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## Genetically modulated educational attainment and coronary disease risk

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<b>Abstract:</b>	<p><b>Aims:</b> Genetic disposition and lifestyle factors are understood as independent components underlying the risk of multiple diseases. In this study, we aim to investigate the interplay between genetics, educational attainment - an important denominator of lifestyle - and coronary artery disease (CAD) risk.</p> <p><b>Methods and Results:</b> Based on the effect sizes of 74 genetic variants associated with educational attainment, we calculated a 'genetic education score' in 13,080 cases and 14,471 controls and observed an inverse correlation between the score and risk of CAD (<math>p=1.52 \times 10^{-8}</math>; odds ratio [OR] 0.79 (95% confidence interval [CI] 0.73-0.85) for the higher compared to the lowest score quintile). We replicated in 146,514 individuals from UK Biobank (<math>p=1.85 \times 10^{-6}</math>) and also found strong associations between the 'genetic education score' with 'modifiable' risk factors including smoking (<math>p=5.36 \times 10^{-23}</math>), body mass index (<math>p=1.66 \times 10^{-30}</math>), and hypertension (<math>p=3.86 \times 10^{-8}</math>). Interestingly, these associations were only modestly attenuated by adjustment for years spent in school. By contrast, a model adjusting for BMI and smoking abolished the association signal between the 'genetic education score' and CAD risk suggesting an intermediary role of these two risk factors. Mendelian randomization analyses performed with summary statistics from large genome-wide meta-analyses and sensitivity analysis using 1271 variants affecting educational attainment (OR 0.68 for the higher compared to the lowest score quintile; 95% CI 0.63-0.74; <math>p=3.99 \times 10^{-21}</math>) further strengthened</p>

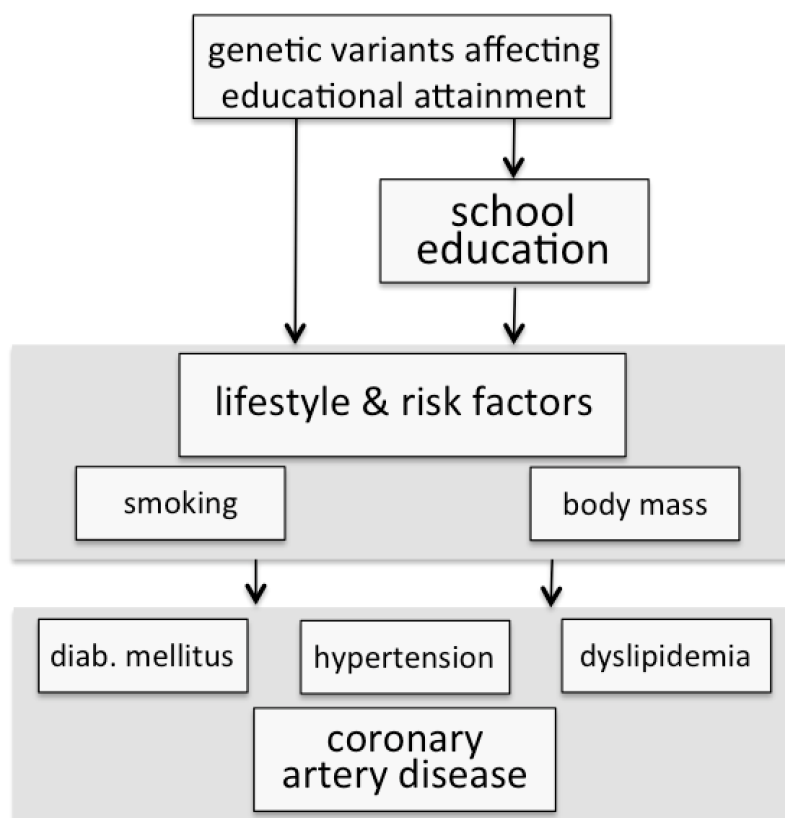
	<p>these findings.</p> <p>Conclusion: Genetic variants known to affect educational attainment may have implications for a health-conscious lifestyle later in life and subsequently affect the risk of coronary artery disease.</p>
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<b>TWITTER message</b> (Please submit a catchy Twitter message of max. 280 characters, which we would use to promote this submission in the event of acceptance - Max 280 characters).	Some gene variants not only affect our success in school but also the risk of having a heart attack
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## Translational Perspective

Genetic disposition and lifestyle factors are understood as independent components underlying the risk of multiple diseases. An important denominator of lifestyle is educational attainment. Here we utilized genetic variants affecting educational attainment as an instrument for studying the interplay between genetics, lifestyle and coronary artery disease (CAD). We found strong associations between the ‘genetic education score’ and CAD and its risk factors which, interestingly, are only partially explained by years spend in school. Our study shows that genetic variants known to affect educational attainment may have broad implications for a health-conscious lifestyle later in life and the risk of CAD.

### 'Take-home figure':



**'One-sentence Summary':** In the present study, we have found that genetic factors known to affect educational attainment may in parallel influence the prevalence of CAD possibly through its influence on the lifestyle-related risk factors.

## Genetically modulated educational attainment and coronary disease risk

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4 **Introduction**  
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7 Epidemiological studies have repeatedly observed an inverse association between years of school  
8 education and coronary artery disease (CAD) risk<sup>1,2</sup>. A number of detrimental lifestyle factors including  
9 smoking, unhealthy diet and less recreational physical activity – observed with less educational attainment  
10 – have been considered for explaining this association<sup>3</sup>. However, the correlation between length of school  
11 education and CAD risk is difficult to untangle<sup>3</sup>. Indeed, compulsory programmes that increased the years  
12 of school education were without measurable effects on CAD risk<sup>4,5</sup>.  
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21 The genetics of CAD as well as those of educational attainment have been widely researched in  
22 recent years<sup>6-12</sup>. Both, are considered as complex traits with a strong genetic component<sup>6-9</sup>. In parallel,  
23 *Mendelian randomisation* has evolved as a valuable tool for investigation of causal relationships between  
24 risk factors and complex traits<sup>13</sup>. This raised our interest to explore the genetic impact of educational  
25 attainment on coronary disease risk.  
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33 In the present study, we specifically analyzed whether there is a genetic component underlying the  
34 relationship between higher educational attainment and lower CAD risk ([Extended Data Figure 1A](#), blue  
35 block). We also aimed to study the potential intermediate role of lifestyle-related risk factors in linking  
36 (the genetic basis of) educational attainment with the prevalence of CAD in the European population  
37 ([Extended Data Figure 1B](#), green block).  
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## Methods

### Study design

The study addresses two major questions. First, we explored the association between the genetic component of educational attainment and CAD as well as its related risk factors. As complex traits are considered to have polygenic genetic architecture, we resorted to the genetic risk score approach to get a cumulative surrogate estimate for the genetic component of educational attainment, utilizing (n=74 and n=1271) independent single nucleotide polymorphisms (SNPs) reported by two recent published genome-wide association studies (GWAS) for educational attainment with the measurement as the years spent in school (EduYears)<sup>12, 14</sup>. The median effect size of a single SNP corresponds to 1.7 weeks of schooling, and a combined polygenic score explains around 11% of the variance in EduYears<sup>12</sup>. Based on genotype data from multiple cohorts we generated for each individual a ‘genetic education score’ which reflects the integrated effect of all SNPs affecting EduYears and associated this score with the susceptibility of CAD and other cardiovascular traits by regression analyses.

### Definition of educational attainment

Educational attainment is the visible output of education systems and a measure of their success, which varies among different countries, as is shown by the European statistics about education ([http://ec.europa.eu/eurostat/statistics-explained/index.php/Educational\\_attainment\\_statistics](http://ec.europa.eu/eurostat/statistics-explained/index.php/Educational_attainment_statistics)). In UKBB, by far the largest cohort explored in our study, educational attainment was available on all cases and controls for subsequent analyses. This information was not available in the nine CAD case-control studies used for discovery. As a standard, the International Standard Classification of Education (ISCED) is nowadays taken as a measure of educational attainment. The details of ISCED codes obtained from UK Biobank phenotypes are described in the [Supplementary Text](#). In the context of genetic association, Okbay et al.<sup>14</sup> have examined two possible indicator variables of educational attainment, namely *EduYear*, i.e. a continuous variable measuring the number of years of schooling completed, and *College*, i.e. a binary variable measuring the successful completion of college education. They revealed that EduYears was

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4 better powered for detecting associations. This EduYear measurement has also been adopted in the latest  
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6 GWAS for educational attainment<sup>12</sup>. Hence, in the present study, we also calculated real EduYears - a  
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8 continuous variable measuring the number of years of schooling completed to represent educational  
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10 attainment - using the same methods that were used in the report that led to the identification of the  
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12 reported EduYear-SNPs<sup>14</sup>.

### 15 16 **Genetic risk score analysis**

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19 Individual-level genotype data were collected from nine CAD case-control studies<sup>15-21</sup> for discovery. All  
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21 subjects were of European origin, most coming from Germany and England, and gave written informed  
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23 consent before participating. Individual-level genotype data were also collected from UK Biobank<sup>22</sup> for  
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25 replication. All data were utilized for sensitivity analysis with the samples size of UK Biobank increased  
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27 from 150k to 500k of the latest release. Details on the participating studies and pre-processing methods  
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29 used are shown in the [Supplement Text](#).

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33 Based on the 74 EduYear SNPs reported by Okbay et al<sup>14</sup> ([Extended Data Table 1](#)), a weighted  
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35 genetic risk score was calculated to evaluate cumulatively the genetic underpinnings of educational  
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37 attainment and their effect on the risk of CAD. We gave a value from minimum 0 to maximum 2 for every  
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39 SNP for every individual according to the sum of the posterior probabilities from the imputation files to  
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41 indicate the number of EduYear-increasing alleles and multiplied the number of alleles by the reported  
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43 effect sizes. Then we totalled these values for each individual across all 74 SNPs to generate a weighted  
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45 genetic risk score (wGRS) of EduYears, namely ‘genetic education score’. Afterwards, all the individuals  
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47 were grouped into quintiles based on their ‘genetic education score’. Likewise, in the sensitivity analysis  
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49 we constructed a second ‘genetic education score’ based on the 1216 SNPs\* independent of the initial 74  
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51 SNPs\* reported by Lee et al<sup>12</sup>, as well as the full 1271 SNPs\* (\*out of the initially reported 74<sup>14</sup> some  
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53 SNPs were not found in the list of 1271 SNPs shown to be genome-wide significantly associated with  
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55 EduYears in the most recent analysis<sup>12</sup> [Extended Data Table 5](#)).



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4 Logistic regression was performed to evaluate the effect size of the wGRS on the risk of CAD in each  
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6 study. The wGRS was modelled as a continuous variable and standardized into Z-scores (centred and  
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8 scaled to have a mean of 0 and standard deviation (SD) of 1) (Extended Data Figure 2). As population  
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10 stratification or batch effects, which could bias prediction accuracy in the genetic risk score analysis<sup>23</sup>,  
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12 should be considered as covariates, we included in the present study, the top two (for nine case-control  
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14 studies) or five (for UK Biobank) principle components based on autosomal genotypes in order to adjust  
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16 for the possible presence of population stratification. In all regression analysis for UK Biobank, genotype  
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18 array (UK Biobank Axiom array vs UK BiLEVE array) was included as an additional covariate to account  
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20 for the differences between the two GWAS arrays used for genotyping of participants. The regression was  
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22 performed for each study separately and afterwards a fixed-effect meta-analysis was performed to  
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24 combine the effects across all studies (Figure 1, Extended Data Figure 3A).  
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30 Using the pooled genotype data of nine CAD case-control cohorts, same logistic regression was  
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32 performed with the cohort center and top 10 principle components included as additional covariates, so as  
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34 to estimate the variance explained by the ‘genetic education score’ on CAD onset in the measure of the  
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36 incremental McFadden’s pseudo R<sup>2</sup>. The incremental part was calculated as the pseudo R<sup>2</sup> difference  
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38 between the regression with and without the score included. The 95% confidence intervals for pseudo R<sup>2</sup>  
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40 were estimated via 1,000 times bootstrapping.  
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43 The ‘genetic education score’ reflects effects of SNPs that were identified for their association  
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45 with EduYears in the first place<sup>14</sup>. However, these SNPs may have other (pleiotropic) effects, which may  
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47 also come into place when the ‘genetic education score’ is associated with CAD risk. Therefore, the real  
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49 number of years spend in school (EduYears) was extracted for each individual and included as adjustment  
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51 to estimate the effect size of the ‘genetic education score’ on the susceptibility of CAD and multiple  
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53 traits (Extended Data Figure 1, blue block). With the aim to further characterize the interplay among the  
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55 genetic basis of educational attainment, the risk of CAD and its related lifestyle risk factors, we included  
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57 additional adjustments of possible confounders such as lifestyle and risk factors, to check the  
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59 (in)dependence of the effect of the genetic component of educational attainment on CAD risk.  
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4 Using UK Biobank data, regression analyses were also performed to evaluate the effect size of the  
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6 wGRS on multiple cardiovascular risk factors, namely hypertension, hypercholesterolemia, type 2  
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8 diabetes, smoking (ever smokers vs. never smokers), and BMI. Furthermore, the same logistic regression  
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10 (risk factors measured in binary value) or linear regression (risk factor measured in continuous values, i.e.  
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12 BMI here) model was performed with adjustment for EduYears, BMI and smoking (ever smokers vs.  
13  
14 never smokers [reference group]). The definition of each risk factor is described in [Supplementary Text](#).  
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16 The same regression of ‘genetic education score’ and CAD and its risk factors was performed with  
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18 EduYears (defined in [Supplementary Text](#)) included as a covariate. We also tested the association between  
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20 a ‘genetic CAD score’ and real EduYears in UK Biobank to investigate the possibility for a reverse  
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22 causation. ([Extended Data Table 2](#))  
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### 27 **Mendelian randomization analysis**

