Where you live matters:

Visualizing environmental effects on reading attainment.

Abbreviated Title: Visualizing Environmental Effects on Reading

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Abstract

Background: The effect of socioeconomic status (SES) on the etiology of reading attainment has been explored many times, with past work often finding that genetic influences are suppressed under conditions of socioeconomic deprivation and more fully realized under conditions of socioeconomic advantage: a gene-SES interaction. Additionally, past work has pointed towards the presence of gene-location interactions, with the relative influence of genes and environment varying across geographic regions of the same country/state.

Method: This study investigates how socioeconomic status (SES) and geographical location interact to influence the genetic and environmental components of reading attainment. Utilizing data from 2,135 twin pairs in Florida, aged between 10.71-17.77 years, the study operationalized reading attainment as reading comprehension scores from a statewide test and SES as household income. We applied a spatial twin analysis procedure to investigate how twin genetic and environmental estimates vary by geographic location. We then expanded this analysis to explore how the moderating role of SES on said genetic and environmental influences also varied by geographic location.

Results:. A gene-SES interaction was found, with heritability of reading being suppressed in lower (23%) versus higher SES homes (78%). The magnitude of the moderating parameters were not consistent by location however, and ranged from -0.10 to 0.10 for the moderating effect on genetic influences, and from -0.30 to 0.05 for the moderating effect on environmental influences. For smaller areas and those with less socioeconomic variability, the magnitude of the genetic moderating parameter was high, giving rise to more fully realized genetic influences on reading there.

Conclusions: SES significantly influences reading variability. However, a child's home location matters in both the overall etiology and how strongly SES moderates said etiologies. These results point towards the presence of multiple significant environmental factors that simultaneously, and inseparably, influence the underlying etiology of reading attainment.

Key Words: geographic location; socioeconomic status; reading attainment; twin analyses; gene-environment interaction

Socioeconomic status (SES) significantly influences children's development, including their academic performance (Coleman, 1966), with meta-analyses revealing an average association of r=0.27 between SES and academic achievement (Sirin, 2005; Harwell, 2017). This link, irrespective of the level (family, neighborhood, regional, or national) at which SES is measured, remains constant (Sirin, 2005; Harwell, 2017; Dearing et al., 2022). Despite numerous attempts to reduce this association's magnitude, significant progress remains elusive (Harwell, 2017), primarily due to its inherent complexity. Therefore, a deeper understanding how and why SES correlates with academic achievement is needed.

In understanding the impact of contextual factors like SES on academic traits such as reading, it is important to discern how much of individual differences stem from the environment. Behavioral genetics research separates trait variance sources into genetic and environmental influences, primarily through twin studies. If a trait's variability predominantly results from genetic influences, it could change the interpretation of SES's impact on it, unlike if driven mostly by environmental factors. Meta-analyses of twin studies suggest that genetic influences (A in an ACE model) account for 54% of the variance in reading comprehension scores, with shared and non-shared environmental influences (C and E respectively in ACE models) accounting for 16% and 30% respectively (Little et al., 2017). However, it should be noted that these influences vary across contexts, leading to a gene-by-environment interaction (GxE) where the context moderates the genetic influence on a trait (Scarr-Salapatek, 1971). SES, a significant measure of context in academic attainment, encapsulates various environmental and personal socio-economic factors. In the case of reading attainment, studies show a GxE interaction where higher-SES groups demonstrate higher genetic influences on reading score variations, whereas lower-SES groups are more environmentally influenced (e.g., Haughbrook et al., 2016; Krapohl & Plomin, 2016; Taylor & Schatschneider, 2010). This pattern, widely replicated in the U.S., has less confirmation outside it (Tucker-Drob & Bates, 2016). In essence, SES impacts academic attainment at the phenotypical and etiological level, with effect magnitudes differing across SES levels.

The Role of Geographic Location on Academic Outcomes

Geographical location, in tandem with socioeconomic status (SES), significantly impacts academic achievement, with notable evidence in spatial inequality and residential stratification. In the U.S., increasing economic segregation has led to a clear demarcation between neighborhoods of varying SES (Duncan et al., 1972; Dearing et al., 2022). This stratification, wherein home and neighborhood SES coincide, enables families in high-SES regions to have access to more academic resources such as books, computers, study spaces, and educational services (Sirin, 2005). Concurrently, a correlation exists between the income segregation of schools and geographic locations, with resource-scarce schools often having a higher population of children from low-SES families and areas (Owens, 2016; Owens et al., 2016; Graham & Provost, 2012; Graham & Teague, 2011). This pattern points towards geographic location as a potential predictor of academic attainment. Nevertheless, within each neighborhood, substantial variability in individual family SES exists. Hence, simultaneously evaluating familial SES and geographic location allows the estimation of their respective roles and the extent to which geographic location further moderates the impact of family SES on academic achievement. The primary aim of this study is to ascertain how family SES influences individual differences in reading achievement across geographic locations.

In the past decade, research has directly examined geographic location's role in individual trait differences. Davis et al. (2012) introduced a spatial analysis method (spACE analysis) to assess how a trait's etiology varies across geographic locations, integrating environmental factors like SES and access to green spaces. Findings indicated that geographic location corresponded with the extent to which cognitive and behavioral measures, including academic achievement, were influenced by genetic or environmental factors, aligning with previous studies that employed family-based SES measures. Further applications of Davis et al.'s (2012) method also identified geographic location as a moderating factor in the etiology of autistic traits, albeit without specifying the particular aspects of the location contributing to these differences (Reed et al., 2021). To build on Davis et al.'s (2012) work, we aim to examine how family-SES moderates genetic and environmental influences on reading achievement and whether this moderation varies with geographic location.

