The transferability of lipid loci across African, Asian and European cohorts

Nikita Telkar[1,25], Theresa Reiker[2,3,4,5,25], Robin G. Walters[6,7], Kuang Lin[7], Anders Eriksson[8], Deepti

Gurdasani[2], Arthur Gilly[2,9], Lorraine Southam[2,9,10], Emmanouil Tsafantakis[11], Maria Karaleftheri[12], Janet

Seeley[13,14,15], Anatoli Kamali[15], Gershim Asiki[15,16,17], Iona Y. Millwood[6,7], Michael Holmes[6,7], HuaidongDu[6,7],

Yu Guo[18], Understanding Society Scientific Group[19], Meena Kumari[19], George Dedoussis[20], Liming

Li[21], Zhengming Chen[7], Manjinder S. Sandhu[22], Eleftheria Zeggini[2,9,], Karoline Kuchenbaecker[2,23,24]*

[1] Department of Genetics, Evolution and Environment, University College London, London WC1E 6BT,

UK

[2] Department of Human Genetics, Wellcome Sanger Institute, Hinxton, CB10 1SA, UK

[3] Department of Public Health and Primary Care, University of Cambridge, Cambridge CB1 8RN, UK

[4] Swiss Tropical and Public Health Institute, Basel, Switzerland

[5] University of Basel, Basel, Switzerland

[6] Medical Research Council Population Health Research Unit (MRC PHRU), Nuffield Department of

Population Health, University of Oxford, Oxford, UK

[7] Clinical Trial Service Unit and Epidemiological Studies Unit (CTSU), Nuffield Department of Population

Health, University of Oxford, Oxford, UK

[8] Department of Medical and Molecular Genetics, King's College London, London SE1 9RT, UK

[9] Institute of Translational Genomics, Helmholtz Zentrum München, German Research Center for

Environmental Health, Neuherberg, Germany

[10] Wellcome Trust Centre for Human Genetics, University of Oxford, Oxford, OX3 7BN, UK

[11] Anogia Medical Centre, Anogia, 740 51, Greece

[12] Echinos Medical Centre, Echinos, Xanthi 67300, Greece

[13] Department of Global Health and Development, London School of Hygiene & Tropical Medicine,

London WC1E 7HT, UK

[14] Faculty of Public Health and Policy, London School of Hygiene & Tropical Medicine, London WC1E

7HT, UK

[15] Medical Research[1] Council/Uganda Virus Research Institute and London School of Hygiene

(MRC/UVRI and LSHTM), Uganda Research Unit, Entebbe, Uganda

[16] African Population and Health Research Center, Nairobi, Kenya

[17] Department of Women's and Children's Health, Karolinska Institutet, Stockholm, Sweden

[18] Chinese Academy of Medical Sciences, Beijing 100730, China

[19] Institute for Social and Economic Research, University of Essex, Wivenhoe Park, Colchester, Essex,

UK

[20] Department of Nutrition and Dietetics, School of Health Science and

Education, Harokopio University of Athens, Greece

[21] Department of Epidemiology and Biostatistics, School of Public Health, Peking University, Beijing

100191, China

[22] Department of Medicine, University of Cambridge, Cambridge CB2 0QQ, UK

[23] Division of Psychiatry, University College of London, London W1T 7NF, UK

[24] UCL Genetics Institute, University College London, London WC1E 6BT, UK

[25] These authors contributed equally to this work

* Correspondence to: k.kuchenbaecker@ucl.ac.uk

Abstract

The majority of genetic studies for cardiometabolic traits were based on samples with European

ancestry. Our aim was to assess whether genetic variants associated with blood lipids, a major risk

factor for CVD, are shared across different populations.

We compared genetic associations with lipids between samples from Uganda (N=6,407), China

(N=21,295), Japan (N=162,255), the UK (N=9,961) and Greece (N=3,586). Using simulations, we

established trans-ethnic colocalization as a method to distinguish shared from population-specific

trait loci.

Genetic correlations for HDL, LDL and triglycerides between European ancestry and Asian cohorts

were close to 1. A polygenic score based on established LDL-cholesterol-associated loci from European

discovery samples had consistent effects on serum levels in samples from the UK, Uganda and Greek

population isolates (r=0.23 to 0.28, $p<1.9 \times 10^{-14}$). Overall, ~75% of the major lipid loci from European

discovery studies displayed evidence of replication at $p<10^{-3}$, except triglyceride loci in the Ugandan

samples of which only 10% replicated. Specific replicating loci were identified using trans-ethnic

colocalization. Ten of the fourteen lipid loci that did not replicate in the Ugandan population had

pleiotropic associations with BMI in European ancestry samples while none of the replicating loci did.

While lipid associations were highly consistent across European and Asian populations, there was a

lack of replication particularly for established triglyceride loci in the Ugandan population. These loci

might affect lipids by modifying food intake or metabolism in an environment offering diets rich in

certain nutrients. This suggests that gene-environment interactions could play an important role for

the transferability of complex trait loci.

Introduction

Cardiovascular disease (CVD) is one of the leading causes of death worldwide[1]. As the predictive ability of common variants for CVD and cardiometabolic traits improves, risk prediction in clinical settings finds increasing consideration[2,3]. The foundations for this were provided by genome "white" association studies: the majority of samples included in these studies were British or US-Americans with European ancestry[4,5] which does not accurately representation the ethnically and ancestrally diverse populations of these nations. Moreover, three quarters of CVD deaths occur in low- and middle-income countries with incidences further rising[6]. Consequently, it is important to determine whether cardiometabolic trait loci are transferable to other populations. We focussed on blood lipids, a major cardiovascular risk factor.