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29 Mendelian randomization (MR) analyses were performed in order to investigate the genetic causal effect  
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31 between educational attainment and CAD or cardiovascular risk factors. The detailed list of the 74 SNPs  
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33 and their reported effect sizes of EduYear are recorded in [Extended Data Table 3](#). The effect sizes of all  
34  
35 these EduYear-SNPs for CAD were extracted from the summary statistics of the CARDIoGRAMplusC4D  
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37 meta-analysis<sup>24</sup>. Summary statistics of the EduYear-SNPs for cardiovascular risk factors were extracted  
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39 from various consortia, including GIANT (BMI)<sup>25</sup>, TAG (smoking behaviour)<sup>26</sup>, and GLGC (LDL-  
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41 cholesterol, HDL-cholesterol, triglycerides, total cholesterol level)<sup>27</sup>. A description of the sample-size  
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43 used in each GWAS and the corresponding phenotypes are shown in [Supplementary Text](#).  
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49 In all traits the effect size for each SNP was first aligned to the reported EduYear-increasing  
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51 allele. Then the genetic causal effect was estimated by regressing the SNP-EduYear effect (exposure) to  
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53 the SNP effect of CAD or risk factors (outcome) in several methods. Inverse-variance-weighted fixed-  
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55 effect meta-analysis (IVW) is the most classic one in MR to combine individual-SNP beta estimates<sup>28</sup>.  
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57 Unfortunately, despite of its efficiency IVW estimate will be biased when there exists genetic variant as an  
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59 invalid instrumental variable (IV). In light of this, modern MR methods such as MR-Egger<sup>29</sup> and weighted  
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4 median<sup>30</sup> have been developed to supplement the IVW performance to account for violations of IV  
5 assumptions and adjust for potential pleiotropic effects. Therefore, we employed all three methods as  
6 recommended by Bowden et al<sup>30</sup>, with MR-egger which has substantially less efficiency and low power to  
7 suggest whether a causal effect is present or not, and with weighted median which has generally greater  
8 power and efficiency to obtain the unbiased estimates.  
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16 Furthermore, we performed sensitivity analysis by applying various filters on the original  
17 selection of 74 SNPs, i.e. to exclude the SNPs at loci known to affect the risk of CAD, as well as loci  
18 known to affect the risk of cardiovascular risk factors ([Extended Data Table 3](#)).  
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## 25 26 **Results**

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29 We studied 13,080 CAD cases and 14,471 controls from 9 genome-wide association studies (GWAS) on  
30 the basis of previously published array data<sup>15-20, 24</sup>. All participants were of Western European decent. The  
31 majority of participants came from the UK or Germany (77.8%). Two multinational studies, MIGen and  
32 Cardiogenics, also contributed to our sample with 12.1%, 5.5%, 2.3%, 1.9%, and 0.4% of individuals  
33 coming from Italy, USA, Spain, Northern Europe, and France, respectively. A detailed cohort description  
34 can be found in the [Supplementary Text](#). For each subject we generated individually a weighted ‘genetic  
35 education score’, based on 74 single nucleotide polymorphisms (SNPs) that have been genome-wide  
36 significantly associated with educational attainment (EduYear-SNPs) through a GWAS on this trait<sup>14</sup>. The  
37 score was normally distributed in the participants ([Extended Data Figure 2](#)). Summary statistics for the  
38 association of the ‘genetic education score’ with CAD in each study are shown in [Figure 1](#). As a result of  
39 meta-analysis, a higher ‘genetic education score’ correlated with a lower odds of coronary disease  
40 ( $p=1.52 \times 10^{-8}$  for fixed-effect meta-analysis). Next, all individuals were grouped into quintiles of the score.  
41 [Figure 2](#) shows a constant decline of CAD risk with increasing quintiles. Individuals in the highest quintile  
42 had about 21% lower odds than those in the lowest quintile, with individuals in the intermediate quintiles  
43 ranging in between ( $p=7.66 \times 10^{-9}$  for trend test across quintiles, [Figure 2](#)). Sex-stratified analysis  
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4 confirmed this inverse correlation in both males and females ([Extended Data Table 4](#)). For sensitivity  
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6 analysis we extracted a new list of 1271 SNPs reported by a larger scale GWAS of educational attainment  
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8 published during the revision process, and studied a second ‘genetic education score’ based on n=1216  
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10 (out of 1271) SNPs who were all in low linkage disequilibrium ( $r^2 < 0.5$ ) with the 74 EduYear-SNPs which  
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12 we had studied initially ([Extended Data Table 5](#)). We observed an even enlarged inverse association  
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14 between the second ‘genetic education score’ and CAD risk, with individuals in the highest quintile had  
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16 about 31% lower odds than those in the lowest quintile ([Extended Data Table 6](#)). Quantitatively, the full  
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18 ‘genetic education score’ in our data based on 1271 SNPs explains 0.37 % variance [95% CI 0.27-0.51] of  
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20 CAD onset ([Methods](#)).

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25 We then set to replicate and extend our findings in a large population cohort, namely the UK  
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27 Biobank<sup>22</sup> ([Supplementary Text](#)). We successfully replicated the primary association between ‘genetic  
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29 education score’ and CAD considering 13,183 CAD cases and 133,203 controls of European ancestry in  
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31 this study ( $p=1.85 \times 10^{-6}$ , [Table 1](#);  $p=7.34 \times 10^{-13}$  for meta-analysis with the discovery set, [Extended Data](#)  
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33 [Figure 3A and Methods](#)). Sensitivity analysis with the second ‘genetic education score’ based on a more  
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35 recent release of the UK Biobank data (38,489 CAD cases and 416,951 controls) also replicated our initial  
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37 finding ( $p=1.02 \times 10^{-122}$ ;  $p=3.88 \times 10^{-132}$  for meta-analysis with the discovery set, [Extended Data Table 6](#)).

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41 We also looked at the countries separately, in that we meta-analysed data from Germany (six  
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43 German MI family studies), the UK (WTCCC, UK Biobank) and a mixture of Western countries (MIGen,  
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45 Cardiogenics). We observed directionally identical effects in these three groups despite substantial  
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47 differences in the educational systems ([http://ec.europa.eu/eurostat/statistics-](http://ec.europa.eu/eurostat/statistics-explained/index.php/Educational_attainment_statistics)  
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49 [explained/index.php/Educational\\_attainment\\_statistics](http://ec.europa.eu/eurostat/statistics-explained/index.php/Educational_attainment_statistics)) ( $p=1.05 \times 10^{-6}$  for the UK;  $p=5.30 \times 10^{-5}$  for  
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51 Germany;  $p=2.40 \times 10^{-5}$  for the mixture of several other Western countries, [Extended Data Figure 3B](#)).

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55 Phenotypically, real EduYears was also significantly associated with CAD (odds ratio 0.72 for 1  
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57 SD increase of education years, 95% CI 0.71, 0.74,  $p=2.65 \times 10^{-281}$ ) ([Extended Data Table 7](#)). However,  
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59 adjustment for real EduYears had only a small effect on the association between the ‘genetic education  
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4 score' and CAD (Table 1), suggesting that the 'genetic education score' mediates its effects on CAD risk  
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6 not entirely through its effects on years spend in school.  
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9 We next asked whether there also exists an effect of 'genetic education score' on traditional CAD  
10 risk factors in UK Biobank (with the exception of lipid levels, which were not available), and whether the  
11 effects were likewise partially independent of the phenotype EduYears. We found strong associations of  
12 the 'genetic education score' with hypertension, body mass index (BMI), and smoking whereas other risk  
13 factors tested gave nominally significant signals (Table 1). Like with CAD, the phenotype real EduYears  
14 was also significantly associated with most cardiovascular risk factors (Extended Data Table 7). However,  
15 adjustment for this measure only marginally attenuated the association signal between the 'genetic  
16 education score' and the most strongly associated risk factors (e.g. BMI and smoking status; Table 1),  
17 again suggesting that school education by itself does not mediate exclusively the association between the  
18 'genetic education score' and risk factors (i.e. higher BMI and smoking) (Extended Data Figure 4, black  
19 lines).  
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34 Given the strong association of 'genetic education score' with BMI and smoking, even after  
35 adjustment for real EduYears in UK Biobank (Table 1), we next tested the effect of the 'genetic education  
36 score' on CAD risk, hypertension, hypercholesterolemia, and type 2 diabetes with additional adjustment  
37 for these two risk factors. The smoking and BMI adjusted model resulted in a marked attenuation of the  
38 association signals for the 'genetic education score' with CAD (OR 0.992 [0.973-1.011],  $p=0.407$ ), and  
39 also with the other risk factors (Extended Data Table 8), suggesting that the effect of the 'genetic  
40 education score' on CAD risk may be mainly mediated through its effects on these two risk factors.  
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51 In order to investigate the possibility for a reverse causation we also tested the association  
52 between a 'genetic CAD score'<sup>31</sup> and real EduYears in UK Biobank (Supplementary Text and Methods)  
53 but found no such signal ( $p=0.58$ ), making reverse causation unlikely.  
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58 To substantiate our previous observations that the genetic component of educational attainment  
59 has significant impact on CAD risk and that this effect may be mediated through its effects on  
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4 intermediate risk factors, we also performed Mendelian randomisation (MR) analyses. We used summary  
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6 statistics from well-powered GWAS for CAD<sup>24</sup>, BMI<sup>25</sup>, smoking behaviour<sup>26</sup>, LDL-cholesterol, HDL-  
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8 cholesterol, triglycerides, total cholesterol level<sup>27</sup>, to regress the SNP-education effect (exposure) with the  
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10 SNP-effects on CAD and its risk factors (outcome), and then several modern methods were employed to  
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12 combine individual-SNP beta estimates ([Supplementary Text and Methods](#)). Using the inverse-variance  
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14 weighted (IVW) and weighted median methods, we observed that risk of CAD decreased by about a third  
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16 per 1-standard deviation (SD) increment in the education years, with odds ratios of 0.64 (95% CI: 0.55,  
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18 0.76,  $p=9.5 \times 10^{-7}$ ) and 0.67 (95% CI: 0.55-0.82,  $p=0.00013$ ) respectively. Among the tested risk factors,  
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20 BMI ( $p=0.04$  for IVW,  $p=0.01$  for weighted median) and triglycerides ( $p=0.03$  for IVW, and  $p=0.06$  for  
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22 weighted median) were also significantly associated with the ‘genetic education score’ in both methods.  
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24 Smoking behaviours measured as either number of cigarettes smoked per day or ever-smoked in the public  
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26 available data collection from 2010<sup>26</sup>, showed marginal genetic association with educational  
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28 attainment ( $p$ -value about 0.06) in either method, which could be due to lack of power ([Extended Data](#)  
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30 [Table 9](#)).

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36 For MR sensitivity analyses we removed from the 74 EduYear-SNPs which had marginal  
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38 associations ( $p<0.01$  in the published summary statistics) with CAD<sup>24</sup> (4 SNPs), BMI<sup>25</sup> (8 SNPs),  
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40 triglycerides<sup>27</sup> (5 SNPs), and smoking behaviours<sup>26</sup> (3 SNPs) ([Extended Data Table 3](#)). The final 56  
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42 EduYear-SNPs still showed a causal effect between higher educational attainment (1-SD increase in  
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44 education years) and 28% lower risk of CAD (odds ratio for weighted median method of 0.72, 95% CI  
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46 0.57, 0.90,  $p=4.3 \times 10^{-3}$ ), which further endorsed the effect found in the initial MR analysis ([Extended Data](#)  
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48 [Figure 5](#)).