Twin Spatial Analysis

Davis et al.'s (2012) twin spACE analysis also allows for a visually appealing way to show the moderating effect. With this technique, we can describe and visualize spatial distributions and discover spatial association patterns applied in twin studies using geographically (Geographic Information System; GIS) coded data. Using this visualization technique, we can highlight genetic and/or environmental hotspots, that is, neighborhoods or areas where genetic and/or environmental variations have more effect on a trait compared to areas where a lesser impact is detected. Here we extend the spACE technique to visualize not only the degree to which family-level SES underlies the genetic and environmental influences on reading attainment but also the extent to which these vary by where a child lives.

The Influence of Within-Sample Heterogeneity

A significant factor in our investigation is the heterogeneity or variability within samples across geographic areas. Reed et al. (2021) found that geographic location's effect on the etiology of autistic traits in Europe was generally associated with the expected heterogeneity levels in these regions. For instance, larger cities with high income variability and diverse cultural and environmental factors exhibited higher heritability estimates. Previous research also suggested that greater heterogeneity might correlate with moderating variables like SES, affecting a trait's etiology differently. A meta-analysis found that samples with higher within-sample heterogeneity (i.e., U.S. samples) were more likely to show that SES significantly moderates the etiology of academic attainment than those with lower heterogeneity (i.e., European samples; Tucker-Drob & Bates, 2015). Thus, it remains uncertain how generalizable European-based findings are to the varied economic environments in the U.S., known for its pronounced inequality and disparities (Filauro & Parolin, 2018).

The U.S., particularly Florida where our sample originates, is notable for its considerable within-sample heterogeneity, characterized by the highest and most rapidly increasing SES variability measured by income inequality using the Gini coefficient (Sorenson et al., 2017). This heterogeneity is likely more pronounced than that of U.K. samples due to factors like Florida's geographic layout, which encompasses vast rural and metropolitan areas. Historic practices such as redlining or gentrification have exacerbated the disparities in SES within small areas of major cities (e.g., Miami area; Sanchez-Arias, 2017; Samara & Chang, 2008). Hence, we expect the current Florida-based sample to exhibit greater between- and within-sample heterogeneity, both within and across geographic areas, compared to U.K. samples.

Research Questions and Hypotheses

This study aimed to answer two research questions. Firstly, we sought to ascertain how the proportion of genetic and environmental influences on reading attainment varies according to geographic location. Informed by prior studies (Davis et al., 2012; Tucker-Drob & Bates, 2015), we postulated that the substantial heterogeneity across Florida would result in significant etiological disparities linked to geographic location. We anticipated that regions with less inequality, namely the greater Orlando and Jacksonville areas, would display the most pronounced genetic influences. Conversely, areas characterized by high heterogeneity and inequality, such as the greater Miami-Dade area, would likely exhibit more substantial environmental influences. Secondly, we aimed to explore how family SES's moderating effects on the genetic and environmental influences on reading attainment differed across geographic locations. We predicted that regions with the greatest heterogeneity in Florida would display the largest moderating effect sizes, considering Tucker-Drob's (2015) findings, which indicated that SES's moderating effect on academic attainment's etiology was more likely to be significant in nations exhibiting high heterogeneity.

Method

Participants

This study drew participants from a broad twin sample from the Florida Twin Project on Reading (FTP – R; Taylor & Schatschneider, 2010). Twins were identified from Florida's Progress Monitoring and Reporting Network (PMRN), a statewide database of standardized achievement tests for children across the state. To be included in this specific study, twins had to have data from the 2013-2014 school year within the PMRN database, which was selected to maximize the sample size for examining the outcome variable (reading attainment). In addition, they needed available data on geocoded home locations and household income. Zygosity of twin pairs was determined by a parental five-item questionnaire obtained during intake into the twin project, which measured the physical similarities of the twins and has shown to have high correspondence to zygosity estimates from genetic markers (Lykken, Bouchard, McGue, & Tellegen, 1990).

The final sample consisted of 4,284 twins, which included 1,448 monozygotic (MZ) and 2,822 dizygotic (DZ) twins. Fourteen twins had missing zygosity information. Gender-based classification resulted in 736 MZ female-female, 710 MZ male-male, 706 DZ female-female, 778 DZ male-male, and 1,340 opposite-gender twins. For the 2013-2014 school year, the average age of the twins was about 13 years and 10 months. The racial composition was as follows: 1.63% Asian, 16.63% Black, 21.25% Hispanic, 0.19% Native American/Pacific Islander, 2.74% Multiple Races, 56.35% White, with 1.21% not reporting data. Concerning socio-economic status, data from the U.S. census was used for household income: 2.71% of twins reported incomes of less than US $30,000, 22.79% reported incomes from US $30,000 to US $49,999, 34.56% from US $50,000 to US $69,999, 24.61% from US $70,000 to US $99,999, 12.19% from US $100,000 to US $149,999, and 3.13% reported incomes of US $150,000 or more. The median household income in Florida in 2014 was estimated to be US $53,267.

(https://www.census.gov/quickfacts/fact/table/FL,US/RHI125219). Regarding the socio-economic status, U.S. census data was used for household income, with 2.71% of twins from the present sample reporting incomes of US $30,000, 22.79% reporting incomes of US $30,000 to US $49,999, 34.56% reporting incomes of US $50,000 to US $69,999, 24.61% with incomes of US $70,000 to US $99,999, 12.19% with incomes of US $100,000 to US $149,999, and 3.13% with incomes of US $150,000 or more (https://www.census.gov/search-results.html?searchType=web&cssp=SERP&q=household%20income%202014).

Measures

In this study, we examined a gene by SES (operationalized as household income) interaction for reading attainment based on household location.