Previous research assessed the effects of different allele frequencies and linkage disequilibrium (LD) on genetic associations across ancestry groups[7]. Here we ask the fundamental question whether causal variants for lipid biomarkers are shared across populations. Heterogeneity in effects of variants could result from epistasis or gene-environment interactions. However, differences in LD structure between populations make it difficult to compare associations between ancestry groups because the observable effect of a variant depends on its correlation with the causal variant(s)[7]. Differences in frequency also impact on the power to detect associations in other ancestry groups.

We employed several strategies which account for these effects to quantify the extent to which genetic variants affecting lipid biomarkers are shared between individuals from Europe/North America, Asia, and Africa. We assessed the transferability of individual signals and compared association patterns across the genome using data from the African Partnership for Chronic Disease Research – Uganda (APCDR-Uganda, N=6,407)[8], China Kadoorie Biobank (CKB, N=21,295)[9], the Hellenic Isolated Cohorts (HELIC-MANOLIS, N=1,641 and HELIC-Pomak, N=1,945)[10,11], and the UK Household Longitudinal Study (UKHLS, N=9,961)[12]. We also used summary statistics from Biobank Japan (BBJ, N=162,255)[13] and the Global Lipid Genetics Consortium (European ancestry, GLGC2013 N=188,577, GLGC2017 N=237,050)[14,15].

Results

We assessed replication rates across established lipid-associated variants in different populations. We

distinguished major lipid loci, i.e. those with $p<10^{-100}$ in the largest European ancestry GWAS. In this

context, replication was operationalised as at least one variant from the credible set associated at

$p<10^{-3}$ in the target study. As a benchmark, we also assessed replication in two European ancestry

studies. We found evidence of replication for 76.5% of major HDL loci in these two studies (Table 1).

For the non-European groups replication rates ranged from 70.6 to 82.4%. Similar replication rates

were observed for LDL loci (61.5-76.9%). For major triglycerides (TG) loci, replication rates ranged

from 78.9 to 94.7%, except in APCDR-Uganda. Only 10.5% of these loci showed evidence of replication

in that sample. Replication rates for known loci with $p \geq 10^{-100}$ in the discovery set were generally

moderate to low. However, Biobank Japan, the largest study, had markedly higher replication rates

for these loci than the other studies.

Trans-ethnic genetic correlations were estimated between the three largest studies, China Kadoorie

Biobank, Biobank Japan and GLGC2013. Correlations were high for each biomarker and were not

significantly different from 1 (Figure 1, Supplementary Table 1). We also compared associations across

biomarkers. This consistently showed negative genetic correlations between TG associations and HDL

associations, with estimates ranging from r_{gen}=-0.48 to r_{gen}=-0.86.

In order to assess patterns of sharing of risk alleles for the smaller studies, we constructed polygenic

scores based on the established lipid loci from discovery samples with European ancestry and

estimated the score associations with levels of HDL, LDL and TG in HELIC, APCDR-Uganda and also

UKHLS as a benchmark (Figure 2). All genetic scores were significantly associated with their respective

target lipid in the three European samples with largely consistent correlation coefficients and mutually

overlapping 95% confidence intervals (CIs) (Table 2). For HDL, LDL and TG, the estimated correlation

coefficients had a range of 0.27-0.28, 0.23-0.28 and 0.20-0.24, respectively. In APCDR-Uganda, the

strongest association was observed for LDL (r=0.28, SE=0.01, p=1.9x10^{-107}). The HDL association was

attenuated compared to the European samples (r=0.12, SE=0.01, p=6.1x10^{-22}). The effect of the TG

score was markedly weaker (r=0.06, SE=0.01, p=4.5x10^{-7}). We also assessed associations between a

given score and levels of each of the other biomarkers (Supplementary Table 2). In line with the trans-

ethnic genetic correlation results, we observed inverse associations between the HDL score and TG

levels and vice versa in all studies, except APCDR-Uganda.

Differences in LD structure, MAF and sample size make it difficult to assess replication for individual

loci. Therefore, we propose a new strategy to assess evidence for shared causal variants between two

populations: trans-ethnic colocalization. For this we re-purposed a method that was originally

developed for colocalization of GWAS and eQTL results: Joint Likelihood Mapping (JLIM)[16]. In order to

assess its performance for GWAS results from samples with different ancestry, we carried out a

simulation study. UK Biobank (UKB) was used as a European ancestry reference and compared to CKB

and APCDR-Uganda. Phenotypes were simulated. In the simulations of distinct causal variants in the

non-European and the reference group, the frequencies of false negatives were close to 0.05 as

expected (Table 3), with an almost uniform distribution of p-values (Supplementary Figure 1). The

power to detect shared associations was good for both populations: 73.1% for APCDR-Uganda and

93.1% for CKB. To investigate whether the lower power for APCDR-Uganda could be due to its smaller

sample size, we reran the analyses for CKB using a random subset of samples matching the sample

size of APCDR-Uganda. The results were similar to the ones for the full CKB set, suggesting that the

power of this trans-ethnic colocalization method decreases somewhat with greater genetic distance

between the populations that are compared.

We applied trans-ethnic colocalization for established lipid loci to each study with UKHLS as the

reference. There was evidence for significant (p$_{jlim}$<0.05) colocalization with at least one of the target

studies for about half of the major lipid loci (Supplementary Table 3). For several major TG loci, such

as *GCKR* at 2p23.3 or *LPL* at 8p21.3, strong evidence of replication in the Asian studies was observed

while there was no evidence of association in APCDR-Uganda (Figure 3b,c).