## 55 **Discussion**

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58 Educational attainment is well known for its inverse association with cardiovascular diseases<sup>1, 2, 3</sup>. Here we  
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60 show that a genetic score based on cumulative effects of variants associated with the number of years  
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4 spend in school<sup>14</sup> is associated with multiple cardiovascular risk factors and the manifestation of CAD.  
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6 Interestingly, these associations were only ameliorated by adjustment for real years of schooling  
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8 suggesting that the genetic component of educational attainment may have more complex phenotypic  
9  
10 consequences that all contribute to the observed statistical findings (Figure 3 and Extended Data Figure  
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12 4A). Furthermore, we show that the genetic effect between educational attainment and CAD risk is  
13  
14 partially mediated via specific lifestyle and risk factors (BMI and smoking status) (Figure 3).  
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18 Notably, our findings imply that the health benefits related to higher educational attainment or  
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20 more years in education *per se* might have been over-estimated, given that the associations observed for  
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22 the ‘genetic education score’ with CAD risk as well as a number of health-related outcomes are not  
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24 exclusively mediated by EduYears. Our data suggest these health-related outcomes are in part modulated  
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26 by certain genetic variants, which lead, on the one hand, to more EduYears, and on the other hand, to  
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28 characteristics that are independent of EduYears but go along with a healthier lifestyle (Figure 3). This  
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30 notion possibly explains why previous compulsory programmes that increased the years of school  
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32 education were not showing a measurable reduction of CAD risk<sup>4, 5</sup>. However, we do not want to  
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34 conclude that a causal relation between EduYears and CAD risk does not exist. Indeed, the effect size of  
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36 the ‘genetic education score’ and CAD was markedly weakened – but nevertheless remained to be  
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38 significant – after adjustment for actual EduYears.  
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43 Indeed, the ‘genetic education score’ may have broader implications since it may relate to a  
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45 number of socioeconomic measures in respective individuals as well as the parental generation (Extended  
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47 Figure 4B illustrates some hypothetical consequences)<sup>1, 2,3,8, 32-40</sup>. Given such complexity of phenotypes  
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49 studied here, our findings fall short delineating the precise mechanism for each SNP. However, we  
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51 uncover that smoking and obesity may be key intermediary factors for the link between the ‘genetic  
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53 education score’ as a whole and CAD risk, as they not only blunted the association but also appeared to be  
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55 very robust in mediating the effects of the score on other cardiovascular risk factors, including  
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57 hypertension, hypercholesterolemia, and type 2 diabetes (Extended Data Table 8). Given these and  
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59 probably more intermediate factors to be discovered we obviously do not aim to implement an actionable  
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4 genetic test in a clinical environment but rather aim to claim a genetic link between educational  
5 attainment, intermediate risk factors, and CAD risk.  
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9 Since both intermediate risk factors – smoking and obesity – reflect modifiable health-relevant  
10 lifestyle decisions, we hypothesize that addressing these factors in Western societies could attenuate  
11 largely the inequality of CAD risk related to the EduYear-SNPs. Our findings therefore further suggest  
12 that genetics contribute to the variability of health-relevant lifestyles in Western societies and thereby  
13 have an effect on CAD risk later in life (Figure 3). Consistent with our findings, e.g. Marioni et al reported  
14 a higher life expectancy in parents of subjects with a higher ‘genetic education score’<sup>37</sup> and Arden et al  
15 revealed that the association between a longer lifespan and intelligence is mostly genetic<sup>38</sup>. In synthesis  
16 these observations suggest that genetic components and their underlying biological traits may influence  
17 the length of educational attainment but also the decision-making process in lifestyle choices that underpin  
18 cardiovascular risk factors such as smoking and obesity<sup>33</sup>. Our findings also emphasize that future studies  
19 on factors contributing to CAD risk should pay more attention to a standardized data collection on  
20 educational attainment as a potential factor.  
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36 We focused our analyses on CAD and cardiovascular outcomes. However, the lifestyle-related  
37 intermediary phenotypes such as smoking and obesity may have implications for the risk of other complex  
38 conditions as well, e.g. malignant, pulmonary or infectious diseases. In an exploratory analysis we also  
39 observed a strong association between the ‘genetic education score’ and chronic obstructive pulmonary  
40 disease (COPD) in UK Biobank but no statistically significant association with peripheral arterial disease,  
41 lung cancer or stroke (Extended Data Figure 6). Thus, the health implications of the EduYear-SNPs may  
42 be even be broader.  
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53 Our study has a number of limitations. Firstly, the level of educational attainment and the number  
54 of years spend in school are different among countries. Likewise, lifestyle, cultural background and  
55 environmental exposures also differ between countries<sup>41</sup>. The EduYear-SNPs utilized in this study were  
56 identified from a GWAS meta-analysis largely based on individuals of European descent<sup>14</sup>. To avoid any  
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4 extrapolation bias we have restricted our analysis to individuals from the UK, Germany and other Western  
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6 European countries, which limits the interpretation for other ethnic groups or countries. Secondly, it is  
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8 likely that a number of further genetic and socioeconomic factors<sup>8</sup> are involved in the interplay of  
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10 educational attainment, intermediary factors and prevalence of CAD ([Extended Data Figure 4B](#)).  
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12 Specifically, environmental exposures may differ between countries and could also be confounders of the  
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14 genetic effects of education on CAD risk, which we lacked investigating in the current study. Moreover,  
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16 we arbitrarily restricted our analysis to EduYear-SNPs with established genome-wide significance for  
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18 association with educational attainment. It is likely that larger meta-analyses will identify more genetic  
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20 variants affecting school attainment as well as other socioeconomic factors<sup>42</sup>, such that the genetic effects  
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22 unravelled here are likely to underestimate the true effect. Thirdly, many of the lifestyle and risk factors  
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24 reported in the UK Biobank are self-reported and not externally validated, which might have  
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26 underestimated some of the effects. Calculating years of school attainment for participants of the UK  
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28 Biobank may also have some limitations<sup>14</sup>. We employed the same methods that were used in the report  
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30 that led to the identification of the EduYear-SNPs<sup>14</sup>. The fact that years of school attainment were also  
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32 strongly related to CAD and its risk factors supports the validity of this calculation. Next, the currently  
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34 available functional information on the EduYear-SNPs is fairly basic. It includes the genomic position,  
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36 allele frequencies, genes in the vicinity and signals from GWAS studies on other traits including CAD and  
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38 risk factors ([Extended Data Table 3](#)). It has been inferred that the ‘genetic education score’ may reflect  
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40 motivation<sup>39</sup>, cognitive ability<sup>35, 36</sup>, as well as an array of biological pathways<sup>14</sup> which also could influence  
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42 lifetime cardiovascular risk. However, we still have no precise information on the mechanisms by which  
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44 the EduYear-SNPs led to differences in educational attainment or even more complex traits such as  
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46 smoking and therefore coronary disease risk. We annotated these SNPs to physically nearby genes and  
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48 putative functions ([Extended Data Table 1](#)), with the hope to provide some information on the biological  
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50 context and the diversity of mechanisms underlying the SNPs affecting educational attainment. Future  
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52 research will need to unravel how these variants affect educational attainment or the prevalence of  
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54 smoking and obesity.  
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4 Finally, association findings in such complex settings – even if they are based on genetic variants  
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6 which allow inferring directionality in terms of a Bayesian approach – may reflect reverse causation. In  
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8 this sense a reflection of the Bradford Hill Criteria<sup>43</sup> may be of help. The associations reported here show  
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10 1.) substantial **strength** (effect size), i.e. over 20% difference between the highest/lowest quintile, 2.)  
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12 **consistency** (reproducibility) as they were reproduced in an independent sample, and with an independent  
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14 set of SNPs. 3.) **specificity**, i.e. causation was built on the Mendelian randomization approach, 4.)  
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16 **temporality**, i.e. genetics come first - by nature, 5.) a **biological gradient**, i.e. there is a stepwise effect  
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18 across the quintiles, 6.) **plausibility**, i.e. the chain of events between SNPs → school attainment →  
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20 smoking/obesity → CAD is clearly plausible, 7.) **coherence** with the literature on educational attainment  
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22 and cardiovascular risk, and 8.) **analogy** in that the effect size of ‘educational attainment’ on ‘CAD risk’ is  
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24 analogous with that of other risk factors. We have to admit, however, that 9.) **experimental validation**  
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26 cannot be obtained in this setting. Rather, we want to suppose that with the event of large-scale GWAS  
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28 statistical significance—not necessarily the magnitude of association—is the accepted benchmark for  
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30 judging the strength of an observed association between a genetic variant and a phenotype, and thus its  
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32 potential causality<sup>44</sup>.

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38 Genetic and lifestyle factors are often contrasted regarding their influence on coronary disease  
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40 risk<sup>31</sup>. An important determinant of lifestyle and related health outcomes is educational attainment. Our  
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42 study revealed that the genetic basis of educational attainment – like educational attainment itself<sup>6-9, 14, 31, 37</sup>  
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44 – is a partly independent element linked with lifestyle factors affecting CAD risk. Thus, our data give rise  
45  
46 to the hypothesis that the attitude towards a health-conscious lifestyle includes an inherited component  
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48 affecting educational attainment and decision making later in life, a finding which may have broad  
49  
50 implications for battling cardiovascular risks in Western societies.  
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### 28 **Conflict of Interest**

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48 submitted work.  
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## References

1. Manrique-Garcia E, Sidorchuk A, Hallqvist J, Moradi T. Socioeconomic position and incidence of acute myocardial infarction: a meta-analysis. *Journal of epidemiology and community health* 2011;**65**(4):301-9.
2. Veronesi G, Ferrario MM, Kuulasmaa K, Bobak M, Chambless LE, Salomaa V, Soderberg S, Pajak A, Jorgensen T, Amouyel P, Arveiler D, Drygas W, Ferrieres J, Giampaoli S, Kee F, Iacoviello L, Malyutina S, Peters A, Tamosiunas A, Tunstall-Pedoe H, Cesana G. Educational class inequalities in the incidence of coronary heart disease in Europe. *Heart (British Cardiac Society)* 2016;**102**(12):958-65.
3. Brunello G, Fort M, Schneeweis N, Winter-Ebmer R. The Causal Effect of Education on Health: What is the Role of Health Behaviors? *Health economics* 2016;**25**(3):314-36.
4. Lager AC, Torssander J. Causal effect of education on mortality in a quasi-experiment on 1.2 million Swedes. *Proceedings of the National Academy of Sciences of the United States of America* 2012;**109**(22):8461-6.
5. Clark D, Royer H. The Effect of Education on Adult Mortality and Health: Evidence from Britain. *American Economic Review* 2013;**103**(6):2087-2120.
6. Benjamin DJ, Cesarini D, van der Loos MJHM, Dawes CT, Koellinger PD, Magnusson PKE, Chabris CF, Conley D, Laibson D, Johannesson M, Visscher PM. The genetic architecture of economic and political preferences. *Proceedings of the National Academy of Sciences of the United States of America* 2012;**109**(21):8026-8031.
7. Rietveld CA, Medland SE, Derringer J, Yang J, Esko T, Martin NW, Westra HJ, Shakhbazov K, Abdellaoui A, Agrawal A, Albrecht E, Alizadeh BZ, Amin N, Barnard J, Baumeister SE, Benke KS, Bielak LF, Boatman JA, Boyle PA, Davies G, de Leeuw C, Eklund N, Evans DS, Ferhmann R, Fischer K, Gieger C, Gjessing HK, Hagg S, Harris JR, Hayward C, Holzapfel C, Ibrahim-Verbaas CA, Ingelsson E, Jacobsson B, Joshi PK, Jugessur A, Kaakinen M, Kanoni S, Karjalainen J, Kolcic I, Kristiansson K, Kutalik Z, Lahti J, Lee SH, Lin P, Lind PA, Liu Y, Lohman K, Loitfelder M, McMahon G, Vidal PM, Meirelles O, Milani L, Myhre R, Nuotio ML, Oldmeadow CJ, Petrovic KE, Peyrot WJ, Polasek O, Quaye L, Reinmaa E, Rice JP, Rizzi TS, Schmidt H, Schmidt R, Smith AV, Smith JA, Tanaka T, Terracciano A, van der Loos MJ, Vitart V, Volzke H, Wellmann J, Yu L, Zhao W, Allik J, Attia JR, Bandinelli S, Bastardot F, Beauchamp J, Bennett DA, Berger K, Bierut LJ, Boomsma DI, Bultmann U, Campbell H, Chabris CF, Cherkas L, Chung MK, Cucca F, de Andrade M, De Jager PL, De Neve JE, Deary IJ, Dedoussis GV, Deloukas P, Dimitriou M, Eiriksdottir G, Elderson MF, Eriksson JG, Evans DM, Faul JD, Ferrucci L, Garcia ME, Gronberg H, Guethnason V, Hall P, Harris JM, Harris TB, Hastie ND, Heath AC, Hernandez DG, Hoffmann W, Hofman A, Holle R, Holliday EG, Hottenga JJ, Iacono WG, Illig T, Jarvelin MR, Kahonen M, Kaprio J, Kirkpatrick RM, Kowgier M, Latvala A, Launer LJ, Lawlor DA, Lehtimaki T, Li J, Lichtenstein P, Lichtner P, Liewald DC, Madden PA, Magnusson PK, Makinen TE, Masala M, McGue M, Metspalu A, Mielck A, Miller MB, Montgomery GW, Mukherjee S, Nyholt DR, Oostra BA, Palmer LJ, Palotie A, Penninx BW, Perola M, Peyser PA, Preisig M, Raikonen K, Raitakari OT, Realo A, Ring SM, Ripatti S, Rivadeneira F, Rudan I, Rustichini A, Salomaa V, Sarin AP, Schlessinger D, Scott RJ, Snieder H, St Pourcain B, Starr JM, Sul JH, Surakka I, Svento R, Teumer A, Tiemeier H, van Rooij FJ, Van Wagoner DR, Vartiainen E, Viikari J, Vollenweider P, Vonk JM, Waeber G, Weir DR, Wichmann HE, Widen E, Willemsen G, Wilson JF, Wright AF, Conley D, Davey-Smith G, Franke L, Groenen PJ, Hofman A, Johannesson M, Kardina SL, Krueger RF, Laibson D, Martin NG, Meyer MN, Posthuma D, Thurik AR, Timpson NJ, Uitterlinden AG, van Duijn CM, Visscher PM, Benjamin DJ, Cesarini D, Koellinger PD. GWAS of 126,559 individuals identifies genetic variants associated with educational attainment. *Science* 2013;**340**(6139):1467-71.
8. Rietveld CA, Conley D, Eriksson N, Esko T, Medland SE, Vinkhuyzen AA, Yang J, Boardman JD, Chabris CF, Dawes CT, Domingue BW, Hinds DA, Johannesson M, Kiefer AK, Laibson D, Magnusson PK, Mountain JL, Oskarsson S, Rostapshova O, Teumer A, Tung JY, Visscher PM, Benjamin DJ, Cesarini D, Koellinger PD. Replicability and robustness of genome-wide-association studies for behavioral traits. *Psychological science* 2014;**25**(11):1975-86.
9. Davies G, Marioni RE, Liewald DC, Hill WD, Hagenaars SP, Harris SE, Ritchie SJ, Luciano M, Fawns-Ritchie C, Lyall D, Cullen B, Cox SR, Hayward C, Porteous DJ, Evans J, McIntosh AM, Gallacher J, Craddock N, Pell JP, Smith DJ, Gale CR, Deary IJ. Genome-wide association study of cognitive functions and educational attainment in UK Biobank (N=112 151). *Molecular psychiatry* 2016;**21**(6):758-67.
10. Nikpay M, Goel A, Won HH, Hall LM, Willenborg C, Kanoni S, Saleheen D, Kyriakou T, Nelson CP, Hopewell JC, Webb TR, Zeng L, Dehghan A, Alver M, Armasu SM, Auro K, Bjornes A, Chasman DI, Chen S, Ford I, Franceschini N, Gieger C, Grace C, Gustafsson S, Huang J, Hwang SJ, Kim YK, Kleber ME, Lau KW, Lu X, Lu Y, Lyytikainen LP, Mihailov E, Morrison AC, Pervjakova N, Qu L, Rose LM, Salfati E, Saxena R, Scholz M, Smith AV, Tikkanen E, Uitterlinden A, Yang X, Zhang W, Zhao W, de Andrade M, de Vries PS, van Zuydam NR, Anand SS, Bertram L, Beutner F, Dedoussis G, Frossard P, Gauguier D, Goodall AH, Gottesman O, Haber M, Han BG,

