to identify a student's most recent pre-K experience. Students from low-income backgrounds were identified as economically disadvantaged if at any point during the school year the student was eligible for Free/Reduced Meals or Medicaid and/or received TANF. English Learner (EL) students were identified using the VDOE EL Code and whether they received EL services or were within 40 years of exiting EL services. Students were coded as having a disability if any VDOE Disability Code was present except Qualified Individual under Section 504. These data were merged with VKRP data.

TABLE 2 School readiness rate and student race and ethnicity by segregation type and level.

Segregation type and level	*N* SAB	*N* students	Mean school readiness rate	Mean % Asian	Mean % Black	Mean % Hispanic	Mean % White
Entropy							
Low Segregation	259	26,187	53.01	9.1	18.9	20.5	34.9
Medium Segregation	518	42,267	55.90	4.0	20.2	12.0	52.6
High Segregation	257	16,266	58.71	0.7	12.1	3.5	79.6
Exposure							
Not Segregated	831	71,158	56.59	5.2	14.8	13.3	54.6
Segregated Black/Hispanic	100	7,928	46.01	1.0	60.5	12.9	16.3
Segregated White/Asian	103	5,634	59.65	2.0	1.5	0.82	94.0
Share							
Not Segregated	828	70,870	56.73	5.2	14.7	13.0	55.1
Segregated Black/Hispanic	103	8,263	45.46	1.2	59.9	15.4	13.2
Segregated White/Asian	103	5,587	59.38	1.9	1.3	0.82	94.2

SAB, school attendance boundary.

Analytic approach

Both research questions examined whether neighborhood resources were correlated with a child's likelihood of being overall school ready, or school readiness likelihood. To answer each, a series of logistic regressions were estimated that predicted whether a student was ready for school as defined by the statewide readiness assessment. The key explanatory variable for the analyses was the standardized weighted average SAB COI score.

The base model specification, given in Equation 4, generated results to answer research question 1. This model predicted the likelihood student *i* in SAB *s* was school ready as a function of the weighted average COI in the student's SAB and the student's characteristics. The coefficient β_1 was the coefficient of interest. It represented the change in school readiness likelihood associated with an additional one standard deviation increase to COI, controlling for student characteristics (i.e., race/ethnicity, gender, pre-K experience, English Learner status, economically disadvantaged status, and disability status).

$$\mathrm{PR}\left(\mathrm{KR}_{is}\right)=\frac{1}{1+e^{\beta X}} \tag{4}$$

where $\beta X=\beta_0+\beta_1\mathrm{COI}_s+\theta'\left(\text{Student Chars}\right)_i$

One assumption of the logit model is linearity between the log odds of the dependent variable and continuous variables. Each model only included one continuous variable, SAB-overall COI score. Nonlinearity was tested using kernel density and by running models including both the score's natural and higher order forms. Neither of these tests supported the presence of functional form misspecification (Stoltzfus, 2011). The presence of outliers and multicollinearity were also tested using the Pregibon Delta Beta Statistic test and Variance Inflation Factor, respectively. Both tests strongly suggested that neither were a concern (UCLA Statistical Consulting Group, 2006; Akinwande et al., 2015).

Next, each measure of community segregation (Entropy, Exposure, and Share) was added to the base model one at a time, as shown in Equation 5. Due to high correlations among the segregation types, separate models were run for each variable. For each measure, two of the three levels were added as indicators (i.e., Low and Medium Segregation for the Entropy measure and Segregated Black/Hispanic and Segregated White/Asian for the Exposure and Share measures). These models test the association between COI and school readiness change when controlling for community segregation (comparing the β_1 coefficients from Equations 4, 5). Interaction terms were then added between the community segregation variables and COI to assess how the association between COI and school readiness varies with community segregation.

$$\mathrm{PR}\left(\mathrm{KR}_{is}\right)=\frac{1}{1+e^{\beta X}} \tag{5}$$

Where
$\beta X=\beta_0+\beta_1\mathrm{COI}_s+\beta_2 Seg1_s+\beta_3 Seg2_s+\theta'\left(\text{Student Chars}\right)_i$