We compared major lipid loci showing evidence of replication in APCDR-Uganda with those not

displaying any suggestion of replication. The proximal genes of replicating loci were enriched for lipid

pathways including lipoprotein metabolism, lipid digestion mobilisation and transport, chylomicron-

mediated lipid transport and metabolism of lipids and lipoproteins. The proximal genes of the non-

replicating loci were enriched for several other pathways in addition to lipid metabolism, including

SHP2 signalling, ABV3 integrin pathway, cytokine signalling in immune system, cytokine-cytokine

receptor interaction and transmembrane transport of small molecules (Supplementary Figures 2 and

3). We also assessed the associations of these loci with BMI in samples with European ancestry using

publicly available summary statistics from the GIANT consortium[17] (N≥484,680) (Table 4). Ten of the

fourteen non-replicating lipid loci had pleiotropic associations with BMI at a Bonferroni-adjusted

threshold of p<0.0024. None of the seven replicating lipid loci were associated with BMI. We also

assessed four additional loci that were not significant in the trans-ethnic colocalization but displayed

small regional p-values in APCDR-Uganda. Out of these only APOE was significantly associated with

BMI (p=4×10^{-21}).

Discussion

Recent efforts to increase global diversity in genetics studies have been vital, enabling this

comprehensive cross-population comparison of genetic associations with blood lipids. We provide

evidence for extensive sharing of genetic variants that affect levels of HDL- and LDL-cholesterol and

triglycerides between individuals with European ancestry and samples from China, Japan and Greek

population isolates. There was evidence of replication for about three quarters of major HDL and LDL

loci (and triglyceride loci except in APCDR-Uganda). This was highly consistent across all studies.

Estimates of trans-ethnic genetic correlations between European, Chinese and Japanese samples were

close to 1. Associations of polygenic scores for LDL were not attenuated in the Ugandan population

compared to the UK samples. All PRS associations in the two Greek isolated populations were also

highly consistent with those in the UK samples.

Previous studies that compared the direction of effect of established loci or assessed associations of

polygenic scores reported differing degrees of consistency[18–29]. However, most of them were

conducted in American samples with diverse ancestry, had smaller sample sizes and applied a single-

variant look-up or PRS for a limited number of genetic variants. The high degree of consistency for

cholesterol biomarkers we observed also contrasts with previously reported trans-ethnic genetic

correlations for other traits, such as major depression, rheumatoid arthritis, or type 2 diabetes, which

were substantially different from 1[30,31]. In a recent application using data from individuals with

European and Asian ancestry from the UK and USA, the average genetic correlation across multiple

traits was 0.55 (SE = 0.14) for GERA and 0.54 (SE=0.18) for UK Biobank[32].

Differences in LD structure, MAF and sample size make it difficult to assess replication of individual

loci. We therefore propose a new approach: trans-ethnic colocalization. Simulations showed

consistent control of type I error rates as well as good power to detect associations. Colocalization

identified shared causal variants even at loci where none of the individual variants were associated at

stringent p-value thresholds. However, for many of the major lipid loci, more than one independent

association signal was identified in discovery GWAS[15]. When these are located in close proximity to

each other, they can interfere with the trans-ethnic colocalization analysis because JLIM assumes a

single causal variant (Figure 3d). Therefore, future work should extend this approach to accommodate

loci harbouring multiple causal variants. Using trans-ethnic colocalization, we showed that many

established loci for triglycerides did not affect levels of this biomarker in Ugandan samples. This

included loci associated at genome-wide significance in all the other studies, such as *GCKR* at 2p23.3

or *LPL* at 8p21.3. The polygenic score for triglycerides had a weak effect on measured levels in APCDR-

Uganda. This is unlikely to be an artefact of unreliable measurement: triglyceride levels had a heritable

component in this sample (SNP heritability of 0.25, SE=0.05[8]) and there were some genome-wide

significant associations (Supplementary Figure 6e). It is also unlikely that this can be explained purely

by differences in LD and MAF because they would affect the analyses of the other two biomarkers as

well. Instead these discrepancies could be caused by gene-environment interactions. Most of the lipid

loci that did not replicate in the Ugandans had pleiotropic associations with BMI in European ancestry

samples while none of the replicating loci were linked to BMI. It is possible that the non-replicating

variants affect the amount of food intake with downstream consequences for lipid levels. This might

require an environment offering diets that are rich in certain nutrients. While the replicating genes

were almost exclusively linked to pathways of lipid metabolism, the non-replicating genes were

involved in a diverse pathways which is in line with hypothesis. An alternative explanation could be

that the non-replicating loci are involved in metabolising nutrients given a particular diet that is not

common in Uganda with downstream consequences for weight.

Overall, this could suggest an important role of environmental factors in modifying which genetic

variants affect lipid levels. Studying the causes for discordant loci between groups has promise to

further elucidate the biological mechanisms of lipid regulation and other complex traits. Applying

genetic risk prediction within clinical settings is receiving increasing attention. Our findings

demonstrate that the transferability of genetic associations across different ancestry groups and

environmental settings should be assessed comprehensively for medically relevant traits. This is

important in order to maximise the potential of precision medicine to yield health benefits that are

widely shared within and across populations. Ongoing programs in underrepresented countries[33],

such as the Human Hereditary and Health in Africa Initiative[34], and programs focussing on

underrepresented groups, such as PAGE[35], All of Us[36], or East London Genes and Health[37], could

provide the basis for this.

Methods

Data resources

We included data from the Global Lipid Genetics Consortium (European ancestry samples only, GLGC),

The UK Household Longitudinal Study (UKHLS), two isolated populations from the Greece Hellenic

Isolated Cohorts (HELIC) , a rural West Ugandan population from the African Partnership for Chronic

Disease Research (APCDR-Uganda) study, China Kadoorie Biobank (CBK), and Biobank Japan (BBJ). In

addition, we used data from European ancestry samples from the eMERGE network to confirm

replication rates of known loci. Raw genotype and phenotype data were available for UKHLS, APCDR-

Uganda, CKB, HELIC-MANOLIS, HELIC-Pomak and eMERGE. Our analyses were based on summary

statistics for BBJ and GLGC. Study details are provided in Supplementary Table 3.

