



# Exploring the Relationships Between Autozygosity, Educational Attainment, and Cognitive Ability in a Contemporary, Trans-Ancestral American Sample

Sarah MC Colbert<sup>1</sup> · Matthew C Keller<sup>2,3</sup> · Arpana Agrawal<sup>1</sup> · Emma C Johnson<sup>1</sup>

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## Abstract

Previous studies have found significant associations between estimated autozygosity - the proportion of an individual's genome contained in homozygous segments due to distant inbreeding - and multiple traits, including educational attainment (EA) and cognitive ability. In one study, estimated autozygosity showed a stronger association with parental EA than the subject's own EA. This was likely driven by parental EA's association with mobility: more educated parents tended to migrate further from their hometown, and because of the strong correlation between ancestry and geography in the Netherlands, these individuals chose partners farther from their ancestry and therefore more different from them genetically. We examined the associations between estimated autozygosity, cognitive ability, and parental EA in a contemporary subsample of adolescents from the Adolescent Brain Cognitive Development Study<sup>SM</sup> (ABCD Study<sup>®</sup>) (analytic N=6,504). We found a negative association between autozygosity and child cognitive ability consistent with previous studies, while the associations between autozygosity and parental EA were in the expected direction of effect (with greater levels of autozygosity being associated with lower EA) but the effect sizes were significantly weaker than those estimated in previous work. We also found a lower mean level of autozygosity in the ABCD sample compared to previous autozygosity studies, which may reflect overall decreasing levels of autozygosity over generations. Variation in spousal similarities in ancestral background in the ABCD study compared to other studies may explain the pattern of associations between estimated autozygosity, EA, and cognitive ability in the current study.

**Keywords** Runs of homozygosity · Autozygosity · Educational attainment · Assortative mating · Cognitive ability

## Introduction

Runs of homozygosity (ROHs) are stretches of DNA that are identical by descent (Wright 1922); these arise when an individual's parents share a common ancestor. While greater

numbers of and longer ROHs tend to be associated with more recent inbreeding (e.g., cousin-cousin inbreeding), ROHs occur even in seemingly outbred populations (McQuillan et al. 2008). Previous studies have found that individuals with a greater level of autozygosity ( $F_{ROH}$ ; the proportion of the genome contained in ROHs) tend to have lower values on fitness-related traits, such as cognitive ability (Howrigan et al. 2016; Joshi et al. 2015), respiratory function (e.g., forced expiratory volume; Johnson et al. 2018; Joshi et al. 2015), and reproductive characteristics such as number of offspring (Clark et al. 2019; Johnson et al. 2018; Yengo et al. 2017). This phenomenon, known as inbreeding depression, suggests that these traits have been under selection pressures over evolutionary time, with selection more easily removing common and dominant deleterious alleles, and therefore biasing the persisting deleterious variants that influence those traits towards being more rare and recessive.

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✉ Sarah MC Colbert  
sarah.colbert@wustl.edu

<sup>1</sup> Department of Psychiatry, Washington University School of Medicine, Saint Louis, MO, USA

<sup>2</sup> Department of Psychology, University of Colorado Boulder, Boulder, CO, USA

<sup>3</sup> Institute for Behavioral Genetics, University of Colorado Boulder, Boulder, CO, USA

ROHs have been used to examine evolutionary hypotheses about quantitative traits (e.g., cognitive performance) and case-control phenotypes (e.g., psychiatric diagnoses). For example, multiple studies have shown that increased autozygosity is associated with decreased cognitive ability (Abdellaoui et al. 2015; Howrigan et al. 2016), consistent with the hypothesis that alleles decreasing cognitive ability have been biased towards recessivity due to selection against them. Associations have been less consistent for case-control phenotypes such as schizophrenia (Johnson et al. 2016; Keller et al. 2012), potentially due to ascertainment differences in cases and controls and/or sociodemographic factors that may play a role in assortative mating (Abdellaoui, Hottenga, Xiao, et al., 2013; Clark et al. 2019). To adequately account for these potential confounding factors requires familial data—either parent-offspring or sibling (Clark et al. 2019; Johnson et al. 2018)—but this type of familial phenotypic and genotypic data is rarely available in large enough samples to achieve adequate statistical power.