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2  
3  
4 Huang J, Jalilzadeh S, Kessler T, Konig IR, Lannfelt L, Lieb W, Lind L, Lindgren CM, Lokki ML, Magnusson PK,  
5 Mallick NH, Mehra N, Meitinger T, Memon FU, Morris AP, Nieminen MS, Pedersen NL, Peters A, Rallidis LS,  
6 Rasheed A, Samuel M, Shah SH, Sinisalo J, Stirrups KE, Trompet S, Wang L, Zaman KS, Ardissino D, Boerwinkle  
7 E, Borecki IB, Bottinger EP, Buring JE, Chambers JC, Collins R, Cupples LA, Danesh J, Demuth I, Elosua R,  
8 Epstein SE, Esko T, Feitosa MF, Franco OH, Franzosi MG, Granger CB, Gu D, Gudnason V, Hall AS, Hamsten A,  
9 Harris TB, Hazen SL, Hengstenberg C, Hofman A, Ingelsson E, Iribarren C, Jukema JW, Karhunen PJ, Kim BJ,  
10 Kooner JS, Kullo IJ, Lehtimaki T, Loos RJJ, Melander O, Metspalu A, Marz W, Palmer CN, Perola M, Quertermous  
11 T, Rader DJ, Ridker PM, Ripatti S, Roberts R, Salomaa V, Sanghera DK, Schwartz SM, Seedorf U, Stewart AF,  
12 Stott DJ, Thiery J, Zalloua PA, O'Donnell CJ, Reilly MP, Assimes TL, Thompson JR, Erdmann J, Clarke R, Watkins  
13 H, Kathiresan S, McPherson R, Deloukas P, Schunkert H, Samani NJ, Farrall M. A comprehensive 1,000 Genomes-  
14 based genome-wide association meta-analysis of coronary artery disease. *Nature genetics* 2015;**47**(10):1121-1130.  
15 11. Nelson CP, Goel A, Butterworth AS, Kanoni S, Webb TR, Marouli E, Zeng L, Ntalla I, Lai FY, Hopewell  
16 JC, Giannakopoulou O, Jiang T, Hamby SE, Di Angelantonio E, Assimes TL, Bottinger EP, Chambers JC, Clarke R,  
17 Palmer CNA, Cubbon RM, Ellinor P, Ermel R, Evangelou E, Franks PW, Grace C, Gu D, Hingorani AD, Howson  
18 JMM, Ingelsson E, Kastrati A, Kessler T, Kyriakou T, Lehtimaki T, Lu X, Lu Y, Marz W, McPherson R, Metspalu  
19 A, Pujades-Rodriguez M, Ruusalepp A, Schadt EE, Schmidt AF, Sweeting MJ, Zalloua PA, AlGhalayini K,  
20 Keavney BD, Kooner JS, Loos RJJ, Patel RS, Rutter MK, Tomaszewski M, Tzoulaki I, Zeggini E, Erdmann J,  
21 Dedoussis G, Bjorkegren JLM, Schunkert H, Farrall M, Danesh J, Samani NJ, Watkins H, Deloukas P. Association  
22 analyses based on false discovery rate implicate new loci for coronary artery disease.  
23 *Nat Genet* 2017 Sep; **49**(9):1385-1391.  
24 12. Lee JJ, Wedow R, Okbay A, Kong E, Maghziyan O, Zacher M, Nguyen-Viet TA, Bowers P, Sidorenko J,  
25 Karlsson Linner R, Fontana MA, Kundu T, Lee C, Li H, Li R, Royer R, Timshel PN, Walters RK, Willoughby EA,  
26 Yengo L, Alver M, Bao Y, Clark DW, Day FR, Furlotte NA, Joshi PK, Kemper KE, Kleinman A, Langenberg C,  
27 Magi R, Trampush JW, Verma SS, Wu Y, Lam M, Zhao JH, Zheng Z, Boardman JD, Campbell H, Freese J, Harris  
28 KM, Hayward C, Herd P, Kumari M, Lencz T, Luan J, Malhotra AK, Metspalu A, Milani L, Ong KK, Perry JRB,  
29 Porteous DJ, Ritchie MD, Smart MC, Smith BH, Tung JY, Wareham NJ, Wilson JF, Beauchamp JP, Conley DC,  
30 Esko T, Lehrer SF, Magnusson PKE, Oskarsson S, Pers TH, Robinson MR, Thom K, Watson C, Chabris CF, Meyer  
31 MN, Laibson DI, Yang J, Johannesson M, Koellinger PD, Turley P, Visscher PM, Benjamin DJ, Cesarini D. Gene  
32 discovery and polygenic prediction from a genome-wide association study of educational attainment in 1.1 million  
33 individuals. *Nat Genet* 2018;**50**(8):1112-1121.  
34 13. Jansen H, Samani NJ, Schunkert H. Mendelian randomization studies in coronary artery disease. *European*  
35 *heart journal* 2014;**35**(29):1917-24.  
36 14. Okbay A, Beauchamp JP, Fontana MA, Lee JJ, Pers TH, Rietveld CA, Turley P, Chen GB, Emilsson V,  
37 Meddens SF, Oskarsson S, Pickrell JK, Thom K, Timshel P, de Vlaming R, Abdellaoui A, Ahluwalia TS, Bacelis J,  
38 Baumbach C, Bjornsdottir G, Brandsma JH, Pina Concas M, Derringer J, Furlotte NA, Galesloot TE, Girotto G,  
39 Gupta R, Hall LM, Harris SE, Hofer E, Horikoshi M, Huffman JE, Kaasik K, Kalafati IP, Karlsson R, Kong A, Lahti  
40 J, van der Lee SJ, deLeeuw C, Lind PA, Lindgren KO, Liu T, Mangino M, Marten J, Mihailov E, Miller MB, van der  
41 Most PJ, Oldmeadow C, Payton A, Pervjakova N, Peyrot WJ, Qian Y, Raitakari O, Rueedi R, Salvi E, Schmidt B,  
42 Schraut KE, Shi J, Smith AV, Poot RA, St Pourcain B, Teumer A, Thorleifsson G, Verweij N, Vuckovic D,  
43 Wellmann J, Westra HJ, Yang J, Zhao W, Zhu Z, Alizadeh BZ, Amin N, Bakshi A, Baumeister SE, Biino G,  
44 Bonnelykke K, Boyle PA, Campbell H, Cappuccino FP, Davies G, De Neve JE, Deloukas P, Demuth I, Ding J, Eibich  
45 P, Eisele L, Eklund N, Evans DM, Faul JD, Feitosa MF, Forstner AJ, Gandin I, Gunnarsson B, Halldorsson BV,  
46 Harris TB, Heath AC, Hocking LJ, Holliday EG, Homuth G, Horan MA, Hottenga JJ, de Jager PL, Joshi PK,  
47 Jugessur A, Kaakinen MA, Kahonen M, Kanoni S, Keltigangas-Jarvinen L, Kiemeny LA, Kolcic I, Koskinen S,  
48 Kraja AT, Kroh M, Kutalik Z, Latvala A, Launer LJ, Lebreton MP, Levinson DF, Lichtenstein P, Lichtner P,  
49 Liewald DC, LifeLines Cohort S, Loukola A, Madden PA, Magi R, Maki-Opas T, Marioni RE, Marques-Vidal P,  
50 Meddens GA, McMahon G, Meisinger C, Meitinger T, Milanese Y, Milani L, Montgomery GW, Myhre R, Nelson  
51 CP, Nyholt DR, Ollier WE, Palotie A, Paternoster L, Pedersen NL, Petrovic KE, Porteous DJ, Raikonen K, Ring  
52 SM, Robino A, Rostapshova O, Rudan I, Rustichini A, Salomaa V, Sanders AR, Sarin AP, Schmidt H, Scott RJ,  
53 Smith BH, Smith JA, Staessen JA, Steinhagen-Thiessen E, Strauch K, Terracciano A, Tobin MD, Ulivi S, Vaccargiu  
54 S, Quaye L, van Rooij FJ, Venturini C, Vinkhuyzen AA, Volker U, Volzke H, Vonk JM, Vozzi D, Waage J, Ware  
55 EB, Willemsen G, Attia JR, Bennett DA, Berger K, Bertram L, Bisgaard H, Boomsma DI, Borecki IB, Bultmann U,  
56 Chabris CF, Cucca F, Cusi D, Deary IJ, Dedoussis GV, van Duijn CM, Eriksson JG, Franke B, Franke L, Gasparini  
57 P, Gejman PV, Gieger C, Grabe HJ, Gratten J, Groenen PJ, Gudnason V, van der Harst P, Hayward C, Hinds DA,  
58 Hoffmann W, Hypponen E, Iacono WG, Jacobsson B, Jarvelin MR, Jockel KH, Kaprio J, Kardina SL, Lehtimaki T,  
59 Lehrer SF, Magnusson PK, Martin NG, McGue M, Metspalu A, Pendleton N, Penninx BW, Perola M, Pirastu N,  
60 Pirastu M, Polasek O, Posthuma D, Power C, Province MA, Samani NJ, Schlessinger D, Schmidt R, Sorensen TI,  
61  
62  
63  
64  
65

1  
2  
3  
4 Spector TD, Stefansson K, Thorsteinsdottir U, Thurik AR, Timpson NJ, Tiemeier H, Tung JY, Uitterlinden AG,  
5 Vitart V, Vollenweider P, Weir DR, Wilson JF, Wright AF, Conley DC, Krueger RF, Davey Smith G, Hofman A,  
6 Laibson DI, Medland SE, Meyer MN, Yang J, Johannesson M, Visscher PM, Esko T, Koellinger PD, Cesarini D,  
7 Benjamin DJ. Genome-wide association study identifies 74 loci associated with educational attainment. *Nature*  
8 2016;**533**(7604):539-42.