Reporting results

To facilitate the interpretation of these models' findings, the results were reported as odds-ratios which show the change in likelihood of the student being school ready relative to a baseline, holding all else constant. In all models, standard errors were reported that were robust to the clustering of students within SABs. Furthermore, presented are two sets of predicted probabilities that the average student is school ready when in an SAB with a COI one-half of a standard deviation below the mean and when in a SAB with a COI one-half of a standard deviation above the mean. These predicted probabilities were provided for each segregation type and level.

These predicted probabilities for an average student were defined in two ways. The first was the average student among all students (aka Grand). These probabilities were predicted holding all other variables constant at their analytic sample mean. The second was the average student within a segregation type and level (aka Group). Here, the predicted probabilities held all other covariates at their mean within a given segregation type and level. The results from each prediction differ from one another as the two means correspond to two different points along the nonlinear estimates produced by the logit model. Each set of predictions offered unique advantages and disadvantages to the analyses. While the Grand means allowed for comparisons where the only difference was the segregation level, it belied the significantly different student characteristics within each type of segregation previously shown in Table 1. Conversely, using Group means limits the ability to compare effects across segregation levels, but allows for testing the predicted change for the average student within that segregation level.

Results

Descriptive statistics

Students were racially (6.9% Asian, 20.8% Black, 17.6% Hispanic, 47% White, and 7% two or more races), socioeconomically (38% identified as economically disadvantaged), and linguistically (15% English Learner) diverse. The children in the sample also had a breadth of preschool experiences. Over 77% of students had some preschool experience, with the majority in public (34%) and private/daycare (36%) programs. Readiness rates by student characteristics are shown in Table 3.

TABLE 3 School readiness rates by student demographic groups.

Student demographics	*N*	%	% ready (Non-missing)	% ready (All)
Total students	84,720		56.1	53.1
Total schools	1,034			
Gender				
Female	41,307	48.8	62.4	59.2
Male	43,413	51.2	50.2	47.3
Race/Ethnicity				
Asian	5,897	6.9	66.3	62.3
Black	17,589	20.8	47.1	45.4
Hispanic	14,923	17.6	41.6	36.8
White	39,976	47.2	63.2	60.6
2 or more	5,954	7.0	59.6	57.2
Other	381	0.5	53.2	48.6
Disadvantaged				
Disadvantaged	32,182	38.0	44.4	41.3
Not disadvantaged	52,538	62.0	63.2	60.3
Disabled				
Disabled	7,431	8.8	34.4	30.4
Not disabled	77,289	91.2	58.1	55.3
EL Status				
EL	12,699	15.0	35.7	30.5
Not EL	72,021	85.0	59.4	57.1
Pre-K experience				
No PK	19,447	23.0	41.5	38.3
Headstart	3,905	4.6	45.1	43.3
Public	28,823	34.0	53.6	50.1
Private/Daycare	30,470	36.0	68.7	66.6
Dept. of defense	653	0.8	54.3	53.0
Family home	1,422	1.7	57.1	55.8

*998 and 467 students dropped due to missing characteristic data and missing readiness data on any domain, respectively.

As shown earlier in Table 2, significant differences existed between the average SAB readiness rate across segregation levels within the overall and two race-specific segregation variables. First, comparing school readiness using Entropy levels, the mean readiness rate in High Segregation SABs was nearly 11% greater than that of the most diverse SABs. However, when arranging SAB by their race-specific type of segregation, the mean readiness rate in White/Asian segregated SABs were between 30% (Exposure) to 33% (Share) greater than those in Black/Hispanic segregated schools. Additionally, a significant difference was found in the student racial composition at each neighborhood opportunity level. As shown in Figure 3, Black students were overrepresented in low-resourced SABs, while White and Asian students were overrepresented in the highest resourced areas.

Is a child's likelihood of being school ready associated with the neighborhood opportunity within their school attendance boundary?