Abdellaoui et al. demonstrated the utility of including both parental and offspring phenotypes in ROH analyses in a 2015 study where they found a stronger negative association between the offspring's autozygosity and *parental* educational attainment (EA) ( $p < 9e-5$ ) than between the offspring's autozygosity and their own EA ( $p = 0.045$ ). This negative association between parental EA and offspring autozygosity was entirely mediated by the distance between parental birthplaces, with evidence to suggest that more highly educated parents tended to be more mobile on average and thus more likely to mate with an individual who shares more distant ancestors, potentially inducing  $F_{ROH} \sim$  trait associations that are due to sociological factors rather than reflecting a genetic effect arising from recessive/partially recessive alleles.

The Adolescent Brain Cognitive Development Study<sup>SM</sup> (ABCD Study<sup>®</sup>) is a large, longitudinal study with genetic and phenotypic data available for approximately 11,000 adolescents, as well as limited phenotypic data on their parents. The baseline sample includes children who were 9–11 years old in 2016–2017 and, importantly, also includes EA data for both parents. Additionally, the ABCD Study is diverse and includes a substantial number of individuals of non-European genetic ancestry. As such, this sample provides us an opportunity to examine (1) the distribution of autozygosity in a contemporary, trans-ancestral North American sample and (2) whether increased autozygosity is associated with decreased cognitive ability and parental EA.

## Methods

### Preregistration

We preregistered our analysis (osf.io/eqkty). Data and analyses presented in this manuscript closely resemble those described in the preregistration; any exceptions are described here. First, while we perform analyses separately for genetically confirmed non-Hispanic European ancestry and non-Hispanic African ancestry samples, we eventually chose to meta-analyze across ancestry groups. Deviations in sample sizes reflect a better understanding of the information available for each individual as we began implementing the analyses in the data. We also recoded the parental EA measure using codes different from those in the preregistration so that our measure of EA might more closely resemble that used by Abdellaoui et al. (2015). Lastly, we included additional sensitivity analyses not described in the preregistration which are strictly exploratory and can be found in the Supplementary Note.

### Sample

This study used genetic and phenotypic data from the ABCD study version 3.0, a long-term study of brain development through adolescence in over 11,000 children (Jernigan et al. 2018). Data were initially collected in children ages 9–10 across 21 sites and have subsequently been collected each year. Genetic samples were collected from the children in addition to demographic and phenotypic data on both the children and their parents.

Using a combination of self-report race and ethnicity and genetic principal component analysis (PCA), we separated the 11,875 ABCD Study participants into a predominantly European genetic ancestry subset ( $N = 5,556$ ) and predominantly African genetic ancestry subset ( $N = 1,584$ ), to account for differences in allele frequencies and linkage disequilibrium across populations (see *Genotypic Data Cleaning*), which can lead to differences in mean  $F_{ROH}$  across ancestry groups. We then called runs of homozygosity (ROHs) and estimated  $F_{ROH}$  (the proportion of the genome contained in ROHs) for the PCA-selected European- and African-ancestry individuals separately (see *ROH Calling*). To maximize sample size in each analysis, we included any individual if data for the necessary variables (outcome and covariates) were available. For example, if EA data were available for an individual's mother but not father, that individual was included in the test for an association between child's  $F_{ROH}$  and maternal EA, but excluded from the sample used to test for an association between child's  $F_{ROH}$  and paternal EA. As such,  $N$ s varied depending on data availability for each

individual and specific Ns are defined for each analysis in Table S1.

## Phenotypes

Parental EA was measured using the question “What is the highest grade or level of school you have completed or the highest degree you have received?” This field was only considered for individuals for whom we could confirm that the answer was for the biological parent of the child. To approximate the coding for EA in Abdellaoui et al., responses were recoded into the three categories: (1) Completed High school, GED or less: included individuals who reported never attending kindergarten or that they completed a grade between first and 12th, High school, a GED or equivalent diploma; (2) Completed higher education up to Bachelor’s Degree: included individuals who reported completing some college, an occupational Associate degree, an academic Associate degree or a Bachelor’s degree; and (3) Completed Master’s or Doctoral degree: included individuals who reported completing a Master’s or Doctoral degree.