Each study underwent standard quality control. Details of the genome-wide association analyses with

lipid traits have been previously described for GLGC[14], BBJ[13], HELIC[10], and UKHLS[12]. The association

analysis for APCDR-Uganda was carried out within a mixed model framework using GEMMA[38]. Rank-

based inverse normal transformation was applied to the lipid biomarkers after adjusting for age and

gender. In China Kadoorie Biobank, lipid levels were regressed against eight principle components,

region, age, age^2, sex, and - for LDL and TG - fasting $time^2$. LDL levels were derived using the Friedewald

formula. After rank-based inverse normal transformation, the residuals were used as the outcomes in

the genetic association analyses using linear regression. In eMERGE, biomarkers were adjusted for

age, gender, kidney disease, statin use, type 2 diabetes status and disorders relating to growth

hormones. Associations were carried out within a mixed model framework using BOLT-LMM[39].

Manhattan plots for eMerge, UKHLS, BBJ, CKB, and APCDR-Uganda are shown in Supplementary

Figures 4-6.

Established lipid loci

A list of established lipid-associated loci was extracted from the latest Global Lipid Genetics

Consortium (GLGC2017) publication[15] reporting 444 independent variants in 250 loci

associated at genome-wide significance with HDL, LDL, and triglyceride levels. We excluded three LDL

variants where the association was not primarily driven by the samples with European ancestry. We

assessed evidence of replication of the loci, applied trans-ethnic colocalization and used them to

construct polygenic scores.

Replication of established lipid loci

We assessed evidence of replication across these established lipid variants. For loci harbouring

multiple signals, we only kept the most strongly associated variant. This left 170 HDL, 135 LDL and 136

TG variants. We distinguished major loci, i.e. those with $p<10^{-100}$ in GLGC2017. For each lead SNP we

identified all variants in LD ($r^2>0.6$) based on the European ancestry 1000 Genomes data. We assessed

whether the lead or any of the correlated variants, henceforth called credible set, displayed evidence

of association in the target study. We used a p-value threshold of $p<10^{-3}$. If this was not the case, we

tested whether there was any other variant with evidence of association within a 50Kb window. While

this p-value threshold might not be appropriate to provide conclusive evidence of replication for

individual loci, we used this to test evidence of replication across sets of loci. As a benchmark, we

computed the minimum p-value in 1000 random windows of 50Kb for each study. Less than 5% of

random windows had a minimum $p<10^{-3}$ for the non-European ancestry studies.

Trans-ethnic genetic correlations

We used the popcorn software[30] to estimate trans-ethnic genetic correlations between studies while

accounting for differences in LD structure. This provides an indication of the correlation of causal-

variant effect sizes across the genome at SNPs common in both populations. Variant LD scores were

estimated for ancestry-matched 1000 Genomes data for each study combination. The estimation of

LD scores failed for chromosome 6 for some groups. We therefore left out chromosome 6 from all

comparisons. Variants with imputation accuracy $r^2<0.8$ or MAF<0.01 were excluded. Popcorn did not

converge for any of the studies with less than 20,000 samples. Therefore, results are presented for

comparisons between GLGC2013, CKB and BBJ. We estimated effect rather than impact correlations.

Polygenic scores

We created polygenic scores based on the established lipid loci and assessed their associations with

lipid levels in UKHLS, the HELIC cohorts, and APCDR-Uganda, as it was not possible to compute trans-

ethnic genetic correlations for these studies. For HELIC and UKHLS, extreme values ($\mu \pm 3\,SD$, sex

stratified) were filtered. Age, age^2 and sex were adjusted for by regressing them on the biomarker

values and using the residuals as outcomes for subsequent analyses. For each biomarker in each

sample set, we checked normality and homoscedasticity. HDL and LDL were approximately normally

distributed. For TG levels, a Box Cox transformation was used to normalize the data. APCDR-Uganda

phenotype data were rank-based inverse normally transformed.

To make sure PRS were comparable across studies, we excluded variants that were absent, rare

(MAF<0.01) or badly imputed (r^2<0.8) in any of the studies and variants that had different alleles from

those in the GLGC. The variant with larger discovery p-value from each correlated pair of SNPs (r^2>0.1)

was also removed. This left 120, 103 and 101 variants for HDL, LDL and TG, respectively. We created

trait-specific weighted PRS. The β-regression coefficients from SNP-trait associations in GLGC2017[15]

were used as weights. All biomarkers and scores were scaled to mean=0 and standard deviation=1 for

each study so that the regression coefficient represent estimates of the correlation between scores

and biomarkers.

We carried out association analyses between each polygenic score and each biomarkers using a linear

mixed model with random polygenic effect implemented in GEMMA[38] in order to account for

relatedness and population structure. We used a Bonferroni correction to adjust for multiple testing

of three PRS with three different biomarker outcomes (p<0.05/9=0.0056).

Trans-ethnic colocalization

Differences in allele frequency, LD structure and sample size make it difficult to assess whether a given

GWAS hit replicates in samples with different ancestries. Therefore, we applied trans-ethnic

colocalization. Colocalization methods test whether the associations in two studies can be explained

by the same underlying signal even if the specific causal variant is unknown. The joint likelihood

mapping (JLIM) statistic was developed by Chun and colleagues to estimate the posterior probabilities

for colocalization between GWAS and eQTL signals and compare them to probabilities of distinct

causal variants[16]:

$$\Lambda = \sum_{i \in N_\theta^1(m^*)} L_1(i) \times log \frac{L_1(i)L_2(i)}{\max_{j \notin N_\theta^2(i)} L_1(i)L_2(j)}$$

i SNP
m^* lead SNP
$L_1(i)$ likelihood of SNP i being causal for trait 1
$L_2(i)$ likelihood of SNP i being causal for trait 2
$N_\theta^1(i), N_\theta^2(i)$ sets of SNPs in LD with i
θ LD threshold

JLIM explicitly accounts for LD structure. Therefore, we assessed whether it is suitable for trans-ethnic

colocalization. For samples with summary statistics, LD scores were estimated using ancestry matched

samples from the 1000 Genomes Project v3. JLIM assumes only one causal variant within a region in

each study. We therefore used a small windows of 50Kb for each known locus to minimise the risk of

interference from additional association signals. Distinct causal variants were defined by separation

in LD space by $r^2 \geq 0.8$ from each other. We excluded loci within the major histocompatibility region

due to its complex LD structure. We used a significance threshold of $p<0.05$ given the evidence of

association of the established lipid loci in Europeans and the overall evidence for shared causal genetic

architecture across populations for most lipid traits from our other analyses. We compared each

target study to UKHLS because of their high level of homogeneity in terms of ancestry, biomarker

quantification and study design.