9 15. Samani NJ, Erdmann J, Hall AS, Hengstenberg C, Mangino M, Mayer B, Dixon RJ, Meitinger T, Braund P,  
10 Wichmann HE, Barrett JH, König IR, Stevens SE, Szymczak S, Tregouet DA, Iles MM, Pahlke F, Pollard H, Lieb  
11 W, Cambien F, Fischer M, Ouwehand W, Blankenberg S, Balmforth AJ, Baessler A, Ball SG, Strom TM, Braenne I,  
12 Gieger C, Deloukas P, Tobin MD, Ziegler A, Thompson JR, Schunkert H. Genomewide association analysis of  
13 coronary artery disease. *The New England journal of medicine* 2007;**357**(5):443-53.

14 16. Erdmann J, Grosshennig A, Braund PS, König IR, Hengstenberg C, Hall AS, Linsel-Nitschke P, Kathiresan  
15 S, Wright B, Tregouet DA, Cambien F, Bruse P, Aherrahrou Z, Wagner AK, Stark K, Schwartz SM, Salomaa V,  
16 Elosua R, Melander O, Voight BF, O'Donnell CJ, Peltonen L, Siscovick DS, Altshuler D, Merlini PA, Peyvandi F,  
17 Bernardinelli L, Ardissino D, Schillert A, Blankenberg S, Zeller T, Wild P, Wild P, Schwarz DF, Tiret L, Perret C, Schreiber  
18 S, El Mokhtari NE, Schafer A, Marz W, Renner W, Bugert P, Kluter H, Schrezenmeir J, Rubin D, Ball SG,  
19 Balmforth AJ, Wichmann HE, Meitinger T, Fischer M, Meisinger C, Baumert J, Peters A, Ouwehand WH, Deloukas  
20 P, Thompson JR, Ziegler A, Samani NJ, Schunkert H. New susceptibility locus for coronary artery disease on  
21 chromosome 3q22.3. *Nat Genet* 2009;**41**(3):280-2.

22 17. Erdmann J, Willenborg C, Nahrstaedt J, Preuss M, König IR, Baumert J, Linsel-Nitschke P, Gieger C,  
23 Tennstedt S, Belcredi P, Aherrahrou Z, Klopp N, Loley C, Stark K, Hengstenberg C, Bruse P, Freyer J, Wagner AK,  
24 Medack A, Lieb W, Grosshennig A, Sager HB, Reinhardt A, Schafer A, Schreiber S, El Mokhtari NE, Raaz-  
25 Schrauder D, Illig T, Garlachs CD, Ekici AB, Reis A, Schrezenmeir J, Rubin D, Ziegler A, Wichmann HE, Doering  
26 A, Meisinger C, Meitinger T, Peters A, Schunkert H. Genome-wide association study identifies a new locus for  
27 coronary artery disease on chromosome 10p11.23. *European heart journal* 2011;**32**(2):158-68.

28 18. Stitzel NO, Won HH, Morrison AC, Peloso GM, Do R, Lange LA, Fontanillas P, Gupta N, Duga S, Goel  
29 A, Farrall M, Saleheen D, Ferrario P, König I, Asselta R, Merlini PA, Marziliano N, Notarangelo MF, Schick U,  
30 Auer P, Assimes TL, Reilly M, Wilensky R, Rader DJ, Hovingh GK, Meitinger T, Kessler T, Kastrati A, Laugwitz  
31 KL, Siscovick D, Rotter JI, Hazen SL, Tracy R, Cresci S, Spertus J, Jackson R, Schwartz SM, Natarajan P, Crosby J,  
32 Muzny D, Ballantyne C, Rich SS, O'Donnell CJ, Abecasis G, Sunaev S, Nickerson DA, Buring JE, Ridker PM,  
33 Chasman DI, Austin E, Kullo IJ, Weeke PE, Shaffer CM, Bastarache LA, Denny JC, Roden DM, Palmer C,  
34 Deloukas P, Lin DY, Tang ZZ, Erdmann J, Schunkert H, Danesh J, Marrugat J, Elosua R, Ardissino D, McPherson  
35 R, Watkins H, Reiner AP, Wilson JG, Altshuler D, Gibbs RA, Lander ES, Boerwinkle E, Gabriel S, Kathiresan S.  
36 Inactivating mutations in NPC1L1 and protection from coronary heart disease. *The New England journal of*  
37 *medicine* 2014;**371**(22):2072-82.

38 19. WTCC Consortium.. Genome-wide association study of 14,000 cases of seven common diseases and 3,000  
39 shared controls. *Nature* 2007;**447**(7145):661-78.

40 20. Kathiresan S, Voight BF, Purcell S, Musunuru K, Ardissino D, Mannucci PM, Anand S, Engert JC, Samani  
41 NJ, Schunkert H, Erdmann J, Reilly MP, Rader DJ, Morgan T, Spertus JA, Stoll M, Girelli D, McKeown PP,  
42 Patterson CC, Siscovick DS, O'Donnell CJ, Elosua R, Peltonen L, Salomaa V, Schwartz SM, Melander O, Altshuler  
43 D, Ardissino D, Merlini PA, Berzuini C, Bernardinelli L, Peyvandi F, Tubaro M, Celli P, Ferrario M, Faveau R,  
44 Marziliano N, Casari G, Galli M, Ribichini F, Rossi M, Bernardi F, Zoncin P, Piazza A, Mannucci PM, Schwartz  
45 SM, Siscovick DS, Yee J, Friedlander Y, Elosua R, Marrugat J, Lucas G, Subirana I, Sala J, Ramos R, Kathiresan S,  
46 Meigs JB, Williams G, Nathan DM, MacRae CA, O'Donnell CJ, Salomaa V, Havulinna AS, Peltonen L, Melander  
47 O, Berglund G, Voight BF, Kathiresan S, Hirschhorn JN, Asselta R, Duga S, Spreafico M, Musunuru K, Daly MJ,  
48 Purcell S, Voight BF, Purcell S, Nemes J, Korn JM, McCarroll SA, Schwartz SM, Yee J, Kathiresan S, Lucas G,  
49 Subirana I, Elosua R, Surti A, Guiducci C, Gianniny L, Mirel D, Parkin M, Burt N, Gabriel SB, Samani NJ,  
50 Thompson JR, Braund PS, Wright BJ, Balmforth AJ, Ball SG, Hall A, Schunkert H, Erdmann J, Linsel-Nitschke P,  
51 Lieb W, Ziegler A, König I, Hengstenberg C, Fischer M, Stark K, Grosshennig A, Preuss M, Wichmann HE,  
52 Schreiber S, Schunkert H, Samani NJ, Erdmann J, Ouwehand W, Hengstenberg C, Deloukas P, Scholz M, Cambien  
53 F, Reilly MP, Li M, Chen Z, Wilensky R, Matthai W, Qasim A, Hakonarson HH, Devaney J, Burnett MS, Pichard  
54 AD, Kent KM, Satler L, Lindsay JM, Waksman R, Knouff CW, Waterworth DM, Walker MC, Mooser V, Epstein  
55 SE, Rader DJ, Scheffold T, Berger K, Stoll M, Hage A, Girelli D, Martinelli N, Olivieri O, Corrocher R, Morgan T,  
56 Spertus JA, McKeown P, Patterson CC, Schunkert H, Erdmann E, Linsel-Nitschke P, Lieb W, Ziegler A, König IR,  
57 Hengstenberg C, Fischer M, Stark K, Grosshennig A, Preuss M, Wichmann HE, Schreiber S, Holm H, Thorleifsson  
58 G, Thorsteinsdottir U, Stefansson K, Engert JC, Do R, Xie C, Anand S, Kathiresan S, Ardissino D, Mannucci PM,  
59 Siscovick D, O'Donnell CJ, Samani NJ, Melander O, Elosua R, Peltonen L, Salomaa V, Schwartz SM, Altshuler D.  
60  
61  
62  
63  
64  
65

- 1  
2  
3  
4 Genome-wide association of early-onset myocardial infarction with single nucleotide polymorphisms and copy  
5 number variants. *Nat Genet* 2009;**41**(3):334-41.
- 6 21. CARDIoGRAM Consortium, Deloukas P, Kanoni S, Willenborg C, Farrall M, Assimes TL, Thompson JR,  
7 Ingelsson E, Saleheen D, Erdmann J, Goldstein BA, Stirrups K, Konig IR, Cazier JB, Johansson A, Hall AS, Lee JY,  
8 Willer CJ, Chambers JC, Esko T, Folkersen L, Goel A, Grundberg E, Havulinna AS, Ho WK, Hopewell JC,  
9 Eriksson N, Kleber ME, Kristiansson K, Lundmark P, Lyytikainen LP, Rafelt S, Shungin D, Strawbridge RJ,  
10 Thorleifsson G, Tikkanen E, Van Zuydam N, Voight BF, Waite LL, Zhang W, Ziegler A, Absher D, Altschuler D,  
11 Balmforth AJ, Barroso I, Braund PS, Burgdorf C, Claudi-Boehm S, Cox D, Dimitriou M, Do R, Consortium D,  
12 Consortium C, Doney AS, El Mokhtari N, Eriksson P, Fischer K, Fontanillas P, Franco-Cereceda A, Gigante B,  
13 Groop L, Gustafsson S, Hager J, Hallmans G, Han BG, Hunt SE, Kang HM, Illig T, Kessler T, Knowles JW,  
14 Kolovou G, Kuusisto J, Langenberg C, Langford C, Leander K, Lokki ML, Lundmark A, McCarthy MI, Meisinger  
15 C, Melander O, Mihailov E, Maouche S, Morris AD, Muller-Nurasyid M, Mu TC, Nikus K, Peden JF, Rayner NW,  
16 Rasheed A, Rosinger S, Rubin D, Rumpf MP, Schafer A, Sivananthan M, Song C, Stewart AF, Tan ST,  
17 Thorgeirsson G, van der Schoot CE, Wagner PJ, Wellcome Trust Case Control C, Wells GA, Wild PS, Yang TP,  
18 Amouyel P, Arveiler D, Basart H, Boehnke M, Boerwinkle E, Brambilla P, Cambien F, Cupples AL, de Faire U,  
19 Dehghan A, Diemert P, Epstein SE, Evans A, Ferrario MM, Ferrieres J, Gauguier D, Go AS, Goodall AH, Gudnason  
20 V, Hazen SL, Holm H, Iribarren C, Jang Y, Kahonen M, Kee F, Kim HS, Klopp N, Koenig W, Kratzer W,  
21 Kuulasmaa K, Laakso M, Laaksonen R, Lee JY, Lind L, Ouwehand WH, Parish S, Park JE, Pedersen NL, Peters A,  
22 Quertermous T, Rader DJ, Salomaa V, Schadt E, Shah SH, Sinisalo J, Stark K, Stefansson K, Tregouet DA, Virtamo  
23 J, Wallentin L, Wareham N, Zimmermann ME, Nieminen MS, Hengstenberg C, Sandhu MS, Pastinen T, Syvanen  
24 AC, Hovingh GK, Dedoussis G, Franks PW, Lehtimäki T, Metspalu A, Zalloua PA, Siegbahn A, Schreiber S, Ripatti  
25 S, Blankenberg SS, Perola M, Clarke R, Boehm BO, O'Donnell C, Reilly MP, Marz W, Collins R, Kathiresan S,  
26 Hamsten A, Kooner JS, Thorsteinsdottir U, Danesh J, Palmer CN, Roberts R, Watkins H, Schunkert H, Samani NJ.  
27 Large-scale association analysis identifies new risk loci for coronary artery disease. *Nat Genet* 2013;**45**(1):25-33.
- 28 22. Sudlow C, Gallacher J, Allen N, Beral V, Burton P, Danesh J, Downey P, Elliott P, Green J, Landray M,  
29 Liu B, Matthews P, Ong G, Pell J, Silman A, Young A, Sprosen T, Peakman T, Collins R. UK biobank: an open  
30 access resource for identifying the causes of a wide range of complex diseases of middle and old age. *PLoS Med*  
31 2015;**12**(3):e1001779.
- 32 23. Wray NR, Yang J, Hayes BJ, Price AL, Goddard ME, Visscher PM. Pitfalls of predicting complex traits  
33 from SNPs. *Nature reviews Genetics* 2013;**14**(7):507-15.
- 34 24. Nikpay M, Goel A, Won HH, Hall LM, Willenborg C, Kanoni S, Saleheen D, Kyriakou T, Nelson CP,  
35 Hopewell JC, Webb TR, Zeng L, Dehghan A, Alver M, Armasu SM, Auro K, Bjornes A, Chasman DI, Chen S, Ford  
36 I, Franceschini N, Gieger C, Grace C, Gustafsson S, Huang J, Hwang SJ, Kim YK, Kleber ME, Lau KW, Lu X, Lu  
37 Y, Lyytikainen LP, Mihailov E, Morrison AC, Pervjakova N, Qu L, Rose LM, Salfati E, Saxena R, Scholz M, Smith  
38 AV, Tikkanen E, Uitterlinden A, Yang X, Zhang W, Zhao W, de Andrade M, de Vries PS, van Zuydam NR, Anand  
39 SS, Bertram L, Beutner F, Dedoussis G, Frossard P, Gauguier D, Goodall AH, Gottesman O, Haber M, Han BG,  
40 Huang J, Jalilzadeh S, Kessler T, Konig IR, Lannfelt L, Lieb W, Lind L, Lindgren CM, Lokki ML, Magnusson PK,  
41 Mallick NH, Mehra N, Meitinger T, Memon FU, Morris AP, Nieminen MS, Pedersen NL, Peters A, Rallidis LS,  
42 Rasheed A, Samuel M, Shah SH, Sinisalo J, Stirrups KE, Trompet S, Wang L, Zaman KS, Ardisino D, Boerwinkle  
43 E, Borecki IB, Bottinger EP, Buring JE, Chambers JC, Collins R, Cupples LA, Danesh J, Demuth I, Elosua R,  
44 Epstein SE, Esko T, Feitosa MF, Franco OH, Franzosi MG, Granger CB, Gu D, Gudnason V, Hall AS, Hamsten A,  
45 Harris TB, Hazen SL, Hengstenberg C, Hofman A, Ingelsson E, Iribarren C, Jukema JW, Karhunen PJ, Kim BJ,  
46 Kooner JS, Kullo IJ, Lehtimäki T, Loos RJ, Melander O, Metspalu A, Marz W, Palmer CN, Perola M, Quertermous  
47 T, Rader DJ, Ridker PM, Ripatti S, Roberts R, Salomaa V, Sanghera DK, Schwartz SM, Seedorf U, Stewart AF,  
48 Stott DJ, Thiery J, Zalloua PA, O'Donnell CJ, Reilly MP, Assimes TL, Thompson JR, Erdmann J, Clarke R, Watkins  
49 H, Kathiresan S, McPherson R, Deloukas P, Schunkert H, Samani NJ, Farrall M. A comprehensive 1,000 Genomes-  
50 based genome-wide association meta-analysis of coronary artery disease. *Nat Genet* 2015;**47**(10):1121-30.
- 51 25. Locke AE, Kahali B, Berndt SI, Justice AE, Pers TH, Day FR, Powell C, Vedantam S, Buchkovich ML,  
52 Yang J, Croteau-Chonka DC, Esko T, Fall T, Ferreira T, Gustafsson S, Kutalik Z, Luan J, Magi R, Randall JC,  
53 Winkler TW, Wood AR, Workalemahu T, Faul JD, Smith JA, Hua Zhao J, Zhao W, Chen J, Fehrmann R, Hedman  
54 AK, Karjalainen J, Schmidt EM, Absher D, Amin N, Anderson D, Beekman M, Bolton JL, Bragg-Gresham JL,  
55 Buyske S, Demirkan A, Deng G, Ehret GB, Feenstra B, Feitosa MF, Fischer K, Goel A, Gong J, Jackson AU,  
56 Kanoni S, Kleber ME, Kristiansson K, Lim U, Lotay V, Mangino M, Mateo Leach I, Medina-Gomez C, Medland  
57 SE, Nalls MA, Palmer CD, Pasko D, Pechlivanis S, Peters MJ, Prokopenko I, Shungin D, Stancakova A,  
58 Strawbridge RJ, Ju Sung Y, Tanaka T, Teumer A, Trompet S, van der Laan SW, van Setten J, Van Vliet-  
59 Ostaptchouk JV, Wang Z, Yengo L, Zhang W, Isaacs A, Albrecht E, Arnlov J, Arscott GM, Attwood AP, Bandinelli  
60 S, Barrett A, Bas IN, Bellis C, Bennett AJ, Berne C, Blagieva R, Bluher M, Bohringer S, Bonnycastle LL, Bottcher  
61  
62  
63  
64  
65