Given the age of the children (current ages ranging from 14 to 15) in the study, the above definitions of EA were not applicable to the ABCD Study child subjects. Although EA is a multi-faceted construct, there is substantial evidence for a strong correlation between educational achievement and cognitive ability (Deary et al. 2007; Kaufman et al. 2009; Lynn and Meisenberg 2010; Strenze 2007), and previous studies have identified significant associations between  $F_{ROH}$  and cognitive ability (Clark et al. 2019; Howrigan et al. 2016; Johnson et al. 2018; Yengo et al. 2017); therefore, we also examined the association between  $F_{ROH}$  and the child’s cognitive ability, measured by their Overall Cognition Composite Score (Akshoomoff et al. 2013; Weintraub et al. 2013). We chose to use the score uncorrected for age, as age was already included as a covariate in our model (see *Statistical Analysis*).

## Genotypic Data Cleaning

The Rapid Imputation and COmputational PipeLine for Genome-Wide Association Studies (RICOPILI; Lam et al. 2020) was used to perform quality control (QC) on the ABCD Study phase 3 genotypic data prior to release by the ABCD Study Team, using RICOPILI’s default parameters. Notably, as the data we received from the ABCD Study had already been processed using the RICOPILI pipeline, we were not able to exactly replicate the procedures from Abdellaoui et al. We used the data from the ABCD Study Team to then match individuals to broad self-report racial groups using the ABCD Study parent survey. There were 6,787 individuals for whom their parents/caregivers indicated the

child’s race was only “white”, and 5,561 of those individuals did not endorse any Hispanic ethnicity/origin. We also identified 1,675 individuals for whom their parents/caregivers indicated the child’s race was only “black”, and 1,584 of those individuals did not endorse any Hispanic ethnicity/origin. After performing QC on these sub-samples, 5,556 non-Hispanic White and 1,584 non-Hispanic Black individuals were retained. Principal component analysis (PCA) in RICOPILI (Lam et al. 2020) was used to confirm the genetic ancestry of these individuals by mapping onto the 1000 Genomes reference panel (Auton et al. 2015), resulting in PCA-selected European- and African-ancestry subsets.

## Statistical Analysis

Statistical analyses consisting of ROH calling,  $F_{ROH}$  estimation and association testing were performed separately for the PCA-selected European- and African-ancestry subsets. Results of association tests were then meta-analyzed across the two ancestry groups using a fixed-effect model implemented with the “metafor” package in R (Viechtbauer, 2010). We first tested for heterogeneity using a random-effects model for each meta-analysis; however, tests for heterogeneity were non-significant ( $p > 0.05$ ), thus we chose to use fixed-effect models over random-effect models. We report the meta-analysis results as the main findings. Meta-analysis results were considered significant when  $p$ -value  $< 0.0125$  (significance level determined using a Bonferroni correction for four tests; association tests between  $F_{ROH}$  and cognitive scores, paternal EA, and maternal EA).

## ROH Calling

Following the procedures of previous studies (Clark et al. 2019), we cleaned the data further using PLINK 1.9 (Chang et al. 2015), excluding SNPs with  $> 3\%$  missingness or  $MAF < 5\%$  and excluding individuals with  $> 3\%$  missing data. After QC, 348,855 SNPs remained for the EUR sample and 370,271 SNPs remained for the AFR sample.

We called ROHs using PLINK 1.9 (Chang et al. 2015), following the approach taken in Abdellaoui et al. (2015) and the recommendations of Howrigan et al. (2011). We first pruned SNPs for LD (window size = 50, number of SNPs to shift after each step = 5, based on a variance inflation factor [VIF] of 2) using the following parameters in PLINK 1.9: `--indep 50 5 2`. After LD pruning, 127,679 and 183,624 SNPs were left for analysis of the EUR and AFR samples, respectively. Next, we defined an ROH as  $\geq 65$  consecutive homozygous SNPs, with no heterozygote calls allowed using the following PLINK code: `--homozyg-window-het 0 --homozyg-snp 65 --homozyg-gap 500 --homozyg-density 200`.

We also called ROHs using the method presented by Clark et al. (2019), which differs not only in the ROH calling procedure, but also in that there is no initial LD pruning. To call ROHs we used the following parameters in PLINK 1.9: --homozyg-window-snp 50; --homozyg-snp 50; --homozyg-kb 1500; --homozyg-gap 1000; --homozyg-density 50; --homozyg-window-missing 5; homozyg-window-het 1. Results using this ROH-calling method did not differ substantially from those based on the method described above, and are presented in the Supplementary Note.