Simulation

To test the power of trans-ethnic colocalization to detect associations shared between pairs of

populations with different ancestry, we ran JLIM on two sets of simulated traits with realistic effect

size and environmental noise level. The first set of simulations used the same causal variant in both

populations, whereas the second set of simulations discordant causal variants, chosen randomly. We

sampled 10,000 randomly chosen biallelic variants with MAF>0.05 and simulated random phenotypes

in CKB, APCDR-Uganda und 50,000 individuals with British ancestry from UK Biobank. For each data

set relatives were excluded. We also sub-sampled CKB to match the smaller number of individuals in

APCDR-Uganda in order to test whether different performance is due to ancestry or sample size. We

used a simple linear model to generate the phenotype for each individual i:

$$y_i = \beta * (x_i - 1) + \eta_i$$

where y is the phenotype value, β is the effect size, x is the number of the alternate alleles carried at

the locus and $\eta_i \sim N(0, \sigma^2)$, where σ^2 is the variance of the environmental noise and $Cov(\eta_i, \eta_j) = 0$.

We used β = 0.25 and σ^2 = 1.

Comparison of replicating with non-replicating loci

We aimed to assess whether there are systematic differences between loci that are shared between

European ancestry samples and APCDR-Uganda and loci that are not. We identified all loci with

evidence of replication based on the above definition that also had significant (p<0.05) colocalization.

We only kept one variant per region. We contrasted them with loci where none of the evidence

suggested replication: p>0.05 for colocalization, no variant with a lipid association at $p<10^{-3}$ in the

region and the lead variant from the discovery study was not rare in APCDR-Uganda. We identified

the nearest protein coding gene for each locus and carried out a pathway analyses for the two sets

using FUMA[40]. We also assessed the associations of the lead variants with body mass index (BMI) in

European ancestry samples using results from a meta-analysis between the GIANT consortium and UK

Biobank[17]. We used a Bonferroni adjusted p-value threshold.

Data availability

The UKHLS EGA accession number is EGAD00010000918. Genotype-phenotype data access for UKHLS

is available by application to Metadac (www.metadac.ac.uk). eMERGE is available through dbgap

(study   ID: phs000888.v1.p1).   Summary   statistics   for   GLGC

(http://csg.sph.umich.edu/abecasis/public/) and Biobank Japan (http://jenger.riken.jp/en/) are

publicly available. The HELIC genotype and WGS datasets have been deposited to the European

Genome-phenome   Archive   (https://www.ebi.ac.uk/ega/home):   EGAD00010000518;

EGAD00010000522; EGAD00010000610; EGAD00001001636, EGAD00001001637. The APCDR

committees are responsible for curation, storage, and sharing of the APCDR-Uganda data under

managed access. The array and sequence data have been deposited at the European Genome-

phenome Archive (EGA, http://www.ebi.ac.uk/ega/, study accession number EGAS00001000545,

datasets EGAS00001001558 and EGAD00001001639 respectively) and can be requested through

datasharing@sanger.ac.uk. Requests for access to phenotype data may be directed to

data@apcdr.org.

Supplemental data

The supplemental data contain three figures and two tables.

Funding and acknowledgements

We would like to thank the participants and volunteers of the each of the studies. We appreciate the

advice received from Brielin Brown regarding the use of Popcorn and from Shamil Sunyaev and Sung

Chun regarding the suitability of JLIM for trans-ethnic colocalization.

This work was funded by the Wellcome Trust (WT098051), (212360/Z/18/Z), and the European

Research Council (ERC-2011-StG 280559-SEPI). The MANOLIS study is dedicated to the memory of

Manolis Giannakakis, 1978-2010. We thank the residents of the Pomak villages and of the

Mylopotamos villages for taking part. The HELIC study has been supported by many individuals who

have contributed to sample collection (including Antonis Athanasiadis, Olina Balafouti, Christina Batzaki, Georgios Daskalakis, Eleni Emmanouil, Pounar Feritoglou, Chrisoula Giannakaki, Margarita Giannakopoulou, Kiki Kaldaridou, Anastasia Kaparou, Vasiliki Kariakli, Stella Koinaki, Dimitra Kokori, Maria Konidari, Hara Koundouraki, Dimitris Koutoukidis, Vasiliki Mamakou, Eirini Mamalaki, Eirini Mpamiaki, Nilden Selim, Nesse Souloglou, Maria Tsoukana, Dimitra Tzakou, Katerina Vosdogianni, Niovi Xenaki, Eleni Zengini), data entry (Thanos Antonos, Dimitra Papagrigoriou, Betty Spiliopoulou), sample logistics (Sarah Edkins, Emma Gray), genotyping (Suzannah Bumpstead, Robert Andrews, Hannah Blackburn, Doug Simpkin, Siobhan Whitehead), research administration (Anja Kolb-Kokocinski, Carol Smee, Danielle Walker) and informatics (Kathleen Stirrups, Martin Pollard, Josh Randall).