Reading attainment. The main outcome of interest in the study was reading attainment, measured using the Florida Comprehensive Assessment Test (FCAT) Reading subtest. This is a standardized annual assessment of reading attainment given to students from grades 3 to 10 throughout Florida. For this study, the researchers used the developmental scale score, which is a vertically scaled standard score enabling direct grade-level comparisons. The FCAT reading subtest's reliability is reported to range from 0.89-0.92. (Florida Department of Education, 2011a; Florida Department of Education, 2011b).

Household income. Family SES was measured by median household income by census tract. Median household income, as the reported 5-year rolling average (2010-2014), was obtained from the U.S. Census Bureau's American Community Survey based on family home address (U.S. Census Bureaus, 2014).

Geographic location. Household locations were obtained from twin families' addresses from the Florida Twin Project on Reading. From here, home addresses were converted to geographic coordinates and then a small amount of random error or jitter was applied to each location, providing us with new deidentified locations that were used for the spatial anlaysis. Following this, the distance between each family's geographic location and each of these new "target" locations was then computed, with the inverse of the distance then being applied as the weight for each twin pair for each target locations estimate. That is, the closer a twin pair lives to the target location, the more weight that twin pair carries in the estimation for that specific target location. As such, twin family addresses were used to determine both the family and target locations, as well as the distance between these to be used as model weights. In turn, each twin family contributed to every single estimate, but the weight they carried was directly determined by their distance to said target location. This exact procedure is outlined in detail in Davis et al. (2012). The use of this data again allows us to estimate and visualize the moderating role of geographic location on the genetic and environmental influences of FCAT reading as well as in subsequent analyses including household income to determine how the role of geographic location may affect the moderating role of family SES on FCAT reading.

Analyses

Prior to running the twin and spACE analyses, FCAT reading was prepared by residualizing out student age and sex and then z-scoring to increase the interpretability of the results and to eliminate potential effects that may have arisen from certain areas having higher proportions of older or younger students or areas in which the proportions of male and female students may have differed from average. Household income values were additionally z-scored to increase the interpretability of results.

Spatial Analysis of ACE Estimates (spACE; Research Question #1). To answer the first research question, a series of twin models were fit using R statistical software version 4.1.2 and the OpenMx package, applying the twin spatial weighting procedure described above to get separate estimates at each target location (R Core Team, 2021; Boker et al., 2023). The model that was fit is known as an ACE model, which leverages our understanding of how monozygotic twins and dizygotic twins are differentially related to each other. In this model, the variance in a trait is attributed to genetic and/or environmental (shared or non-shared) influences, and is estimated separately at each target location. The overall weighting procedure is described alongside our earlier description of the geographic location measure and can be found in greater detail in the Davis et al. (2012) article. In short, the ACE model was fit separately at each target location by using the inverse distance between a twin pair and target location as weights for how much each family contributes to each target location's estimate, keeping in mind that every twin pair contributes to every estimate and that those families in closest proximity to the target location will contribute the most weight. The estimates for each target location were then graphed, allowing us to visually identify areas where genetic or environmental hotspots existed. Those are the areas that had unexpectedly larger levels of genetic or environmental influences compared to their immediate surrounding areas.

Spatial Analysis of Moderation Effects (Research Question #2). Following the aforementioned analyses, analyses now shifted to determine the extent to which family SES's moderating effects on reading's underlying genetic and environmental influences differed by geographic location. Several different models are available that can analyze how SES moderates the etiology of reading attainment, and as such prior to computing our spatial analyses, we first determined the best-fitting moderation model for the sample as a whole to be used as the moderation model for each target location. A model comparison approach was taken again using OpenMx to determine this. Several models were fit, determining that the best fitting model was an ACE model in which family SES moderated the genetic and environmental A and C influences. The results from this model were then additionally used as starting values in OpenMx for the subsequent spatial analyses. Following this, the same weighted spatial analysis procedure was applied to again compute weighted covariance matrices for our measures, this time taking the resulting covariances matrices and applying them to the best fitting ACE model with A and C moderation. Results of this analysis allowed us to estimate and visualize the moderating effects of family SES on the A and C influences at each location, allowing us to identify locations where family SES had a greater or lesser than average moderating effect on either the A or C influences. We additionally aimed to visually detect A and C moderation hotspots, areas where the A and C moderation estimates were unexpectedly larger than the same estimates in the immediately surrounding areas.

Results

Results related to both research questions can be found in the section that follows. However, prior to highlight that additional information regarding the layout, population density, and income inqueality of Florida is available in the Supporting Materials and Figure S1.

Results of the ACE model related to research question 1 revealed that, on average, 46% (range ~0.35-0.60), of the variance in reading scores was attributed to genetic influences 38% (range~0.15-0.50), was attributed to aspects of the environment shared across twins in a twin pair and 16% (range~0.17-0.22) attributed to unique environmental factors and measurement error. A histogram (Figure 1) of the effect sizes revealed a relatively normally distributed range for each of these influences. Visualized results of the spatial analysis revealed several hotspots. As expected, areas in the north/northeast of Florida showed higher levels of genetic influences (A), while the southeast area of the state demonstrated higher proportions of shared environmental influences (C) on reading scores.