Neighborhood opportunity was, on average, positively associated with a student's school readiness in the fall of kindergarten. The analysis found that a student in a higher-resourced SAB was 8.4% more likely ($p < 0.001$) to demonstrate school readiness skills than a similar student in a lower-resourced SAB (see Table 4, Model 1). This change corresponds to an increase in expected likelihood of school readiness from 55.4% to 57.4% (2 points or 3.6%).

Does the association between school readiness and neighborhood opportunity within a child's school attendance boundary vary by residential segregation?

To answer the second research question, the models included each segregation variable – Entropy (or overall segregation), Exposure, and Share – along with student characteristics as covariates, as described in Equation 5, before interacting segregation levels with COI. Results from the non-interacted models are displayed in Table 4 (Models 2–4) as

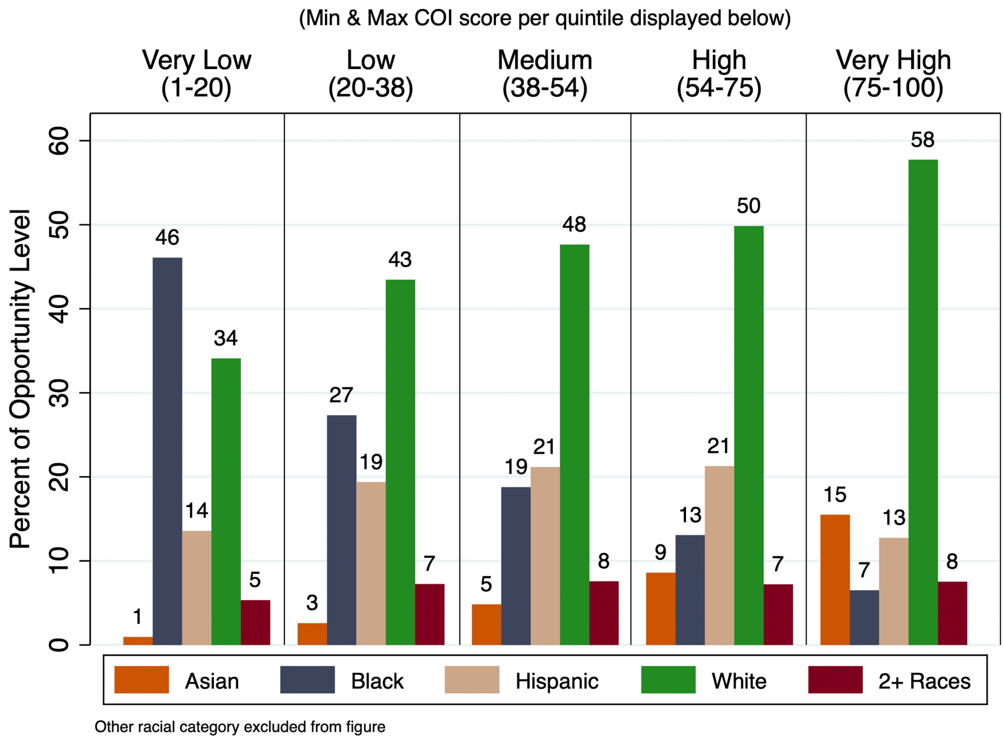

FIGURE 3
Share of observed students by race/ethnicity and COI level.

odds-ratios. The first important finding from these models is that the estimated relationship between COI and school readiness changed very little when any of the segregation types were added to the model. Second, there was little to no difference in average school readiness rates between SABs with different levels of segregation. With respect to the Entropy measure of segregation, a student's likelihood of being school ready is 8.9% lower ($p < 0.05$) in a Low Segregation community than in a High Segregation community. There were no statistically significant differences in predicted readiness rates between Medium and High Segregation communities or between communities using either the Exposure or Share measures of segregation.