1  
2  
3  
4 Y, Boyd HA, Bruinenberg M, Caspersen IH, Ida Chen YD, Clarke R, Daw EW, de Craen AJ, Delgado G, Dimitriou  
5 M, Doney AS, Eklund N, Estrada K, Eury E, Folkersen L, Fraser RM, Garcia ME, Geller F, Giedraitis V, Gigante B,  
6 Go AS, Golay A, Goodall AH, Gordon SD, Gorski M, Grabe HJ, Grallert H, Grammer TB, Grassler J, Gronberg H,  
7 Groves CJ, Gusto G, Haessler J, Hall P, Haller T, Hallmans G, Hartman CA, Hassinen M, Hayward C, Heard-Costa  
8 NL, Helmer Q, Hengstenberg C, Holmen O, Hottenga JJ, James AL, Jeff JM, Johansson A, Jolley J, Juliusdottir T,  
9 Kinnunen L, Koenig W, Koskenvuo M, Kratzer W, Laitinen J, Lamina C, Leander K, Lee NR, Lichtner P, Lind L,  
10 Lindstrom J, Sin Lo K, Lobbens S, Lorbeer R, Lu Y, Mach F, Magnusson PK, Mahajan A, McArdle WL,  
11 McLachlan S, Menni C, Merger S, Mihailov E, Milani L, Moayyeri A, Monda KL, Morken MA, Mulas A, Muller G,  
12 Muller-Nurasyid M, Musk AW, Nagaraja R, Nothen MM, Nolte IM, Pilz S, Rayner NW, Renstrom F, Rettig R, Ried  
13 JS, Ripke S, Robertson NR, Rose LM, Sanna S, Schernagl H, Scholtens S, Schumacher FR, Scott WR, Seufferlein T,  
14 Shi J, Vernon Smith A, Smolonska J, Stanton AV, Steinthorsdottir V, Stirrups K, Stringham HM, Sundstrom J,  
15 Swertz MA, Swift AJ, Syvanen AC, Tan ST, Tayo BO, Thorand B, Thorleifsson G, Tyrer JP, Uh HW, Vandenput L,  
16 Verhulst FC, Vermeulen SH, Verweij N, Vonk JM, Waite LL, Warren HR, Waterworth D, Weedon MN, Wilkens  
17 LR, Willenborg C, Wilsgaard T, Wojczynski MK, Wong A, Wright AF, Zhang Q, Brennan EP, Choi M, Dastani Z,  
18 Drong AW, Eriksson P, Franco-Cereceda A, Gadin JR, Gharavi AG, Goddard ME, Handsaker RE, Huang J, Karpe  
19 F, Kathiresan S, Keildson S, Kiryluk K, Kubo M, Lee JY, Liang L, Lifton RP, Ma B, McCarroll SA, McKnight AJ,  
20 Min JL, Moffatt MF, Montgomery GW, Murabito JM, Nicholson G, Nyholt DR, Okada Y, Perry JR, Dorajoo R,  
21 Reinmaa E, Salem RM, Sandholm N, Scott RA, Stolk L, Takahashi A, Tanaka T, Van't Hooft FM, Vinkhuyzen AA,  
22 Westra HJ, Zheng W, Zondervan KT, Heath AC, Arveiler D, Bakker SJ, Beilby J, Bergman RN, Blangero J, Bovet  
23 P, Campbell H, Caulfield MJ, Cesana G, Chakravarti A, Chasman DI, Chines PS, Collins FS, Crawford DC, Cupples  
24 LA, Cusi D, Danesh J, de Faire U, den Ruijter HM, Dominiczak AF, Erbel R, Erdmann J, Eriksson JG, Farrall M,  
25 Felix SB, Ferrannini E, Ferrieres J, Ford I, Forouhi NG, Forrester T, Franco OH, Gansevoort RT, Gejman PV,  
26 Gieger C, Gottesman O, Gudnason V, Gyllensten U, Hall AS, Harris TB, Hattersley AT, Hicks AA, Hindorf LA,  
27 Hingorani AD, Hofman A, Homuth G, Hovingh GK, Humphries SE, Hunt SC, Hypponen E, Illig T, Jacobs KB,  
28 Jarvelin MR, Jockel KH, Johansen B, Jousilahti P, Jukema JW, Jula AM, Kaprio J, Kastelein JJ, Keinänen-  
29 Kiukaanniemi SM, Kiemeny LA, Knekt P, Kooner JS, Kooperberg C, Kovacs P, Kraja AT, Kumari M, Kuusisto J,  
30 Lakka TA, Langenberg C, Le Marchand L, Lehtimäki T, Lyssenko V, Mannisto S, Marette A, Matise TC, McKenzie  
31 CA, McKnight B, Moll FL, Morris AD, Morris AP, Murray JC, Nelis M, Ohlsson C, Oldehinkel AJ, Ong KK,  
32 Madden PA, Pasterkamp G, Peden JF, Peters A, Postma DS, Pramstaller PP, Price JF, Qi L, Raitakari OT, Rankinen  
33 T, Rao DC, Rice TK, Ridker PM, Rioux JD, Ritchie MD, Rudan I, Salomaa V, Samani NJ, Saramies J, Sarzynski  
34 MA, Schunkert H, Schwarz PE, Sever P, Shuldiner AR, Sinisalo J, Stolk RP, Strauch K, Tonjes A, Tregouet DA,  
35 Tremblay A, Tremoli E, Virtamo J, Vohl MC, Volker U, Waeber G, Willemssen G, Witteman JC, Zillikens MC,  
36 Adair LS, Amouyel P, Asselbergs FW, Assimes TL, Bochud M, Boehm BO, Boerwinkle E, Bornstein SR, Bottinger  
37 EP, Bouchard C, Cauchi S, Chambers JC, Chanock SJ, Cooper RS, de Bakker PI, Dedoussis G, Ferrucci L, Franks  
38 PW, Froguel P, Groop LC, Haiman CA, Hamsten A, Hui J, Hunter DJ, Hveem K, Kaplan RC, Kivimäki M, Kuh D,  
39 Laakso M, Liu Y, Martin NG, Marz W, Melbye M, Metspalu A, Moebus S, Munroe PB, Njolstad I, Oostra BA,  
40 Palmer CN, Pedersen NL, Perola M, Perusse L, Peters U, Power C, Quertermous T, Rauramaa R, Rivadeneira F,  
41 Saaristo TE, Saleheen D, Sattar N, Schadt EE, Schlessinger D, Slagboom PE, Snieder H, Spector TD,  
42 Thorsteinsdottir U, Stumvoll M, Tuomilehto J, Uitterlinden AG, Uusitupa M, van der Harst P, Walker M,  
43 Wallaschofski H, Wareham NJ, Watkins H, Weir DR, Wichmann HE, Wilson JF, Zanen P, Borecki IB, Deloukas P,  
44 Fox CS, Heid IM, O'Connell JR, Strachan DP, Stefansson K, van Duijn CM, Abecasis GR, Franke L, Frayling TM,  
45 McCarthy MI, Visscher PM, Scherag A, Willer CJ, Boehnke M, Mohlke KL, Lindgren CM, Beckmann JS, Barroso  
46 I, North KE, Ingelsson E, Hirschhorn JN, Loos RJ, Speliotes EK. Genetic studies of body mass index yield new  
47 insights for obesity biology. *Nature* 2015;**518**(7538):197-206.

48 26. TAG Consortium. Genome-wide meta-analyses identify multiple loci associated with smoking behavior.  
49 *Nat Genet* 2010;**42**(5):441-7.