APCDR-Uganda was funded by the Wellcome Trust, The Wellcome Trust Sanger Institute (WT098051), the UK Medical Research Council (G0901213-92157, G0801566, and MR/K013491/1), and the Medical Research Council/Uganda Virus Research Institute Uganda Research Unit on AIDS core funding. We thank the African Partnership for Chronic Disease Research (APCDR) for providing a network to support this study as well as a repository for deposition of curated data. We also thank all study participants who contributed to this study.

The UK Household Longitudinal Study was funded by grants from the Economic & Social Research Council (ES/H029745/1) and the Wellcome Trust (WT098051). UKHLS is led by the Institute for Social and Economic Research at the University of Essex and funded by the Economic and Social Research Council. The survey was conducted by NatCen and the genome-wide scan data were analysed and deposited by the Wellcome Trust Sanger Institute.

The Understanding Society Scientific Group are Michaela Benzeval(1), Jonathan Burton(1), Nicholas Buck(1), Annette Jäckle(1), Meena Kumari(1), Heather Laurie(1), Peter Lynn(1), Stephen Pudney(1), Birgitta Rabe(1), Dieter Wolke(2)

1) Institute for Social and Economic Research

2) University of Warwick

Declaration of interests

The authors declare no competing interests.

Web resources

We have made code to run trans-ethnic colocalization using JLIM and simulations available through

github: https://github.com/KarolineKuchenbaecker/TEColoc

References

1. GBD 2013 Mortality and Causes of Death Collaborators. Global, regional, and national age-sex

specific all-cause and cause-specific mortality for 240 causes of death, 1990-2013: a systematic

analysis for the Global Burden of Disease Study 2013. *Lancet Lond. Engl.* **385**, 117–171 (2015).

2. Khera, A. V. *et al.* Genome-wide polygenic scores for common diseases identify individuals with

risk equivalent to monogenic mutations. *Nat. Genet.* **50**, 1219–1224 (2018).

3. Kuchenbaecker, K. B. *et al.* Evaluation of Polygenic Risk Scores for Breast and Ovarian Cancer

Risk Prediction in BRCA1 and BRCA2 Mutation Carriers. *J. Natl. Cancer Inst.* **109**, (2017).

4. MacArthur, J. *et al.* The new NHGRI-EBI Catalog of published genome-wide association studies

(GWAS Catalog). *Nucleic Acids Res.* **45**, D896–D901 (2017).

5. Popejoy, A. B. & Fullerton, S. M. Genomics is failing on diversity. *Nat. News* **538**, 161 (2016).

6. Bovet, P. & Paccaud, F. Cardiovascular Disease and the Changing Face of Global Public Health: A

Focus on Low and Middle Income Countries. *Public Health Rev.* **33**, 397–415 (2011).

7. Martin, A. R. *et al.* Human Demographic History Impacts Genetic Risk Prediction across Diverse

Populations. *Am. J. Hum. Genet.* **100**, 635–649 (2017).

8. Heckerman, D. *et al.* Linear mixed model for heritability estimation that explicitly addresses

environmental variation. *Proc. Natl. Acad. Sci. U. S. A.* **113**, 7377–7382 (2016).

9. Chen, Z. *et al.* China Kadoorie Biobank of 0.5 million people: survey methods, baseline

characteristics and long-term follow-up. *Int. J. Epidemiol.* **40**, 1652–1666 (2011).

10. Gilly, A. *et al.* Cohort-wide deep whole genome sequencing and the allelic architecture of

complex traits. *Nat. Commun.* **9**, 4674 (2018).

11. Gilly, A. *et al.* Very low depth whole genome sequencing in complex trait association studies.

Bioinforma. Oxf. Engl. (2018). doi:10.1093/bioinformatics/bty1032

12. Prins, B. P. *et al.* Genome-wide analysis of health-related biomarkers in the UK Household

Longitudinal Study reveals novel associations. *Sci. Rep.* **7**, 11008 (2017).

13. Kanai, M. *et al.* Genetic analysis of quantitative traits in the Japanese population links cell types

to complex human diseases. *Nat. Genet.* **50**, 390–400 (2018).

14. Global Lipids Genetics Consortium. Discovery and refinement of loci associated with lipid levels.

Nat. Genet. **45**, 1274–1283 (2013).

15. Liu, D. J. *et al.* Exome-wide association study of plasma lipids in >300,000 individuals. *Nat.*

Genet. **49**, 1758 (2017).

16. Chun, S. *et al.* Limited statistical evidence for shared genetic effects of eQTLs and autoimmune-

disease-associated loci in three major immune-cell types. *Nat. Genet.* **49**, 600–605 (2017).

17. Pulit, S. L. *et al.* Meta-analysis of genome-wide association studies for body fat distribution in

694,649 individuals of European ancestry. *Hum. Mol. Genet.* (2018). doi:10.1093/hmg/ddy327

18. Musunuru, K. *et al.* Multi-Ethnic Analysis of Lipid-Associated Loci: The NHLBI CARe Project. *PLoS*

ONE **7**, (2012).

19. Teslovich, T. M. *et al.* Biological, Clinical, and Population Relevance of 95 Loci for Blood Lipids.

Nature **466**, 707–713 (2010).

20. Dumitrescu, L. *et al.* Genetic Determinants of Lipid Traits in Diverse Populations from the

Population Architecture using Genomics and Epidemiology (PAGE) Study. *PLoS Genet.* **7**, (2011).

21. Bryant, E. K. *et al.* A Multiethnic Replication Study of Plasma Lipoprotein Levels-Associated SNPs

Identified in Recent GWAS. *PLoS ONE* **8**, (2013).

22. Wu, Y. *et al.* Trans-Ethnic Fine-Mapping of Lipid Loci Identifies Population-Specific Signals and

Allelic Heterogeneity That Increases the Trait Variance Explained. *PLoS Genet.* **9**, (2013).