### $F_{ROH}$ Calculation and Association Analysis

$F_{ROH}$  was calculated as the total length of ROHs summed for each individual, and then divided by the total SNP-mappable autosomal distance ( $2.77 \times 10^6$  kilobases). We used mixed effect regression models to test the association between (1) child's  $F_{ROH}$  and child's cognitive ability and (2) child's  $F_{ROH}$  and parental EA (both maternal and paternal EA, separately). In each linear regression model, child's  $F_{ROH}$  was the outcome variable and cognitive ability, maternal EA or paternal EA was included as a predictor variable. To account for the non-normal distribution of  $F_{ROH}$ , we calculated empirical p-values using a permutation procedure (as in Abdellaoui et al.) implemented in the permlmer package (Lee and Braun 2012) in R and ran 10,000 permutations to calculate an empirical p-value for each model. All empirical p-values were nearly identical to observed p-values in the original models; thus, we meta-analyzed the original effect sizes. Each model included the following covariates: child's age, child's biological sex, genotyping batch, testing site, family ID, and the first ten ancestry PCs. Testing site and family ID were modeled as random intercepts and all other covariates were fixed. We also performed a test for association between child's  $F_{ROH}$  and child's cognitive ability while accounting for maternal and paternal EA as additional covariates.

## Results

### Descriptive Statistics

We called ROHs and estimated  $F_{ROH}$  in 5,543 PCA-selected European-ancestry individuals and 1,578 PCA-selected African-ancestry individuals (7,121 individuals total). Despite using very similar ROH calling procedures, the estimated extent of inbreeding in the ABCD sample overall (average  $F_{ROH} = 0.00045$ ,  $SD = 0.00170$ ) was quite low compared to previous studies (Abdellaoui et al. (average  $F_{ROH} = 0.0016$ ), Howrigan et al. (average  $F_{ROH} = 0.0041$ ) and Power et al. (average  $F_{ROH} = 0.007$ )), with a minimum

$F_{ROH}$  of 0 (4,509 individuals had zero ROHs) and maximum  $F_{ROH}$  of 0.07967. We also computed the number of ROH segments, with the number of ROHs in each individual ranging from 0 to 33 and averaging at 0.537. The average total amount of ROH — that is, the combined length of all ROH segments — was 1.25 MB. Ancestry-specific estimates are available in the Supplementary Note. For descriptive statistics from child cognition and parental EA please see Table S2.

The relatively low level of autozygosity in the ABCD sample led us to hypothesize that generational differences may be contributing to differences in mean  $F_{ROH}$  across samples, considering the age of the individuals in the young ABCD sample. Using data from another North American sample (the Collaborative Study on the Genetics of Alcoholism (COGA) (Begleiter et al. 1995; Bucholz et al. 2017; Nurnberger et al. 2004)) and a linear mixed model (see Supplementary note), we tested for an association between birth year and  $F_{ROH}$  and did in fact identify a significant effect of birth year on  $F_{ROH}$  (beta = -0.06, s.e. = 0.01,  $p = 2.5e-9$ ).

### Autozygosity, Educational Attainment, and Cognitive Ability in the ABCD Study Sample

#### Association Between Child Cognitive Ability and Child $F_{ROH}$

Of the 7,121 individuals with ROH calls,  $F_{ROH}$  estimates, and information on covariates, data on child cognitive ability were available for 6,504 individuals. Child cognitive ability was negatively associated with  $F_{ROH}$  in the primary meta-analysis across ancestry groups (standardized beta = -0.046, s.e. = 0.013,  $p = 4.31e-4$ ) and the effect was similar to that observed by Abdellaoui et al. (standardized beta = -0.04, s.e. = 0.02). Based on the results from the European-ancestry sample in our study, we would predict on average a 1.59 standard deviation decline in cognitive ability for a 1 unit increase in  $F_{ROH}$ . In general, both the PCA-selected European- and African-ancestry subsamples showed consistent direction of effect, but effect size was larger in the PCA-selected African-ancestry subset (all results provided in Table 1). Using the ROH calling method from Clark et al. (2019), we also detected a negative association between child cognitive ability and  $F_{ROH}$  (see Supplementary Note). We also tested the association between child cognitive ability and  $F_{ROH}$  while accounting for both maternal and paternal EA in 3,983 individuals who had data for all three phenotypes, and found that effect size was slightly weaker than in the analysis where we did not control for parental EA (standardized beta = -0.037, s.e. = 0.017,  $p = 0.031$ ).