50 27. Global Lipids Genetics Consortium, Willer CJ, Schmidt EM, Sengupta S, Peloso GM, Gustafsson S, Kanoni  
51 S, Ganna A, Chen J, Buchkovich ML, Mora S, Beckmann JS, Bragg-Gresham JL, Chang HY, Demirkan A, Den  
52 Hertog HM, Do R, Donnelly LA, Ehret GB, Esko T, Feitosa MF, Ferreira T, Fischer K, Fontanillas P, Fraser RM,  
53 Freitag DF, Gurdasani D, Heikkilä K, Hypponen E, Isaacs A, Jackson AU, Johansson A, Johnson T, Kaakinen M,  
54 Kettunen J, Kleber ME, Li X, Luan J, Lyytikäinen LP, Magnusson PK, Mangino M, Mihailov E, Montasser ME,  
55 Muller-Nurasyid M, Nolte IM, O'Connell JR, Palmer CD, Perola M, Petersen AK, Sanna S, Saxena R, Service SK,  
56 Shah S, Shungin D, Sidore C, Song C, Strawbridge RJ, Surakka I, Tanaka T, Teslovich TM, Thorleifsson G, Van  
57 den Herik EG, Voight BF, Volcik KA, Waite LL, Wong A, Wu Y, Zhang W, Absher D, Asiki G, Barroso I, Been  
58 LF, Bolton JL, Bonnycastle LL, Brambilla P, Burnett MS, Cesana G, Dimitriou M, Doney AS, Doring A, Elliott P,  
59 Epstein SE, Eyjolfsson GI, Gigante B, Goodarzi MO, Grallert H, Gravito ML, Groves CJ, Hallmans G, Hartikainen  
60 AL, Hayward C, Hernandez D, Hicks AA, Holm H, Hung YJ, Illig T, Jones MR, Kaleebu P, Kastelein JJ, Khaw KT,  
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4 Kim E, Klopp N, Komulainen P, Kumari M, Langenberg C, Lehtimaki T, Lin SY, Lindstrom J, Loos RJ, Mach F,  
5 McArdle WL, Meisinger C, Mitchell BD, Muller G, Nagaraja R, Narisu N, Nieminen TV, Nsubuga RN, Olafsson I,  
6 Ong KK, Palotie A, Papamarkou T, Pomilla C, Pouta A, Rader DJ, Reilly MP, Ridker PM, Rivadeneira F, Rudan I,  
7 Ruokonen A, Samani N, Scharnagl H, Seeley J, Silander K, Stancakova A, Stirrups K, Swift AJ, Tired L,  
8 Uitterlinden AG, van Pelt LJ, Vedantam S, Wainwright N, Wijmenga C, Wild SH, Willemsen G, Wilsgaard T,  
9 Wilson JF, Young EH, Zhao JH, Adair LS, Arveiler D, Assimes TL, Bandinelli S, Bennett F, Bochud M, Boehm  
10 BO, Boomsma DI, Borecki IB, Bornstein SR, Bovet P, Burnier M, Campbell H, Chakravarti A, Chambers JC, Chen  
11 YD, Collins FS, Cooper RS, Danesh J, Dedoussis G, de Faire U, Feranil AB, Ferrieres J, Ferrucci L, Freimer NB,  
12 Gieger C, Groop LC, Gudnason V, Gyllensten U, Hamsten A, Harris TB, Hingorani A, Hirschhorn JN, Hofman A,  
13 Hovingh GK, Hsiung CA, Humphries SE, Hunt SC, Hveem K, Iribarren C, Jarvelin MR, Jula A, Kahonen M, Kaprio  
14 J, Kesaniemi A, Kivimaki M, Kooner JS, Koudstaal PJ, Krauss RM, Kuh D, Kuusisto J, Kyvik KO, Laakso M,  
15 Lakka TA, Lind L, Lindgren CM, Martin NG, Marz W, McCarthy MI, McKenzie CA, Meneton P, Metspalu A,  
16 Moilanen L, Morris AD, Munroe PB, Njolstad I, Pedersen NL, Power C, Pramstaller PP, Price JF, Psaty BM,  
17 Quertermous T, Rauramaa R, Saleheen D, Salomaa V, Sanghera DK, Saramies J, Schwarz PE, Sheu WH, Shuldiner  
18 AR, Siegbahn A, Spector TD, Stefansson K, Strachan DP, Tayo BO, Tremoli E, Tuomilehto J, Uusitupa M, van  
19 Duijn CM, Vollenweider P, Wallentin L, Wareham NJ, Whitfield JB, Wolffenbuttel BH, Ordovas JM, Boerwinkle E,  
20 Palmer CN, Thorsteinsdottir U, Chasman DI, Rotter JI, Franks PW, Ripatti S, Cupples LA, Sandhu MS, Rich SS,  
21 Boehnke M, Deloukas P, Kathiresan S, Mohlke KL, Ingelsson E, Abecasis GR. Discovery and refinement of loci  
22 associated with lipid levels. *Nat Genet* 2013;**45**(11):1274-83.
- 23 28. Burgess S, Butterworth A, Thompson SG. Mendelian randomization analysis with multiple genetic variants  
24 using summarized data. *Genet Epidemiol* 2013;**37**(7):658-65.
- 25 29. Bowden J, Davey Smith G, Burgess S. Mendelian randomization with invalid instruments: effect estimation  
26 and bias detection through Egger regression. *International journal of epidemiology* 2015;**44**(2):512-25.
- 27 30. Bowden J, Davey Smith G, Haycock PC, Burgess S. Consistent Estimation in Mendelian Randomization  
28 with Some Invalid Instruments Using a Weighted Median Estimator. *Genet Epidemiol* 2016;**40**(4):304-14.
- 29 31. Khera AV, Emdin CA, Drake I, Natarajan P, Bick AG, Cook NR, Chasman DI, Baber U, Mehran R, Rader  
30 DJ, Fuster V, Boerwinkle E, Melander O, Orho-Melander M, Ridker PM, Kathiresan S. Genetic Risk, Adherence to  
31 a Healthy Lifestyle, and Coronary Disease. *The New England journal of medicine* 2016;**375**(24):2349-2358.
- 32 32. Davies NM, Hemani G, Timpson NJ, Windmeijer F, Davey Smith G. The role of common genetic variation  
33 in educational attainment and income: evidence from the National Child Development Study. *Scientific reports*  
34 2015;**5**:16509.
- 35 33. Marioni RE, Yang J, Dykiert D, Mottus R, Campbell A, Davies G, Hayward C, Porteous DJ, Visscher PM,  
36 Deary IJ. Assessing the genetic overlap between BMI and cognitive function. *Molecular psychiatry*  
37 2016;**21**(10):1477-82.
- 38 34. Trzaskowski M, Harlaar N, Arden R, Krapohl E, Rimfeld K, McMillan A, Dale PS, Plomin R. Genetic  
39 influence on family socioeconomic status and children's intelligence. *Intelligence* 2014;**42**(100):83-88.
- 40 35. Deary IJ, Strand S, Smith P, Fernandes C. Intelligence and educational achievement. *Intelligence*  
41 2007;**35**(1):13-21.
- 42 36. Strenze T. Intelligence and socioeconomic success: A meta-analytic review of longitudinal research.  
43 *Intelligence* 2007;**35**(5):401-426.
- 44 37. Marioni RE, Ritchie SJ, Joshi PK, Hagenaars SP, Okbay A, Fischer K, Adams MJ, Hill WD, Davies G,  
45 Social Science Genetic Association C, Nagy R, Amador C, Lall K, Metspalu A, Liewald DC, Campbell A, Wilson  
46 JF, Hayward C, Esko T, Porteous DJ, Gale CR, Deary IJ. Genetic variants linked to education predict longevity.  
47 *Proceedings of the National Academy of Sciences of the United States of America* 2016;**113**(47):13366-13371.
- 48 38. Arden R, Luciano M, Deary IJ, Reynolds CA, Pedersen NL, Plassman BL, McGue M, Christensen K,  
49 Visscher PM. The association between intelligence and lifespan is mostly genetic. *International journal of*  
50 *epidemiology* 2016;**45**(1):178-85.
- 51 39. Schoon I. A Transgenerational Model of Status Attainment: the Potential Mediating Role of School  
52 Motivation and Education. *National Institute Economic Review* 2008;**205**(1):72-82.
- 53 40. Dubow EF, Boxer P, Huesmann LR. Long-term Effects of Parents' Education on Children's Educational and  
54 Occupational Success: Mediation by Family Interactions, Child Aggression, and Teenage Aspirations. *Merrill-*  
55 *Palmer quarterly* (Wayne State University Press) 2009;**55**(3):224-249.
- 56 41. Dempfle A, Scherag A, Hein R, Beckmann L, Chang-Claude J, Schafer H. Gene-environment interactions  
57 for complex traits: definitions, methodological requirements and challenges. *Eur J Hum Genet* 2008;**16**(10):1164-72.
- 58 42. Chetty R, Stepner M, Abraham S, Lin S, Scuderi B, Turner N, Bergeron A, Cutler D. The Association  
59 Between Income and Life Expectancy in the United States, 2001-2014. *JAMA* 2016;**315**(16):1750-66.
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4 43. Hill AB. THE ENVIRONMENT AND DISEASE: ASSOCIATION OR CAUSATION? Proceedings of the  
5 Royal Society of Medicine 1965;**58**:295-300.  
6 44. Burgess S, Butterworth AS, Thompson JR. Beyond Mendelian randomization: how to interpret evidence of  
7 shared genetic predictors. Journal of clinical epidemiology 2016;**69**:208-16.  
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26 **Figure legends**

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28 **Figure 1. ‘Genetic education score’ and risk of coronary artery disease.**

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31 A weighted genetic risk score (wGRS) based on 74 genetic variants affecting length of education reported  
32 by Okbay et al<sup>14</sup> (“genetic education score”) was calculated in individuals from nine case-control studies  
33 for CAD (total n=27,551). The calculation of the score is described in Methods, and the description for  
34 these 9 studies is provided in Supplementary Text. Logistic regression was performed to evaluate the  
35 effect size of the wGRS on the risk of CAD in each study separately and afterwards meta-analysis was  
36 performed to combine the effects across nine studies. Forest plot displays a consistent inverse correlation  
37 across studies between the ‘genetic education score’ and odds of CAD.  
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48 **Figure 2. Inverse relationship of genetically determined educational attainment and risk of**  
49 **coronary artery disease.**

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52 Individuals from each of the nine studies were grouped into quintiles based on their weighted genetic risk  
53 score for school attainment, with quintile 1 indicating the lowest genetic score and quintile 5 the highest.  
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55 Odds ratios, shown with and 95% confidence intervals, for CAD were 20.8% lower in the quintile with the  
56 highest genetically determined educational attainment as compared to those with the lowest ‘genetic  
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education score'. The distribution of all cases (red bars) with CAD is decreasing with an increasing 'genetic education score', while that of all controls (blue bars) has an opposite trend. P-value=7.66x10<sup>-9</sup> was obtained from Cochran–Armitage trend test.

**Figure 3. Interpretation of findings.**

Educational attainment is partially modulated by common genetic variants<sup>6-9, 14</sup> and inversely associated with cardiovascular diseases<sup>1,2</sup>. In the present study, we have found that the common genetic variants that influence length<sup>8</sup> of school education are also associated with cardiovascular risk factors and the manifestation of CAD. Importantly, the associations between genetic variants with CAD and its risk factors remained to be significant after adjustment for actual length of education. Thus, genetic factors may also influence decision making for a health-conscious lifestyle later in life and affect the prevalence of CAD through its risk factors.

**Text tables**

**Table 1. Associations between the 'genetic education score' and cardiovascular conditions in UK Biobank.**

	Odds ratio [ 95% CI]	p	realEduYear-adj
<b>Coronary artery disease</b>	0.96 [0.94, 0.97]	1.85E-06	no
	0.98 [0.96, 1.00]	0.014	yes
<b>BMI</b>	-0.15 [0.01] *	1.66E-30	no
	-0.12 [0.01] *	7.54E-20	yes
<b>Smoking</b>	0.95 [0.93, 0.96]	5.36E-23	no
	0.96 [0.95, 0.97]	7.68E-12	yes
<b>Hypercholesterolemia</b>	0.98 [0.96, 0.99]	3.42E-04	no
	0.99 [0.98, 1.01]	0.319	yes

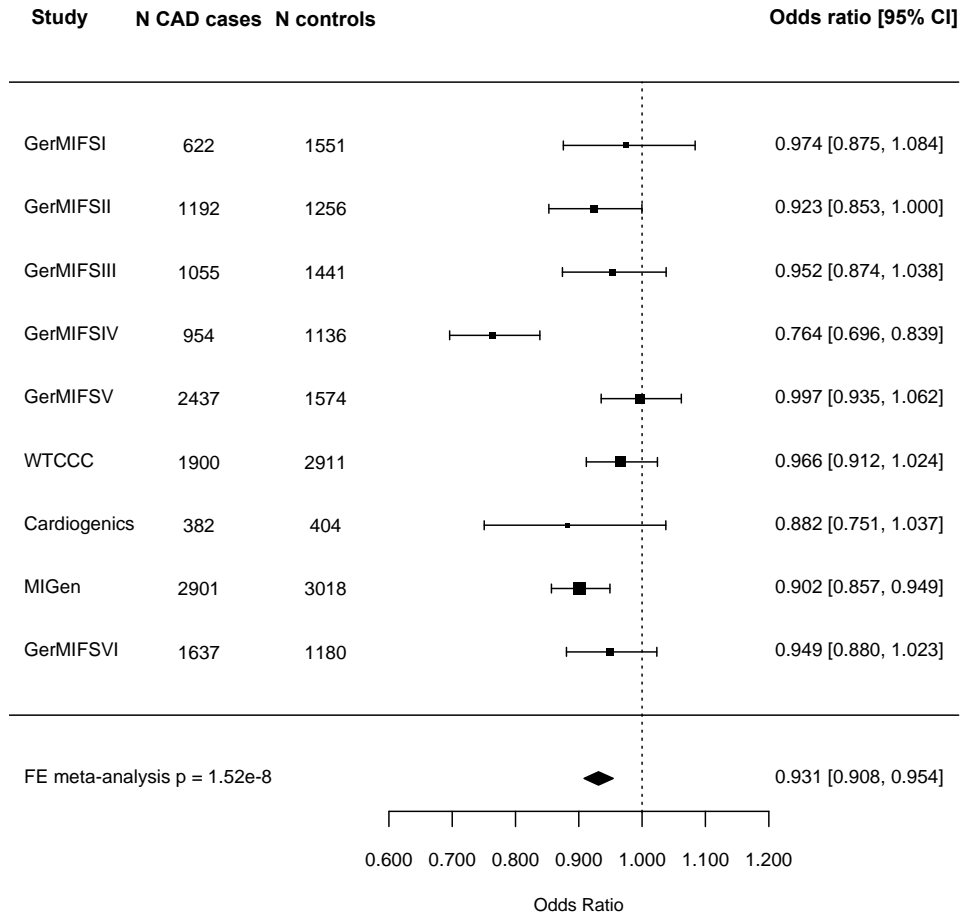
<b>Hypertension</b>	0.97 [0.96, 0.98]	3.86E-08	no
	0.99 [0.98, 1.00]	0.007	yes
<b>Type 2 diabetes</b>	0.96 [0.93, 0.98]	1.73E-04	no
	0.98 [0.95, 1.00]	0.045	yes

Regression models of the ‘genetic education score’ on coronary disease risk and cardiovascular risk factors without (no - unadjusted) and with adjustment (yes) for years of school education completed (real EduYear-adjusted). All models were also adjusted for the first 5 principal components and genotyping array.