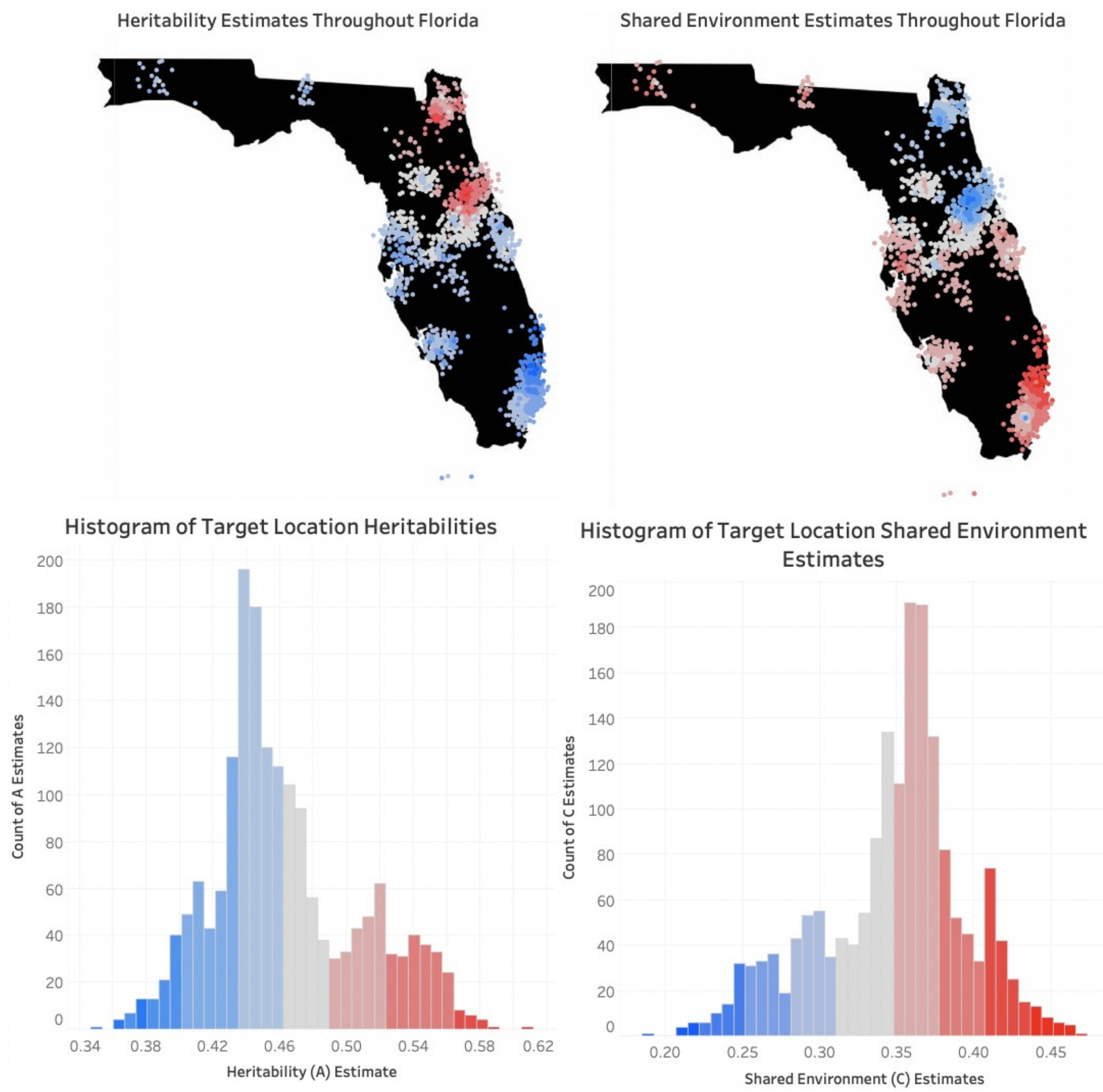

Figure 1. Maps and histograms of A and C estimates for Florida Comprehensive Assessment Test (FCAT) reading in the State of Florida. *Note: The histogram y-axes represent the count of effect sizes falling in a given range, capturing the number of target locations finding given effect sizes.*

For the second research question, it was found that family SES significantly moderated both the A and C influences on reading attainment (Figure 2). On average, higher family SES was associated with larger underlying levels of genetic influences (moderating effect of β_A=0.06)and smaller levels of shared environmental influences (moderating effect of β_C=-0.23) This was in line with previous research which found SES to significantly moderate the etiology of reading in areas with high heterogeneity.