Including interactions between the SABs' segregation and COI, however, showed that segregation in the community moderated the relationship between neighborhood opportunity and school readiness (Table 5). Again, the results from the model including the Entropy measure tell a more complex story. The main effects for segregation now refer to a neighborhood with average conditions (COI). The readiness rates in Medium and Low Segregation communities with average neighborhood opportunity were statistically lower than in High Segregation communities with average neighborhood opportunity (8.4% and 10.2% less likely, $p < 0.01$ and $p < 0.05$, respectively). Next, this study explored the interaction effect of a one standard deviation (SD) increase in COI with each of the segregation levels. Students in a higher-resourced High Segregation SAB had a school readiness likelihood 19% higher ($p < 0.001$) than their peers in a lower-resourced, but similarly segregated SAB. Among Medium Segregation SABs, students in higher-resourced neighborhoods were 5.4% more likely ($p < 0.05$) to be school ready. The same difference among Low Segregation SABs was 7.6% ($p < 0.05$). The change in school readiness likelihood from increased neighborhood resources was also significant between Medium and Low Segregated SABs. While students in less segregated SABs continued to exhibit a lower school readiness likelihood than those in High Segregation areas, the relationship between neighborhood opportunity and school readiness was greatest in the High Segregation communities.

The pattern of differences across community segregation levels in how neighborhood opportunity was related to school readiness with the Entropy measure was echoed with the Share measure. An additional one standard deviation of improved neighborhood opportunity in Segregated Black/Hispanic communities was associated with a 45.3% higher ($p < 0.001$) school readiness rate compared to a 7.6% higher ($p < 0.001$) rate in Not Segregated SABs. The coefficient suggests the relationship between neighborhood opportunity and school readiness was larger in Segregated White/Asian communities than in Not Segregated communities; however, the study lacks sufficient precision to be confident. The results from the model that included the Exposure measure of segregation found no differences in school readiness rates across communities of different segregation types with average neighborhood

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TABLE 4 Estimated coefficients as odds ratios from models predicting school readiness.

	Model 1	Model 2	Model 3	Model 4
	Base	+ Entropy	+ Exposure	+ Share
SAB COI (Standardized)	1.084***	1.089***	1.082***	1.088***
	(0.019)	(0.020)	(0.021)	(0.021)
Asian	1.435***	1.463***	1.442***	1.438***
	(0.065)	(0.066)	(0.066)	(0.066)
Black	0.623***	0.634***	0.631***	0.625***
	(0.017)	(0.017)	(0.017)	(0.017)
Hispanic	0.730***	0.744***	0.735***	0.733***
	(0.022)	(0.022)	(0.022)	(0.022)
Two+ Races	0.893***	0.906**	0.898**	0.896***
	(0.030)	(0.030)	(0.030)	(0.030)
Other	0.769*	0.783*	0.774*	0.771*
	(0.089)	(0.091)	(0.090)	(0.089)
Female	1.628***	1.627***	1.628***	1.628***
	(0.027)	(0.027)	(0.027)	(0.027)
Econ disadvantaged	0.657***	0.655***	0.656***	0.656***
	(0.014)	(0.014)	(0.014)	(0.014)
Disability	0.347***	0.347***	0.346***	0.347***
	(0.011)	(0.011)	(0.011)	(0.011)
EL	0.446***	0.451***	0.447***	0.446***
	(0.017)	(0.017)	(0.017)	(0.017)
Headstart PK	1.332***	1.320***	1.328***	1.331***
	(0.065)	(0.064)	(0.064)	(0.064)
Public PK	2.143***	2.139***	2.142***	2.142***
	(0.061)	(0.061)	(0.061)	(0.061)
Private PK	2.049***	2.056***	2.051***	2.050***
	(0.057)	(0.057)	(0.057)	(0.057)
DoD PK	1.214*	1.230*	1.215*	1.219*
	(0.117)	(0.119)	(0.117)	(0.117)
Family day home	1.448***	1.456***	1.448***	1.450***
	(0.083)	(0.083)	(0.083)	(0.083)
Medium segregation		0.930+		
		(0.038)		
Low segregation		0.911*		
		(0.042)		
Segregated Black/Hisp			0.970	1.021
			(0.052)	(0.056)
Segregated White/Asian			1.049	1.049
			(0.076)	(0.076)
Constant	0.975	1.020	0.962	0.960
	(0.028)	(0.042)	(0.029)	(0.029)
Observations	80,117	80,117	80,117	80,117
Pseudo R^2	0.0859	0.0860	0.0859	0.0859

Robust standard errors in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.