23. Wang, Z. *et al.* Genetic associations with lipoprotein subfraction measures differ by ethnicity in

the multi-ethnic study of atherosclerosis (MESA). *Hum. Genet.* **136**, 715–726 (2017).

24. Keebler, M. E. *et al.* Association of Blood Lipids with Common DNA Sequence Variants at

Nineteen Genetic Loci in the Multiethnic United States National Health and Nutrition

Examination Survey III. *Circ. Cardiovasc. Genet.* **2**, 238–243 (2009).

25. Lanktree, M. B., Anand, S. S., Yusuf, S. & Hegele, R. A. Replication of genetic associations with

plasma lipoprotein traits in a multiethnic sample. *J. Lipid Res.* **50**, 1487–1496 (2009).

26. Chang, M. *et al.* Racial/ethnic variation in the association of lipid-related genetic variants with

blood lipids in the US adult population. *Circ. Cardiovasc. Genet.* **4**, 523–533 (2011).

27. Below, J. E. *et al.* Meta-analysis of lipid-traits in Hispanics identifies novel loci, population-

specific effects, and tissue-specific enrichment of eQTLs. *Sci. Rep.* **6**, (2016).

28. Johnson, L., Zhu, J., Scott, E. R. & Wineinger, N. E. An Examination of the Relationship between

Lipid Levels and Associated Genetic Markers across Racial/Ethnic Populations in the Multi-Ethnic

Study of Atherosclerosis. *PloS One* **10**, e0126361 (2015).

29. Marigorta, U. M. & Navarro, A. High Trans-ethnic Replicability of GWAS Results Implies Common

Causal Variants. *PLoS Genet.* **9**, e1003566 (2013).

30. Brown, B. C., Ye, C. J., Price, A. L. & Zaitlen, N. Transethnic Genetic-Correlation Estimates from

Summary Statistics. *Am. J. Hum. Genet.* **99**, 76–88 (2016).

31. Wray, N. R. *et al.* Genome-wide association analyses identify 44 risk variants and refine the

genetic architecture of major depression. *Nat. Genet.* **50**, 668–681 (2018).

32. Galinsky, K. J. *et al.* Estimating cross-population genetic correlations of causal effect sizes. *Genet.*

Epidemiol. (2018). doi:10.1002/gepi.22173

33. Hindorff, L. A. *et al.* Prioritizing diversity in human genomics research. *Nat. Rev. Genet.* **19**, 175–

185 (2018).

34. Mulder, N. *et al.* H3Africa: current perspectives. *Pharmacogenomics Pers. Med.* **Volume 11**, 59–

66 (2018).

35. Carlson, C. S. *et al.* Generalization and Dilution of Association Results from European GWAS in

Populations of Non-European Ancestry: The PAGE Study. *PLOS Biol.* **11**, e1001661 (2013).

36. Program Overview - All of Us | National Institutes of Health. Available at:

https://allofus.nih.gov/about/about-all-us-research-program. (Accessed: 28th December 2018)

37. Finer, S. *et al.* Cohort Profile: East London Genes & Health (ELGH), a community based

population genomics and health study in people of British-Bangladeshi and -Pakistani heritage.

bioRxiv (2018). doi:10.1101/426163

38. Zhou, X. & Stephens, M. Genome-wide efficient mixed-model analysis for association studies.

Nat. Genet. **44**, 821–824 (2012).

39. Loh, P.-R., Kichaev, G., Gazal, S., Schoech, A. P. & Price, A. L. Mixed-model association for

biobank-scale datasets. *Nat. Genet.* **50**, 906–908 (2018).

40. Watanabe, K., Taskesen, E., van Bochoven, A. & Posthuma, D. Functional mapping and

annotation of genetic associations with FUMA. *Nat. Commun.* **8**, 1826 (2017).

Figures

Figure 1. Trans-ethnic genetic correlations for associations with high-density lipoprotein (HDL), low-

density lipoprotein (LDL) cholesterol and triglycerides (TG). a) shows the comparison of GLGC2013

(European) and Biobank Japan, b) GLGC2013 and China Kadoorie Biobank and c) Biobank Japan and

China Kadoorie Biobank.

Figure 2. Associations of polygenic scores based on established lipid-associated loci with levels of

high-density lipoprotein (HDL), low-density lipoprotein (LDL) cholesterol and triglycerides (TG) in a)

UKHLS, b) HELIC-MANOLIS, c) HELIC-Pomak, d) APCDR-Uganda. Estimates are given as correlation

coefficients. Stars indicate statistically significant associations ($p<0.0056$).

Figure 3. Regional association plots for a selection of established lipid-associated loci for UKHLS,

Biobank Japan, APCDR-Uganda, and China Kadoorie Biobank and p-value p_{jlim} for the trans-ethnic

colocalization with UKHLS.

Table 1. Percentage of established lipid-associated loci with evidence of replication in each target
study. Results shown separately by strength of association (whether $p<10^{-100}$) in the discovery study
(GLGC). Only one SNP was kept for each locus with multiple associated variants in close proximity.
Regions were defined as 25Kb either side of the lead variant. The credible set contains the reported
lead variant and variants in LD (r2>0.6) with it.