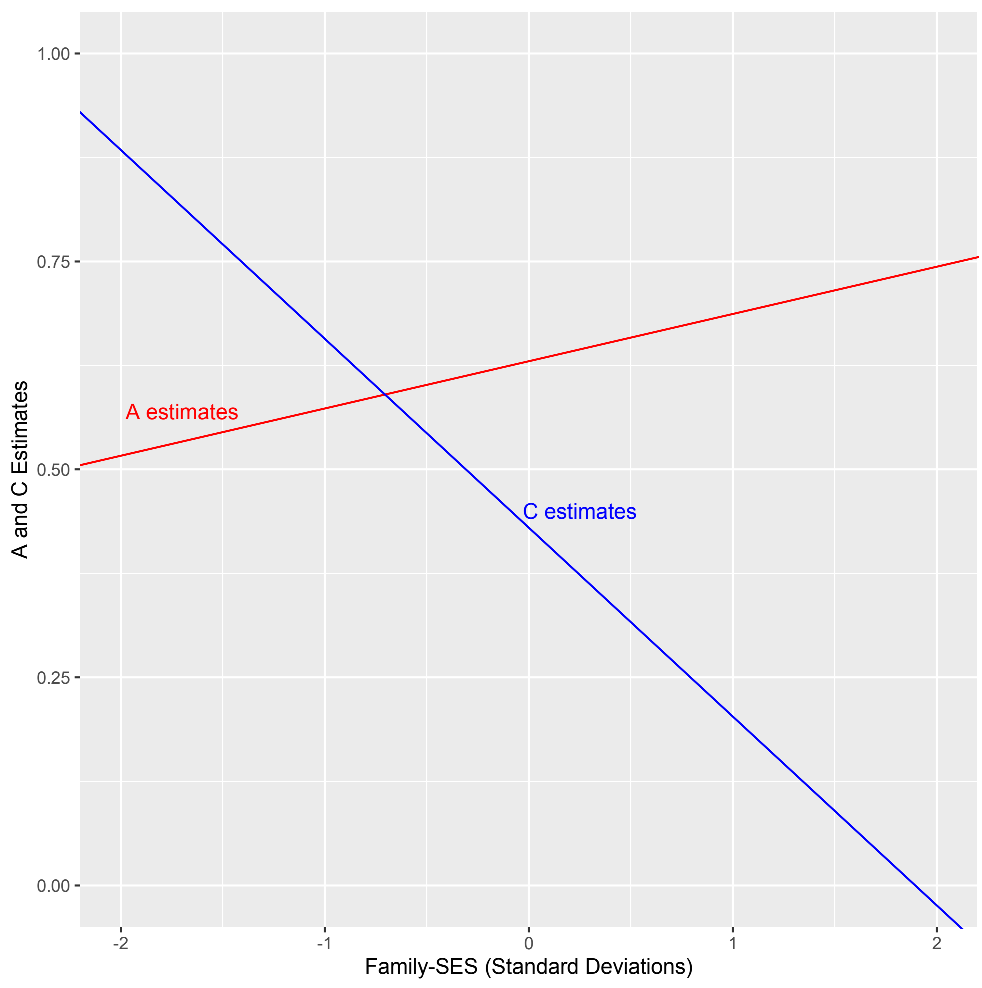

Figure 2. A and C Estimates by Family-SES

The effects of these moderating influences varied by geographic location. In some areas, higher SES was associated with greater proportions of variance attributed to genetics, while in others, higher SES was linked with lower levels of genetic influence (β_A=-0.10 to 0.10).

Similarly, the moderating effects (β_C) on shared environmental influences crossed zero and were primarily negative (β_C=-0.30 to 0.05). The estimates appeared to be normally distributed, highlighting that typical twin estimates are capturing the average effects that exist across a range of normally distributed effects. A key finding was that moderating effects on both genetic and shared environmental influences were strongest (by magnitude/absolute value) in the areas of the state where genetics accounted for a larger proportion of variance on average. However, differences were also found within these areas. For instance, in one are of the greater Miami-Dade area, there were much higher moderating effect sizes on both genetic and shared environmental influences than in the surrounding areas.

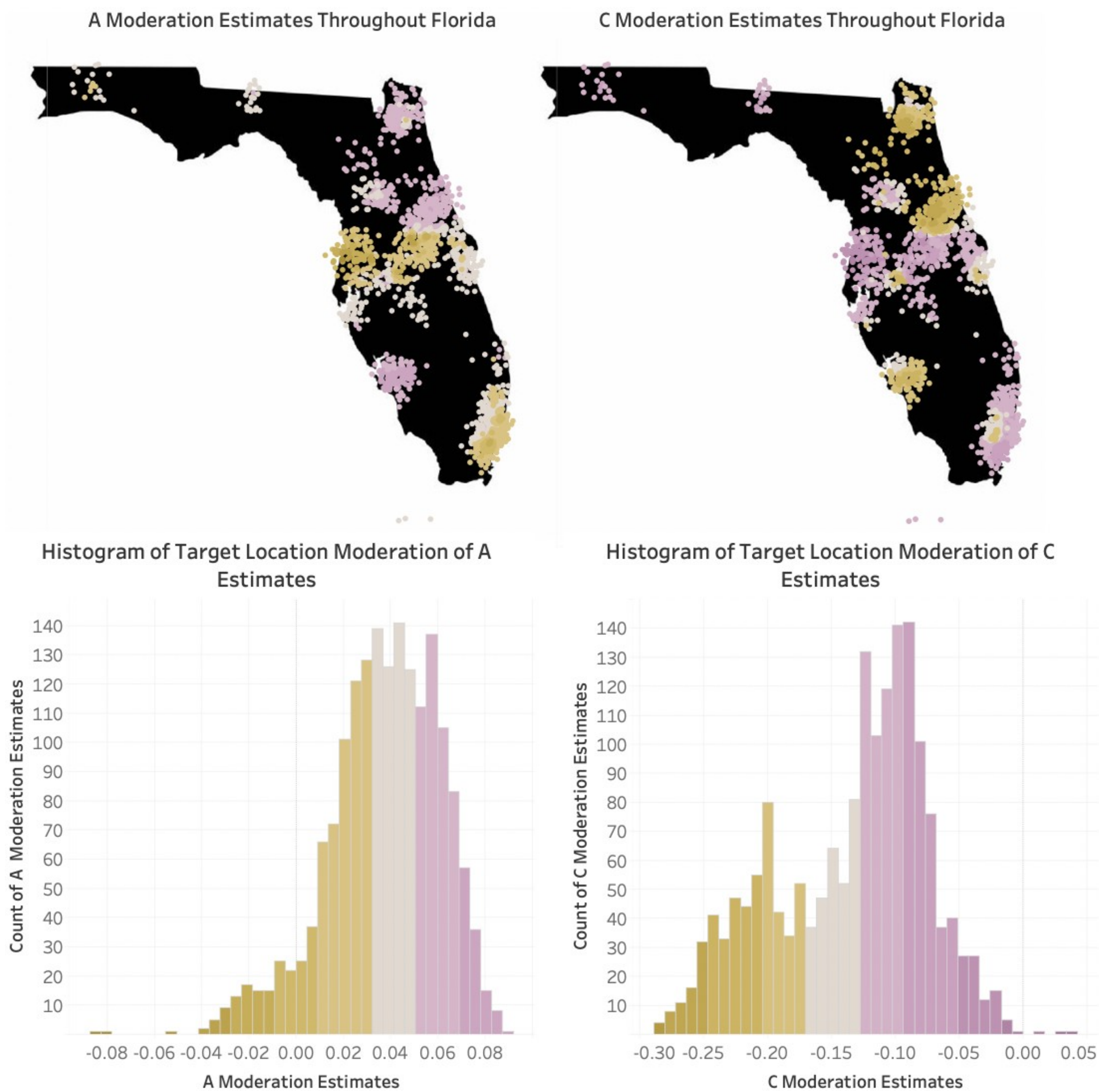

Figure 3. Maps and histograms of family SES moderating influences for Florida Comprehensive Assessment Test (FCAT) reading in the State of Florida. *Note: The histogram y-axes represent the count of effect sizes falling in a given range, capturing the number of target locations finding given effect sizes.*