TABLE 5 Selected estimated coefficients as odds ratio from models predicting school readiness.

	Overall	Race-specific	
	Entropy	Exposure	Share
SAB COI (Standardized)	1.192***	1.074***	1.076***
	(0.041)	(0.022)	(0.022)
Medium Segregation†	0.916*		
	(0.039)		
Low Segregation†	0.898*		
	(0.042)		
Segregated Black/Hispanic†		1.124	1.441***
		(0.144)	(0.150)
Segregated White/Asian†		1.053	1.048
		(0.081)	(0.081)
Medium Segregation * SAB COI (Standardized)	0.884**		
	(0.037)		
Low Segregation * SAB COI (Standardized)	0.903*		
	(0.043)		
Segregated Black/Hisp * SAB COI (Standardized)		1.149	1.350***
		(0.114)	(0.109)
Segregated White/Asian * SAB COI (Standardized)		1.031	1.021
		(0.084)	(0.084)
Observations	80,117	80,117	80,117
Pseudo R^2	0.0864	0.0860	0.0862

All variables include student characteristics as listed in Model 1 of Table 4. Robust standard errors in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; +$p < 0.1$.
†Coefficient represents effect size at mean COI (Main Effects).

opportunity nor that the relationship between neighborhood opportunity and school readiness differed with community segregation.

To assist the interpretation of these changes in likelihood ratios, the predicted school readiness rates in communities defined by the three segregation measures are presented which assign neighborhood opportunity one-half standard deviations below and above the means (Table 6). The predictions for the two types of average students (Grand and Group) as described earlier are shown. Across the segregation measures, more segregated, and particularly Segregated Black/Hispanic, SABs showed a greater increase in predicted school readiness than Low or Not Segregated SABs. While the Grand predicted values suggested that students were most likely to be ready for school in Segregated Black/Hispanic SABs – a significant departure from the related literature – this merely reflects the process of holding all other covariates at the analytic sample mean. To better account for the effect of COI on the average student in each level, the Group predicted values were then used. Again, more segregated SABs consistently showed greater change from increasing COI. Further, despite the average student in a lower-resourced Segregated Black/Hispanic SAB having a school readiness likelihood far below the average student within the other segregation levels at the same COI, the gap was dramatically reduced by increasing neighborhood opportunity.

TABLE 6 Change in predicted school readiness likelihood by interaction term.

	Predicted school readiness probability		Change in predicted probability from +1 SD COI	
	At COI = −0.5	At COI = +0.5	Percentage points	%
Grand[a]				
Entropy				
High segregation	56.2	60.5	4.3***	7.7
Medium segregation	55.6	56.9	1.3*	2.3
Low segregation	54.8	56.6	1.8*	3.3
Exposure				
Not segregated	55.5	57.3	1.8***	3.2
Segregated Black/Hispanic	56.7	61.8	5.1*	9.0
Segregated White/Asian	56.4	58.9	2.5	4.4
Share				
Not segregated	55.4	57.2	1.8***	3.2
Segregated Black/Hispanic	60.6	69.1	8.5***	14.0
Segregated White/Asian	56.3	58.6	2.3	4.1
Group[b]				
Entropy				
High segregation	58.9	63.0	4.1***	7.0
Medium segregation	55.9	57.2	1.3*	2.3
Low segregation	52.6	54.4	1.8*	3.4
Exposure				
Not segregated	56.0	57.8	1.8***	3.2
Segregated Black/Hispanic	48.8	54.0	5.2*	10.7
Segregated White/Asian	60.9	63.3	2.4	3.9
Share				
Not segregated	56.1	57.9	1.8***	3.2
Segregated Black/Hispanic	51.3	60.5	9.2***	17.9
Segregated White/Asian	60.7	62.9	2.2	3.6

Predictions from models presented in Table 5.
[a]All other variables in the models held constant at the mean among all students.
[b]All other variables in the models held constant at the mean among students in SABs of the specific segregation type and level.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; $^{+}p < 0.1$.