**Table 1** Association between child  $F_{ROH}$  and child's cognitive ability, maternal educational attainment and paternal educational attainment. EA = educational attainment, SE = standard error, N = sample size

Model	Primary trans-ancestral meta-analysis		PCA-selected European-ancestry			PCA-selected African-Ancestry		
	Standardized Beta (SE)	P	Standardized Beta (SE)	P	N	Standardized Beta (SE)	P	N
Child cognitive ability	-0.046 (0.013)	4.31e-4	-0.036 (0.015)	0.017	5,181	-0.075 (0.026)	0.004	1,323
Maternal EA	-0.032 (0.014)	0.026	-0.035 (0.016)	0.028	4,623	-0.019 (0.032)	0.545	1,178
Paternal EA	-0.042 (0.016)	0.010	-0.049 (0.017)	0.005	3,770	0.040 (0.057)	0.490	402
Child cognitive ability with parent EA covariates	-0.037 (0.017)	0.031	-0.039 (0.018)	0.031	3,626	-0.017 (0.054)	0.755	357

### Associations Between Parental Educational Attainment and Child $F_{ROH}$

Of the 7,140 individuals with ROH calls,  $F_{ROH}$  estimates, and information on covariates, data on maternal EA and paternal EA were available for 5,801 and 4,172 individuals, respectively. In the primary meta-analysis, maternal EA was negatively associated with  $F_{ROH}$ , although the association was not statistically significant accounting for multiple testing corrections (standardized beta = -0.032, s.e. = 0.014,  $p=0.026$ ). On the other hand, paternal EA was significantly negatively associated with  $F_{ROH}$  (standardized beta = -0.042, s.e. = 0.016,  $p=0.010$ ), but this association was not stronger than the association between  $F_{ROH}$  and child cognitive ability (standardized beta = -0.046) or as strong as the association between  $F_{ROH}$  and paternal EA observed in Abdellaoui et al. (standardized beta = -0.088).

### Discussion

In a sample of approximately 7,000 adolescents of PCA-selected European- and African ancestries, we found a negative association between child  $F_{ROH}$  and child cognitive ability (standardized beta = -0.046, s.e. = 0.013,  $p=4.31e-4$ ), replicating previous findings (Abdellaoui et al. 2015; Howrigan et al. 2016). Effect sizes were of similar magnitude in our study (standardized beta = -0.046, s.e. = 0.013) to Abdellaoui et al.'s study (standardized beta = -0.04; s.e. = 0.02). The negative association we identified between child  $F_{ROH}$  and child cognitive ability was slightly attenuated when maternal and paternal EA were included as covariates in the model (standardized beta = -0.037, s.e. = 0.017). However, given that the effect size did not change substantially in the European subset (standardized beta in model not covarying for parental EA = -0.036, s.e. = 0.015; standardized beta in model covarying for parental EA = -0.039, s.e. = 0.018), this attenuation appeared to be driven by the African ancestry subset in which controlling for EA had a substantial effect (standardized beta in model not covarying for parental EA = -0.075, s.e. = 0.026; standardized beta in model covarying for parental EA = -0.017, s.e. = 0.054).

Given the very high standard errors due to low sample sizes (357 individuals with complete parental EA data vs. 1,323 individuals included in model without parental EA covariates) in the African ancestry subset in which both parent's EA was controlled for, it is impossible to know if this attenuation is the results of a mediating effect of parental EA or due to sampling error. We find further support for the latter explanation by running the model without parental EA covariates in this subset of 357 individuals and observing a similarly attenuated effect size (standardized beta = -0.014, s.e. = 0.051).

While several previous studies suggest that a negative association between cognitive ability and  $F_{ROH}$  may indicate inbreeding depression on cognitive ability (Howrigan et al. 2016), Abdellaoui et al. suggested that their findings were the result of individuals with lower EA being less likely to migrate and more likely to mate with others who are also less educated and less mobile, leading to parents having more similar genetic backgrounds on average and their child therefore displaying more autozygosity while also being genetically predisposed to lower educational attainment. In support of this hypothesis, they found significant associations between child  $F_{ROH}$  and both maternal EA (standardized beta = -0.080; s.e. = 0.021) and paternal EA (standardized beta = -0.089; s.e. = 0.022) that were stronger than the association between  $F_{ROH}$  and the child's own EA (standardized beta = -0.04; s.e. = 0.02). However, not only do we find that our parent EA-child  $F_{ROH}$  associations are significantly weaker (yet still in the same direction of effect) compared to the parent EA-child  $F_{ROH}$  associations found in Abdellaoui et al., but in our sample, child  $F_{ROH}$  is similarly associated with child cognitive ability (standardized beta = -0.046; s.e. = 0.013) and both maternal EA (standardized beta = -0.032; s.e. = 0.014) or paternal EA (standardized beta = -0.042; s.e. = 0.016).