Discussion

The focus of this study was to further our understanding of the association between SES and reading attainment through the exploration of two research questions. First, to what extent do the genetic and environmental influences of reading attainment vary on the basis of geographic location? Second, do the moderating effects of family SES on the genetic and environmental influences of reading vary by geographic location?

The study found geographic location to play a significant role in the genetic and environmental influences of reading attainment. The variance was not uniformly distributed, as the full-sample estimates were not generalizable to all subsamples within the same population. This variance highlights the importance of geographic location in understanding the influence of genetics and the environment on reading attainment. These findings supported earlier research from Davis et al. (2012) and Reed et al. (2021), which suggested differences in the genetic and environmental influences on reading based on geographic location. However, the pattern of these differences didn't entirely align with those previous studies conducted in the UK and Sweden. In those studies, areas with larger cities displayed higher levels of heritability. In contrast, this study found that areas with high population densities but varying levels of socioeconomic inequality presented different genetic and environmental influences on reading. This discrepancy suggests that SES and socioeconomic inequality within the major cities of the US, as opposed to population density and the presence of large cities, are likely driving these findings. This conclusion contrasts with previous studies that couldn't separate out population density and heterogeneity, given that areas of high population density were also the ones with the highest heterogeneity. This discovery suggests the generalizability of research findings might be linked to the level of heterogeneity in the region, pointing to a systematic aspect where the results are most likely to generalize to areas with similar levels of heterogeneity. Therefore, regions with high levels of heterogeneity, like Florida, might face challenges with the generalizability of findings. Beyond this however it is important to note that characteristics beyond heterogeneity likely also contribute to these findings, and exploring generalizability across samples with similar levels of heterogeneity but varying levels of other characteristics could help further elucidate this finding. This study underscores the significance of recognizing these differences and understanding the potential reasons behind them

The study's findings concerning both research questions showed that increased heterogeneity (variety or diversity in attributes) was connected to higher levels of environmental influences on reading attainment, but it had a generally weaker moderating effect of SES (socioeconomic status) on these influences. To explain this, we propose that the moderating effect of SES might be diluted by other sources of environmental heterogeneity in areas with high levels of heritability. In a Supporting analysis (Tables S1-S2 and Figure S2), we correlated the total model variance (a proxy for heterogeneity) at each geographic point with the SES's moderating effect on genetic (A) and shared environmental (C) influences. The results showed strong negative correlations (r=-0.67 and r=-0.80 for A and C respectively), suggesting that when total model variance is high, the SES's moderating effect on genetic influences comprises a smaller proportion of the total genetic influences present. Thus, larger moderation effects of SES on reading attainment might occur when SES comprises a significant proportion of the overall variation in genetic influences. These findings also bring up the concept of sample power and the presence of numerous environmental predictors, similar to genomic studies needing large samples to identify numerous genetic variants each with minimal effects on an outcome. With high levels of environmental variation, many environmental predictors may contribute small amounts of overall variance, requiring increased power to detect. Work by Taylor et al. (2017) further provides support for this, showing that an index of environmental predictors that each contribute small amounts of variance can be used to significantly predict reading attainment. This same idea again works in reverse, potentially explaining how family-SES can have larger moderating effects in areas with lower heterogeneity simply by accounting for a larger proportion of the overall heterogeneity.

We suggest that these findings challenge the effectiveness of generalizing from mean estimates to extreme/subsample cases, emphasizing the practical limitations for predictive models derived from such research, given the presence of varying univariate effect sizes and moderation effects. Further, lower SES has been found to be associated with less predictive power of polygenic scores (PGS; a measure of an individual's genetic predisposition for a given trait) and genetics in general (Papageorge & Thom, 2018). This study produced similar findings, with regions having the most SES inequality showing the least amount of genetic influences. The reasons for these lower genetic influences could be due to either increased variance reducing the overall impact of genetic influences or the influence of certain genetic variants being significant only in the presence of environmental factors associated with areas with the least SES inequality. Additionally, we hypothesize that the application of PGS would likely result in different prediction levels across various samples due to these differential genetic influences. This is supported by recent research showing that polygenic prediction of traits such as autism varies significantly by geographic location (Reed et al., 2021). Furthermore, the study found that the moderating effect of family SES also varies, indicating that not only would PGS predictions need to be differentiated based on SES to account for gene-environment interactions, but also that a gene-environment-environment interaction exists. This suggests that models accounting for family SES should also consider geographic location and the aspects it captures.

The final point of discussion we wanted to address is that differences in racial and ethnic makeup are deeply embedded in these geographic locations. Past research has found that race moderates the influence of SES on reading attainment (Sirin, 2005; Harwell et al., 2017), is correlated with but does not fully explain SES (Battle & Lewis, 2008), and due to the negative environmental factors more present for minoritized groups can moderate the heritability of academic attainment in the same way as family-SES (Pesta et al., 2020). As such, it is important to remember that geographic location is simultaneously and indistinguishably capturing all of these effects, calling for the need for future researcher to fully distinguish what factors are present in given geographic locations and how they relate to the questions at hand.