As shown in Figure 4, in the Share model, this growth in school readiness likelihood propelled the average student in a Segregated Black/Hispanic SAB past that of the average student in a Not Segregated SAB.

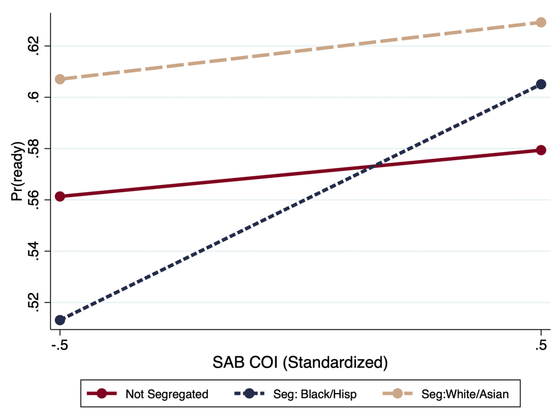

FIGURE 4
Predicted school readiness likelihood for average student, by segregation level (share).

Discussion

This study aimed to expand our understanding of the intersection between children's school readiness and neighborhoods conditions, including neighborhood opportunity and racial segregation, at-scale within a state and utilizing novel geospatial data and techniques. Results point to several key findings. First, neighborhood opportunity relate to differences in the skills children start school with, and access to opportunity varied by race. Specifically, Black and Hispanic children are overrepresented in low resourced neighborhoods, and White and Asian children overrepresented in higher resourced ones. Further, a community's racial composition, above and beyond the level of neighborhood opportunity, additionally contributed to the differences in children's school readiness at the beginning of kindergarten. Findings suggest possible program and policy directions to enhance children's school readiness and will be explored in more detail below.

Community investment in neighborhood opportunity relate to children's school readiness

Results of this study showed consistent evidence that students living in higher-resourced neighborhoods had higher school readiness skills at the start of kindergarten than those in lower-resourced neighborhoods. These results reinforce existing literature relating neighborhood conditions to academic outcomes (Vaden-Kiernan et al., 2010; McCoy et al., 2015) and expand on newer research investigating neighborhoods and early childhood outcomes (Wei et al., 2021; McCoy et al., 2022). Further, while prior research has shown a strong association between children's family income level and children's school readiness skills at kindergarten entry (Isaacs, 2012; Reardon and Portilla, 2016; Latham, 2018), the current study found that utilizing a more comprehensive measure of neighborhood conditions matters for school readiness, as well. Thus, systemic features play a role in children's school readiness skills at kindergarten entry. With this knowledge, future research should evaluate the extent to which higher-resourced neighborhoods may mitigate school readiness gaps and act as a protective factor for low-income students.

Again, it is important to note that results showed a significant overrepresentation of marginalized and non-marginalized children in low- and high-resourced neighborhoods, respectively. These findings align with other recent research that indicated that access to highly resourced neighborhoods varies by children's race and ethnicity (Hardy et al., 2021). As a result, inequitable access to essential neighborhood resources and opportunity may partially explain the racial/ethnic school readiness gap. While this study did not examine the interaction between children's race and COI with school readiness skills, future research is needed to see if higher-resourced neighborhoods serve as a protective factor for students of color.