While we do not rule out lack of power as a contributing factor (Keller et al. 2011), we deem it unlikely to be the sole explanation for our weaker results for parental EA measures, as the current sample size was large ( $N \sim 7,000$ ) relative to Abdellaoui et al.'s study ( $N \sim 2,000$ ), which found a highly significant association between  $F_{ROH}$  and both maternal and paternal EA. Given the smallest reported effect size

in Abdellaoui et al.'s study (standardized beta = -0.04, s.e. = 0.02) and the reported  $N=2,007$ , we estimate that we would have 84% power to detect an effect of the same size in our sample of 5,181 European ancestry individuals, given that the standard deviation of  $F_{ROH}$  is similar across the two studies: 0.002 in our European-ancestry subset vs. 0.003 in Abdellaoui et al. Below, we consider other possible explanations for our differing results.

Notably, the current sample and the sample used in Abdellaoui et al. 2015 were derived from two different countries (the United States and the Netherlands, respectively), which bear varying degrees of resemblance in terms of cultural, social, and economic contexts. The possible influence of these differences across countries are evident in previous studies which have found opposite directions of associations between autozygosity and various phenotypes. For example, previous research has identified a negative association between  $F_{ROH}$  and EA in a Dutch population (Abdellaoui et al. 2015) and cognitive ability in a broader European population (Howrigan et al. 2016), and oppositely, a positive association between  $F_{ROH}$  and cognitive ability in both an American sample (Córdova-Palomera et al. 2018) and a UK sample (Power et al. 2014). We consider that the results of our current study, which uses a contemporary American sample, may differ from previous findings partly as a result of the sample's demographics.

An important aspect of the Abdellaoui et al. study is the discovery that migration is a significant mediator in the relationship between parental EA and child's  $F_{ROH}$ . Individuals with higher EA on average had traveled a greater distance between their birthplace and their spouse's birthplace, as well as between their birthplace and their child's birthplace (Abdellaoui et al. 2015). That is to say, EA and mobility were positively associated, resulting in individuals with higher EA being somewhat more likely to mate with more genetically dissimilar individuals on average. As a result, the offspring of individuals with higher EA may be more outbred as well as inheriting a predisposition for higher EA. In support of this theory, Abdellaoui et al. found that the association between parental EA and child's  $F_{ROH}$  was fully mediated by the distance between maternal and paternal birthplace, although birthplaces for both offspring and parents only included locations within the Netherlands. While the Abdellaoui et al. study only considered internal migration, the ABCD sample includes children born to individuals who may have migrated internationally, not just within the same country, as parents in the ABCD study born in a wide variety of places, which range from the United States (data on exact location not provided) to countries like Mexico and Yemen. We did not have information available on city or state-specific places of birth, leaving us unable to investigate the relationships between EA, mobility, and

$F_{ROH}$  in our sample. While the impact of migration and its relationships with  $F_{ROH}$  and EA were potentially more straightforward and interpretable in the context of domestic migration in the Netherlands, complicated political and historical contexts which influence international migration and differ country to country likely produce variable relationships between EA and autozygosity, and the lack of state- or even region-specific data limit our ability to draw conclusions and comparisons in the ABCD data.

Furthermore, genetic ancestry and geography may relate differently across countries according to historical contexts. Individuals migrated to the US from many different regions much more recently than in the Netherlands, making the relationship between genetic differences and geographical distance in the US less predictable than the established, linear relationship in the Netherlands (Abdellaoui, Hottenga, Knijff, et al., 2013; Byrne et al. 2020). That is to say, a further distance between the birthplaces of two individuals is less likely to correlate with less shared ancestry between those two individuals in the US compared to Europe. As a result, we might expect migration to have a weaker effect on autozygosity's associations with EA in the US.