Overall, results from this study indicated that the role of SES on academic attainment, such as reading, is far more complex than how it is typically studied or modeled. In addition, our results imply that relying on simple mean-based estimates is missing a part of the picture. Beyond the role of SES and the extent to which geographic location captures socioeconomic factors related to the individual in the outer environmental systems, it is important to remember that geographic location is capturing a plethora of different contextual factors beyond SES. As such, we call for the need for future research to fully distinguish what factors are present in given geographic locations. individual differences studies and predictive models should focus on incorporating data and information encapsulating aspects of all contextual systems and their interactions with each other and the individual, rather than simply measuring and assessing one predictor as it relates, on average, to an outcome. Future studies can build on the current work to further understand the roles that these individual systems and the contextual factors present within play in terms of genetic and environmental influences on academic attainment.

Key Points and Relevance

- The genetic and environmental influences on reading attainment differ based on geographic location, as do the moderating role of SES on these influences.

- Increased heterogeneity (or diversity) in a given area was associated with higher environmental influences on reading attainment, but also with a generally weaker moderating effect of socioeconomic status (SES) on these influences.
- Generalizing from mean estimates to specific subsamples within the same population is unlikely to be effective. This observation highlights the need for these models to account for varying genetic and environmental influences as well as SES and geographic location.
- What's relevant? These findings have implications for researchers and practitioners examining or intervening on aspects of the environment thought to impact academic attainment. For policies, the complex role that SES plays makes developing policies targeted at SES difficult and requires policy makers to consider broader contexts as well.

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Supporting Materials

Figure S1 shows the income inequality (measured by the Gini Coefficient) and population density (as a percentage of the total population) for the state, broken down by county. As it can be seen, the areas of the state vary widely in terms of these characteristics, with the highest levels of income inequality existing in the areas of the southeast or Miami-Dade of the state as hypothesized, and less in the areas in the central or Orlando and northeast or Jacksonville areas of the state. Additionally worth mentioning here is the lack of correspondence that exists between population density and income inequality, with some large metropolitan areas having high levels of inequality and others having exceptionally low values. This is in contrast to the aforementioned Reed et al. (2021) and Davis et al. (2012) studies where the same level of inequality doesn't exist and as such the higher population density areas are expected to more closely resemble one another.

Supporting Analysis

After completing the planned analyses, we wanted to explore these results further and subsequently decided to explore the association that the overall variance in a model at each target location had on the results. We hypothesized that model variance would serve as a proxy for target location overall heterogeneity, and as such would be associated with the different findings. As such, to further understand the results of our models, the resulting A, C, E, A moderation, C moderation, the absolute value of the A moderation as a proportion of total A influences, the absolute value of the C moderation as a proportion of total C influences , and the total variances at each target location were compared to one another, allowing us to see how observed variance in this way relates to our findings. Given our expectations that total variance was in some way driving our results, we further mapped the total variance at each target location to visualize differences that arose throughout the state (see Figure S2).

Results for the correlations among all results at each target location were computed and are presented in Table S2. Results of this indicated, both visually and through correlations, that total model variance was significantly related to the ACE and ACE moderation effects at a given location. Comparing total variance to these effects, the strongest relations were observed between total variance and the resulting C influences, with an estimated correlation between variance and C of $r=0.92$. In the opposite direction, variance was also strongly related to A influences at a correlation of $r= -0.87$. Beyond relating to these estimates, model variance was additionally related to the extent that A and C influences were each moderated by family SES at each target location. For the moderating effect of A and C influences by family SES, total variance was correlated at $r= -0.51$ and $r=0.69$ respectively. It is important to note here that with the moderating effects on C being primarily negative but the moderating effects on A being primarily positive, the association between total variance and the moderating effect is such that higher total variance is associated with lower magnitude moderating effect sizes.

Supporting Figures

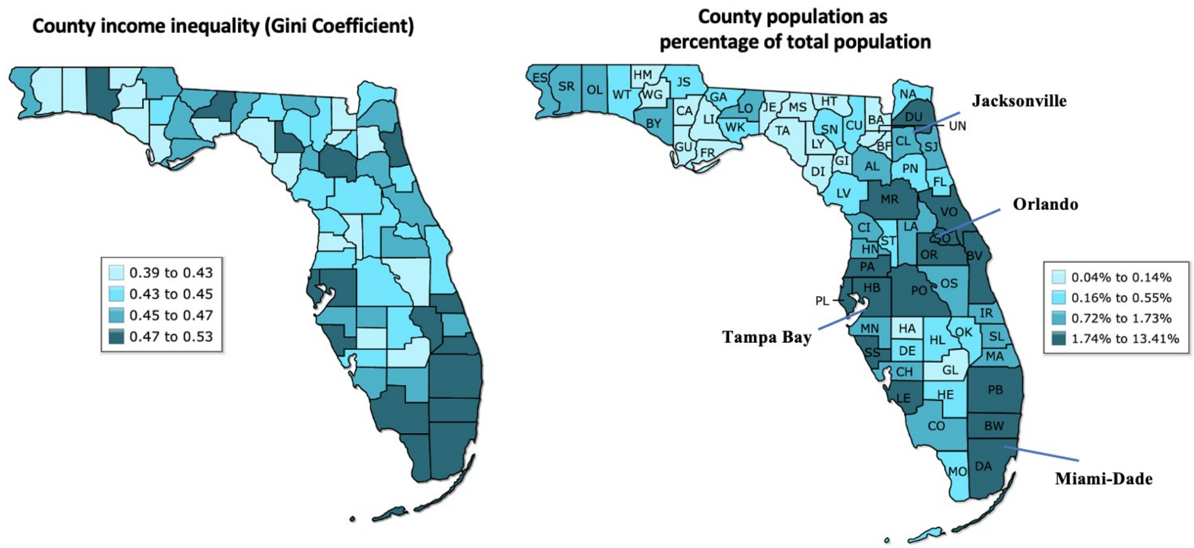

Figure S1. Income inequality and population density by County. *Note: Gini Coefficient values range from 0-1, with a value of 1 indicating perfect inequality.*