P in GLGC:		<10^{-100}			≥10^{-100}		
Study	**Trait**	**n.s.**[a]	**Region**[b]	**Credible**[c]	**n.s.**[a]	**Region**[b]	**Credible**[c]
eMERGE	HDL	11.8	11.8	76.5	73.9	19.0	7.2
	LDL	15.4	7.7	76.9	89.3	9.0	1.6
	TG	10.5	10.5	78.9	81.2	15.4	3.4
UKHLS	HDL	5.9	17.6	76.5	81.0	13.7	5.2
	LDL	7.7	15.4	76.9	77.0	16.4	6.6
	TG	0.0	5.3	94.7	82.1	14.5	3.4
CKB	HDL	11.8	5.9	82.4	71.2	16.4	12.4
	LDL	7.7	30.8	61.5	83.6	7.4	9.0
	TG	5.3	15.8	78.9	82.9	10.3	6.8
BBJ	HDL	11.8	11.8	76.5	47.7	19.6	32.7
	LDL	7.7	30.8	61.5	64.8	10.7	24.6
	TG	5.3	10.5	84.2	55.6	12.8	31.6
UG	HDL	11.8	17.6	70.6	73.2	25.5	1.3
	LDL	23.1	7.7	69.2	73.8	24.6	1.6
	TG	42.1	47.4	10.5	79.5	17.1	3.4

[a] No variant in the region associated in target set at $p<10^{-3}$
[b] No variant in the credible set associated in the target set at $p<10^{-3}$ but an uncorrelated variant in
the region is associated in target set at $p<10^{-3}$
[c] A variant in the credible set is associated in the target set at $p<10^{-3}$

Table 2: Associations of polygenic scores based on established lipid-associated loci and respective
biomarkers levels in UKHLS, HELIC-MANOLIS, -Pomak, and APCDR-Uganda using a linear mixed
model analysis.

Trait	N	Correlation (SE[a])	P-value
UKHLS			
HDL	9706	0.284 (0.010)	8.34×10^{-165}
LDL	9767	0.273 (0.010)	8.38×10^{-155}
Triglycerides	9635	0.203 (0.010)	2.62×10^{-86}
HELIC-MANOLIS			
HDL	1186	0.276 (0.029)	8.65×10^{-20}
LDL	1186	0.230 (0.029)	1.89×10^{-14}
Triglycerides	1176	0.237 (0.030)	3.01×10^{-14}
HELIC-Pomak			
HDL	1078	0.272 (0.030)	9.67×10^{-18}
LDL	1075	0.285 (0.030)	1.35×10^{-18}
Triglycerides	1066	0.235 (0.030)	1.68×10^{-13}
APCDR-Uganda			
HDL	6407	0.121 (0.012)	6.06×10^{-22}
LDL	6407	0.280 (0.012)	1.91×10^{-107}
Triglycerides	6407	0.063 (0.013)	4.46×10^{-7}

537 [a] SE=standard error
538

Table 3: 10,000 simulation runs to assess the performance of trans-ethnic colocalization.
Phenotypes were simulated for CKB and APCDR-Uganda and trans-ethnic colocalization was run to compare each to a reference set of 50,000 samples with British ancestry from UK Biobank.

Sample, N	Power	Type I error rate
CKB, 72,473	93.1%	5.2%
APCDR-Uganda, 4,597	73.1%	4.6%
CKB, 4,597	94.8%	4.5%

543 **Table 4. Association of established lipid-associated loci with body mass index** by locus replication
544 status in APCDR-Uganda. Association results are based on N≥484,680 samples from the meta-
545 analysis between GIANT and UK Biobank

Replication	Trait	rs-id	Chr	Position	Annotation	beta	SE	P-value
no	HDL	rs11755393	6	34824636	*UHRF1BP1*	-0.025	0.002	**9.8x10⁻⁴⁸**
no	HDL	rs1178979	7	72856430	*BAZ1B*	-0.010	0.002	**3.1x10⁻⁶**
no	HDL	rs4731702	7	130433384	*KLF14*	0.008	0.002	**3x10⁻⁷**
no	HDL	rs2954033	8	126493746	*NSMCE2*	-0.010	0.002	**6.4x10⁻⁸**
no	LDL	rs4245791	2	44074431	*ABCG8*	0.002	0.002	0.22
no	LDL	rs3846662	5	74651084	*HMGCR*	0.020	0.002	**1.9x10⁻³⁵**
no	LDL	rs2737229	8	116648565	*TRPS1*	0.014	0.002	**1.9x10⁻¹⁵**
no	LDL	rs635634	9	136155000	*IL6R*	0.005	0.002	0.03
no	LDL	rs2000999	16	72108093	*HPR*	0.011	0.002	**8.6x10⁻⁸**
no	TG	rs1260326	2	27730940	*GCKR*	-0.011	0.002	**1.2x10⁻¹⁰**
no	TG	rs2943641	2	227093745	*IRS1*	0.006	0.002	**5.8x10⁻⁴**
no	TG	rs6905288	6	43758873	*VEGFA*	-0.010	0.002	**1.9x10⁻⁹**
no	TG	rs11820589	11	116633862	*APOA5*	-0.003	0.003	0.41
no	TG	rs58542926	19	19379549	*TM6SF2*	-0.003	0.003	0.33
yes	HDL	rs643531	9	15296034	*TTC39B*	0.000	0.002	0.92
yes	HDL	rs1800588	15	58723675	*LIPC*	-0.002	0.002	0.25
yes	HDL	rs3764261	16	56993324	*CETP*	-0.002	0.002	0.39
yes	HDL	rs16942887	16	67928042	*PSKH1*	-0.005	0.003	0.06
yes	LDL	rs12740374	1	109817590	*CELSR2*	0.003	0.002	0.18
yes	LDL	rs1367117	2	21263900	*APOB*	-0.002	0.002	0.19
yes	LDL	rs6511720	19	11202306	*LDLR*	0.006	0.003	0.03
suggestive	HDL	rs4841132	8	9183596	*PPP1R3B*	0.000	0.003	0.88
suggestive	HDL	rs328	8	19819724	*LPL*	0.005	0.003	0.10
suggestive	HDL	rs769449	19	45410002	*APOE*	-0.026	0.003	**4.4x10⁻²¹**
suggestive	HDL	rs386000	19	54792761	*LILRB2*	0.001	0.002	0.60

Figure 1

Figure 2

9q31.1 _ABCA1_ - HDL

2p23 _GCKR_ - TG

7q11.23 _BAZ1B_ - TG

1p13.3 _CELSR2_ - LDL