Incidentally, we found very low levels of autozygosity in the ABCD sample compared to previous studies. Whereas the variance of  $F_{ROH}$  was similar to that of previous studies, the mean  $F_{ROH}$  observed in the current study (average  $F_{ROH} = 0.0005$ ) was much lower than that observed in Abdellaoui et al. (average  $F_{ROH} = 0.0016$ ), Howrigan et al. (average  $F_{ROH} = 0.0041$ ) and Power et al. (average  $F_{ROH} = 0.007$ ). While the mean  $F_{ROH}$  in a sample is not pertinent to the statistical power to detect associations between  $F_{ROH}$  and complex traits, we suspect that generational differences in mean  $F_{ROH}$  may still be relevant to the findings of this and other studies which examine  $F_{ROH}$ . The participants of the ABCD study were primarily born between 2006 and 2007, with the median birth year of *parents* of ABCD individuals being 1976, compared to Abdellaoui et al.'s study in which two-thirds of the offspring studied were born in 1984 or earlier. To our knowledge, there are few ROH studies that have included young (birth year > 1990) US samples, but one study of 809 North Americans of European descent aged 19–99 years old found that ROH significantly decreased in size and frequency as chronological age decreased; furthermore, the authors predicted a decline in percent  $F_{ROH}$  of ~0.1 for every 20 years' difference in birth year (Nalls et al. 2009). Given that the ABCD participants are around 20 years younger than the subjects in Abdellaoui et al., and the average percent  $F_{ROH}$  in Abdellaoui et al.'s sample was ~0.16, we might expect the average percent  $F_{ROH}$  in ABCD to be ~0.06, or an average  $F_{ROH}$  of 0.0006; this is similar to the observed average  $F_{ROH}$  of 0.0005.

We conducted our own assessment of this phenomenon by measuring this trend within COGA (Begleiter et al. 1995; Bucholz et al. 2017; Nurnberger et al. 2004) to assess differences in autozygosity over time. We ran a linear mixed model which further confirmed a significant effect of birth year on  $F_{ROH}$  (beta = -0.06, s.e. = 0.01,  $p = 2.5e-9$ ). Furthermore, we compared two cohorts from similar geographic regions in Howrigan et al.'s 2016 study to assess differences in autozygosity according to generation in a UK sample, to see if the pattern held across cultures. In the young (average age = 11.67 years old) GAIN UK cohort, the average  $F_{ROH}$  was 0.0019, while the average  $F_{ROH}$  calculated in the older English MANC cohort (average age = 64.9 years old) was 0.0047 (from Tables 1 and 2 in Howrigan et al.).

Therefore, we hypothesize that year of birth may be impacting  $F_{ROH}$  estimates across studies, given exponential increases in population size and urbanization (Bongaarts 2009) contributing to decreasing levels of inbreeding over time (Bittles and Black 2010; Campbell et al. 2009; Nalls et al. 2009). Thus, the generational difference between our study sample, ABCD, and those of previous ROH studies may partly explain the lower levels of autozygosity observed in the current study. The ABCD sample was genotyped on the Smokescreen array (Baurley et al. 2016), which is built on an Affymetrix backbone with additional addiction-focused content. As Abdellaoui et al.'s sample was genotyped on the Affymetrix 6.0 array, and we followed as similar genotyping QC and ROH calling procedures as possible, it seems unlikely that differences in SNP panel or calling algorithms are responsible for the lower levels of autozygosity observed in our study.

In summary, we found a negative association between estimated autozygosity and child cognitive ability, such that individuals with lower estimates of  $F_{ROH}$  tended to have higher levels of cognitive ability, replicating previous findings. Given the age of the sample, we were not able to assess the association between  $F_{ROH}$  and individual's own EA, but we could assess the association between  $F_{ROH}$  and their parents' EA. We found weaker associations between  $F_{ROH}$  and maternal EA or paternal EA than observed by Abdellaoui et al., although findings were generally in the expected, negative direction of effect. We hypothesize that these mixed results are due to a combination of generational differences in autozygosity and the complex mechanisms which influence both EA and mobility in different countries. Future studies should carefully characterize and consider how the effects of assortative mating, migration patterns, and generational differences in the distribution of  $F_{ROH}$  may influence autozygosity-trait associations across samples.

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**Data Availability** Genetic and phenotypic data in the ABCD sample are available for download for approved researchers from the NIMH Data Archive.

## Declarations

**Conflict of Interest** The authors report no conflicts of interest to disclose.

**Ethics Approval** This study was approved by the local Institutional Review Board.

**Consent to Participate** All participants in ABCD provided informed consent (or assent).

**Consent for Publication** Not applicable.

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