Segregation adds another element to school readiness

Two out of the three segregation measures found that, holding all else constant at the average COI, racial residential segregation among zero-to-four-year-olds was correlated with the likelihood of demonstrating school readiness skills. Importantly, the level and type of residential racial segregation, in combination with neighborhood opportunity, also mattered for children's school readiness skills. Results using the Entropy model indicated that the effect of COI on school readiness grew with each ascending level of segregation. That is, the change in a student's predicted school readiness likelihood from increased community resources was smallest for Low Segregation SAB and greatest in High Segregation SAB. This finding implies that improving community opportunity in highly segregated neighborhoods may help young children be more ready to enter school. Further, results from the Share model showed a greater effect for students in predominantly marginalized communities. Students from Segregated Black/Hispanic neighborhoods were predicted to be much less likely to be ready for school than students from Not Segregated and Segregated White/Asian neighborhoods at the lower-resourced neighborhood level. This model also indicated that students in Segregated Black/Hispanic neighborhoods saw the greatest gains to their school readiness likelihood from an increase in COI. In other words, neighborhood opportunity seems to play a significant role in school readiness for children from Segregated Black/Hispanic SABs. This finding corresponds to recent research on the importance of accessible and equitable neighborhood resources (Wei et al., 2021), especially for children from marginalized communities (Hardy et al., 2021). While these results should be interpreted cautiously, the patterns suggest that improving neighborhood opportunity could serve as an avenue for remedying gaps in children's school readiness skills.

Interestingly, the predicted probabilities from both the Entropy and Share segregation models show that, holding all else constant at either the Grand or Group means, a student from a more segregated SAB was more likely to have higher school readiness skills at the start of kindergarten. This finding diverged from expected results, given that the literature suggested that less racial segregation may lead to better student outcomes. Previous research found that children who experience diverse and integrated early childhood settings were more likely to have positive academic and social outcomes (Reid and Kagan, 2015; Wells et al., 2016; McArdle and Acevedo-Garcia, 2017). For instance, children who were exposed to a diverse classroom were more likely to have improved critical thinking and problem-solving skills (Wells et al., 2016) and cross-racial friendships (Aboud et al., 2003). Further, being exposed to racial diversity at a young age may help counter racial prejudice and implicit bias later in life (Cloutier et al., 2014; Reid and Kagan, 2015). While some research suggests that higher levels of segregation may have the potential to serve as a protective factor for children of color, particularly if children's early childhood teachers are the same race as them (Downer et al., 2016; Redding, 2019; Wymer et al., 2022), the majority of the more segregated SABs in the Entropy model were disproportionately White neighborhoods. As such, it is difficult to speculate possible underlying mechanisms that may play a role in the association given this sample. Thus, as this is one of the first studies to examine the role of segregation and neighborhood opportunity on school readiness skills, more research is needed to parse out this association.

One possible explanation for this unexpected finding may be that children's experiences of segregation may vary based on urbanicity, shifts in demographics, and location. Virginia is a fairly segregated state, and recent research indicates that racial segregation remains high across and within school districts, especially at the elementary school boundary zone level (Siegel-Hawley et al., 2020). Urbanicity may also play a role in children's experiences of racial segregation, as students are unevenly distributed by race across the state. White students predominantly make up a larger share of school enrollment in Virginia's rural areas, whereas students of color are more concentrated in urban and suburban settings (Siegel-Hawley et al., 2020). Many neighborhoods in Virginia have also seen a shift in demographics over the past decade, as people of color now make up the majority of people under 18 in the Commonwealth (U.S. Census Bureau, 2020). These shifts in demographics have led to school enrollment changes, such that students of color now make up the majority of student enrollment in Virginia (Siegel-Hawley et al., 2020). Research also suggests that as neighborhood racial composition changes, school boundary zones may, as well. A case study of Loudoun County Public Schools, an affluent Washington, D.C. suburb, found that as the county grew more diverse, the district's attendance zones became more gerrymandered (Richards, 2014). Finally, regional differences may also play a role in children's experiences of racial segregation. Rural areas make up a majority of the state's geography, while urban and suburban pockets are primarily located in the state's northern, central, and southeastern regions. Thus, future research could employ geospatial analysis techniques to locate and compare neighborhoods from different areas around the state to examine regional variation in racial segregation.