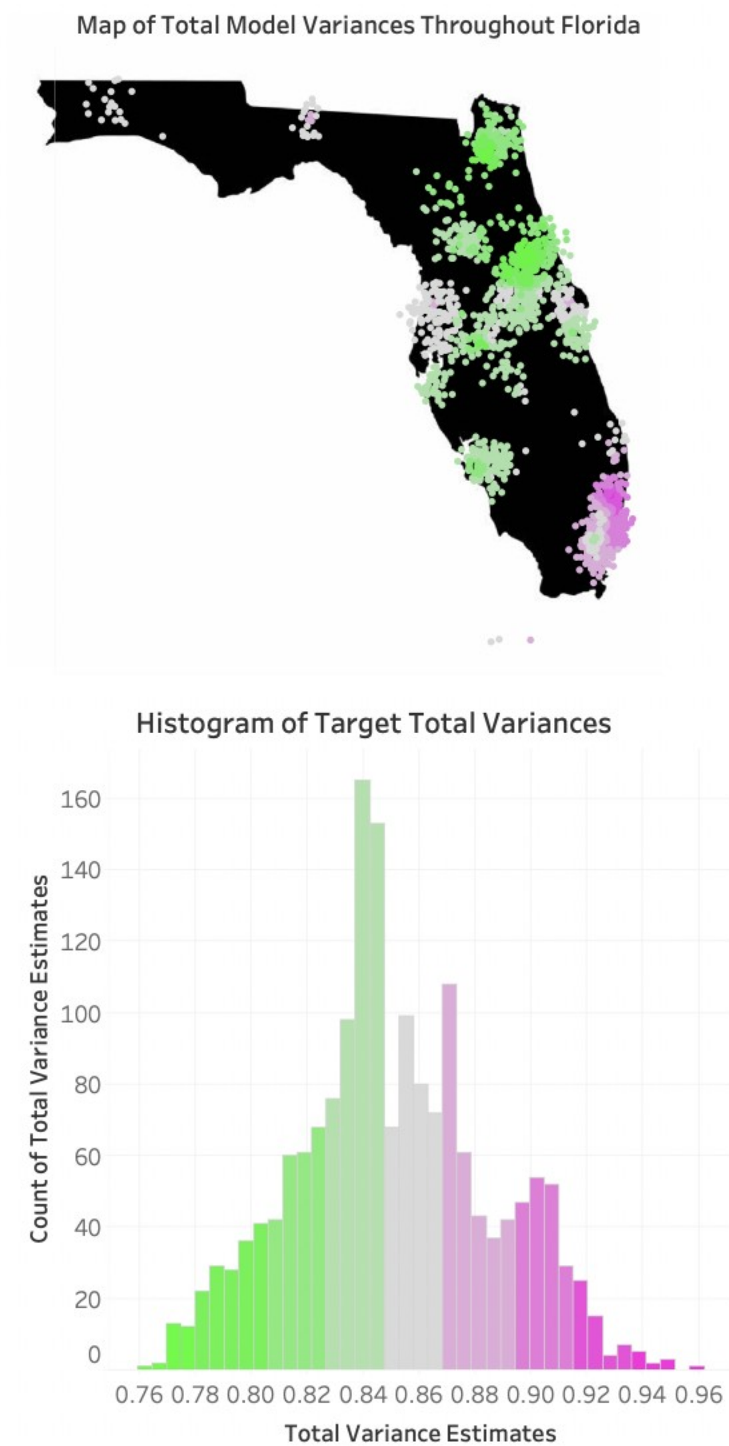

Figure S2. Map and histogram of total model variance in FCAT reading in the State of Florida

Supporting Tables

Table S1

Best Fitting Moderation Model Results

	-2 Log Likelihood	df	AIC	$\chi^2\Delta$	dfΔ	p-value
Full Model	8229.87	3545	1139.87			
No Effect of SES	8430.20	3549	1332.20	200.33	4	<0.001
Means Effect Only	8254.51	3548	1158.51	24.637	3	<0.001
Means Effect, Moderation of C and E	8236.19	3546	1144.19	6.32	1	0.012
Means Effect, Moderation of A and E	8251.60	3546	1159.60	21.73	1	<0.001
Means Effect, Moderation of A and C	**8230.75**	**3546**	**1138.75**	**0.88**	**1**	**0.348**
Means Effect, Moderation of A	8254.21	3547	1169.21	24.334	2	<0.001
Means Effect, Moderation of C	8240.45	3547	1146.45	10.58	2	0.005
Means Effect, Moderation of E	8251.81	3547	1157.81	21.94	2	<0.001

Note: Best fitting model bolded.

Table S2

Correlations between Target Location ACE, ACE Moderation, and Total Variance Estimates

	Heritability (A)	Shared Environment (C)	Non-Shared Environment (E)	A Mod.	C Mod.	A Mod./ A Estimate	C Mod./ C Estimate	Variance
Heritability (A)	1.00							
Shared Environment (C)	-0.985	1.000						
Non-Shared Environment (E)	0.303	-0.462	1.000					
A Moderation	0.346	-0.401	0.435	1.000				
C Moderation	-0.635	0.679	-0.487	-0.857	1.000			
A Moderation / A Estimate	0.562	-0.610	0.485	0.961	-0.936	1.00		
C Moderation/ C Estimate	0.792	-0.825	0.488	0.722	0.955	0.872	1.00	
Variance	-0.872	0.923	-0.619	-0.515	0.698	-0.673	-0.795	1.000

Note: All p=values significant at p<0.001.