Limitations and future directions

There are several key limitations that affect the current findings. First, the use of a dichotomous outcome reduces both the power and validity of this study. As mentioned earlier in this study, this binary outcome was chosen to be consistent with the VDOE definition of school readiness which carries significant policy relevance. Analytically, however, an equally reliable continuous school readiness variable would result in stronger and more robust findings.

Next, lacking student addresses, the analysis is reliant on SAB-wide averages for neighborhood opportunity and demographic values. Such aggregation naturally reduces the analytic precision as well as introduces a multi-level component to an otherwise student-level analysis. Additionally, the process to construct these averages assumes that neighborhood opportunity and demographics are uniformly distributed across both the census tract and SAB. This assumption is almost certainly flawed and likely misrepresents the living conditions in these areas.

Another limitation is the ~4-year gap between the 2015 COI 2.0 and SAB Survey with the 2019 VKRP assessment. This gap opens the door to measurement error if the SAB-level values no longer reflect the actual conditions in these areas. For this not to be an issue, the 2019 SABs must (1) cover the same area as they did in the survey and (2) the COI must be relatively stable over the period. While the latter has yet to be empirically tested, the former is presumably violated as rezoning of SABs has likely occurred since the 2015 survey was collected (Siegel-Hawley et al., 2020). Many school districts in Virginia have started or are considering rezoning their school attendance boundary zones, likely a result of population changes (Siegel-Hawley et al., 2020). Rezoning practices have also primarily affected students of color in Virginia. Among the districts that rezoned, students were still overexposed to same-race peers, especially Black and Latinx students (Siegel-Hawley et al., 2020). Thus, this study may inform Virginia school districts as they consider their attendance boundary rezoning policies.

Additionally, although the composite measure of neighborhood opportunity had a significant association with school readiness, the current study does not evaluate whether particular types of resources have a greater role on school readiness than others. Included in the COI 2.0 are neighborhood indices capturing socioeconomics, health, and education. Future research should investigate whether similar results are achieved using one of these alternative indices to get a more nuanced understanding of how neighborhoods may affect school readiness.

Despite these limitations, study findings provide insights to state and local policymakers to more precisely identify high-need communities and provide the resources and supports necessary to increase equitable access to high-quality early educational opportunities. At a practical level, these findings may help educators and policymakers better understand the needs of children and communities to prepare students for school. Many states use kindergarten readiness assessments, and these findings suggest local and state leaders could use this combination of data to consider the roles neighborhoods and the policies that shape them play in enhancing children's early skills (Regenstein et al., 2017; Olson and LePage, 2021).

Understanding the magnitude of readiness gaps, along with the factors linked to these gaps, can help educators and policymakers support the various systems that affect school readiness. These findings suggest that more targeted and equitable policy decisions could mitigate disparities in students' early childhood experiences, resulting in higher levels of children's school readiness. This opens the door to more kinds of investment, including in communities, as a pathway to more effectively support all young children. Results reinforce an expanding literature suggesting that improving educational equity requires addressing neighborhoods and not just school or classroom conditions. Thus, this study has broad implications for considering who has access to high-quality early childhood neighborhood opportunities, and how to improve access and quality regardless of zip code or race.

Data availability statement

The datasets presented in this article are not readily available because access to student-level readiness assessment data requires a data use agreement with the Virginia Kindergarten Readiness Program. Requests to access the datasets should be directed to Virginia Kindergarten Readiness Program, vkrp@virginia.edu.

Ethics statement

The studies involving human participants were reviewed and approved by Institutional Review Board Social and Behavioral Sciences (IRB-SBS) – University of Virginia. Written informed consent from the participants' legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

TL contributed to the conception for the study, designed and performed the statistical analysis, and primarily wrote the measures, methods, and results sections. JL-C and CC contributed to the conception of the study, wrote the introduction and discussion, and provided input to the methods section. AW, JD, and JW revised and reviewed the manuscript. LM oversaw and revised the methodology and results section. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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