\* Odds ratio [95% CI] is reported for each binary phenotype (except for BMI) as per one SD increase in the ‘genetic education score’. The slope [SE] of the linear regression is reported for the continuous phenotype – BMI per one SD increase in the ‘genetic education score’.

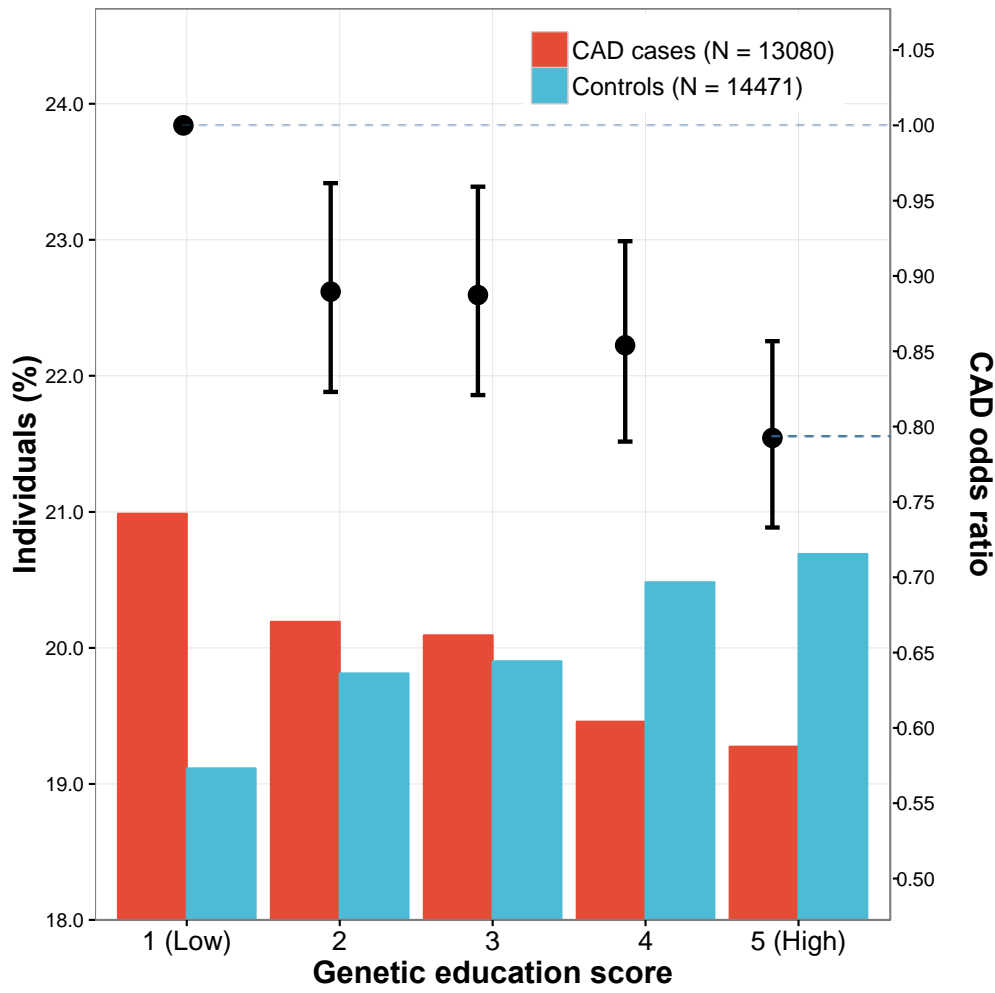
Smoking: ever smokers vs. never smokers. BMI in kg/m<sup>2</sup>. CI: confidence interval. SE: standard error.

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4 **Figures**  
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42 **Figure 1. ‘Genetic education score’ and risk of coronary artery disease.**  
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**Figure 2. Inverse relationship of genetically determined educational attainment and risk of coronary artery disease.**

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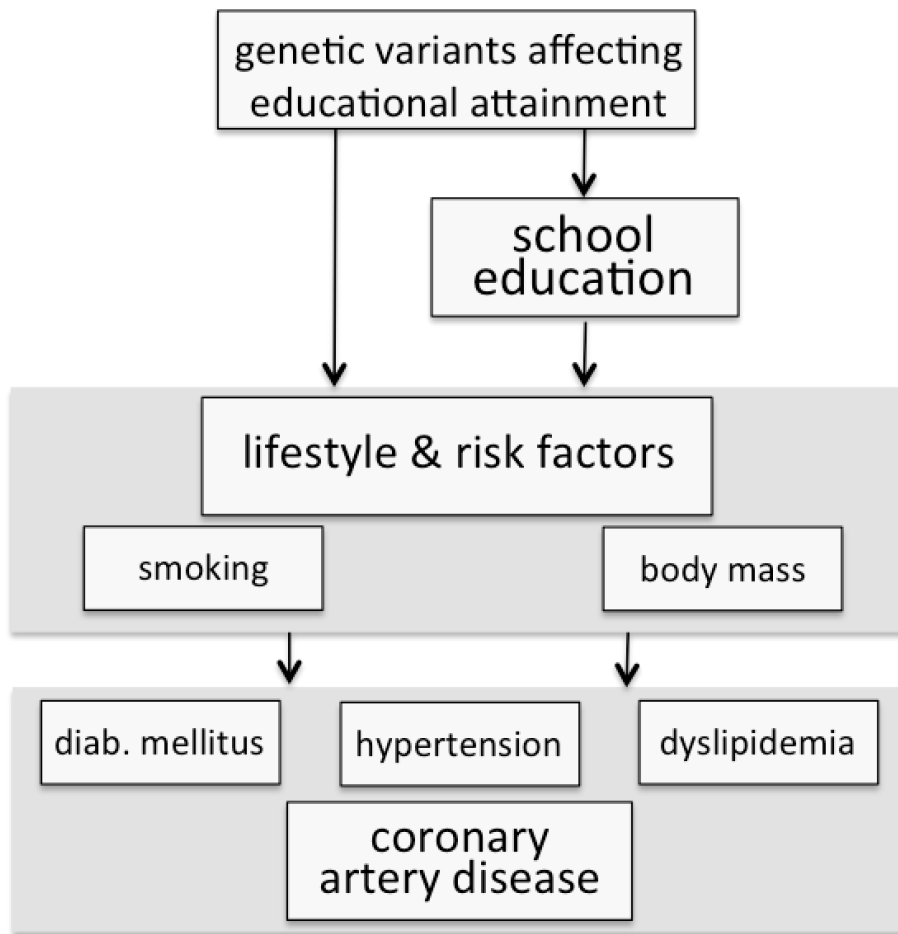


Figure 3. Interpretation of findings.

## **Supplementary Text**

### **Genetically modulated educational attainment and coronary disease risk**

#### **Table of contents**

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## Supplementary reference

### 1. Description of data sets and cohorts

#### 1.1 CAD case-controls studies

Individual level data were obtained from nine case-control studies for coronary artery disease. Most individuals came from Germany: the German Myocardial Infarction Family Studies (GerMIFS) I<sup>1</sup>, II<sup>2</sup>, III<sup>3</sup> (KORA), IV<sup>4</sup>, V<sup>5</sup>, VI<sup>6</sup>, and/or England: Wellcome Trust Case Control Consortium (WTCCC)<sup>7</sup> and/or France: Cardiogenics<sup>8</sup>. Others included subjects from Italy and the United States: Myocardial Infarction Genetics Consortium (MIGen)<sup>9</sup>. All subjects were of Western European descent and gave a broad written informed consent before participating in these studies on the understanding of genetic underpinnings of cardiovascular disease. All individuals provided informed consent that specifically addresses that the materials will be used for studying the effect of genetic variants on coronary risk. And all respective studies have obtained IRB approval from their local Ethical Committees. In the all German MI Family studies, Cardiogenics, WTCCC and MIGen, the information on CAD manifestation was validated by medical records. The detail assessment of CAD was given in the respective references.

Genome-wide genotype data and associated phenotype data for GerMIFS I-VI were collected by our group. Data for MIGen were obtained via the database of Genotypes And Phenotypes (dbgap)<sup>10</sup> (project ID #49717-3). Data for WTCCC and Cardiogenics were obtained via the Leducq network “CADgenomics” (<https://www.fondationleducq.org/network/understanding-coronary-artery-disease-genes/>). A summary of individual statistics is shown below and more detailed cohort descriptions could be sourced from the corresponding references.

Study	CAD cases		Controls	
	N	Female N (%)	N	Female N (%)
GerMIFSI	622	207 (33.2)	1551	795 (51.3)
GerMIFSI	1192	244 (20.5)	1256	604 (48.1)
GerMIFSI	1055	212 (20.1)	1441	696 (48.3)
GerMIFSI	954	336 (35.2)	1136	697 (61.4)
GerMIFSI	2437	593 (24.3)	1574	827 (52.5)
GerMIFSI	1637	492 (30.1)	1180	607 (51.4)
Cardiogenics	382	49 (12.8)	404	239 (59.1)
WTCCC	1900	395 (20.8)	2911	1481 (50.9)
MIGen	2901	646 (22.3)	3018	733 (24.3)

## 1.2 UK-Biobank

UK Biobank (UKBB) was established to improve understanding of the causes of common diseases including CAD ([www.ukbiobank.ac.uk/](http://www.ukbiobank.ac.uk/)) and completed the recruitment of 502,713 (94% of self-reported European ancestry) individuals aged 40-69 years across England, Scotland and Wales between 2005 and 2010 (94% of self-reported European ancestry). UKBB adopted the current worldwide practice of consenting subjects using a 'broad informed consent' from ([http://www.ukbiobank.ac.uk/wp-content/uploads/2011/06/Consent\\_form.pdf](http://www.ukbiobank.ac.uk/wp-content/uploads/2011/06/Consent_form.pdf)) to cater both for technological advances as well as the ability to maximise the use of data i.e. by addressing a broad spectrum of scientific questions. This consent covers the present research question. UKBB covers the thousands of phenotypes collected. In addition to self-reported disease outcomes as well as extensive health and life-style questionnaire data, UKBB participants are being tracked through their NHS records and national registries (including cause of death and Hospital Episode Statistics [HES]). In July 2015, UKBB released genotype data imputed to the 1000 Genomes panel for 152,249 participants profiled with a SNP array harboring 820,967 variants comprising a backbone of common variants optimized for imputation, a validated subset of rare coding variants from the Exomechip array ([http://genome.sph.umich.edu/wiki/Exome\\_Chip\\_Design](http://genome.sph.umich.edu/wiki/Exome_Chip_Design)) and a set of likely functional variants or their proxies

(e.g. GWAS catalogue). Analyses were performed on 146,514 participants of European ancestry after standard quality control.

During the revision process of this manuscript, a latest version of UKBB data were released which increased the sample size from 150k to 500k. We utilized this larger set of data in the sensitivity analysis, including 455,440 participants of European ancestry after standard quality control.

### 1.3 Consortia for coronary risk factors

The CARDIoGRAMplusC4D consortium<sup>4</sup> reported summary statistics of genome-wide association studies for coronary artery disease (CAD) for participants of multiple European states, the US, Iceland, Australia as well as some other countries. The ethnic origin of the vast majority of individuals in this consortium is European. Summary statistics for other CAD risk factors were obtained from other consortia, including GLGC (LDL-c, HDL-c, triglyceride, total cholesterol level), GIANT<sup>11</sup> (body-mass index), and TAG (smoking behaviour)<sup>12</sup>. A description of consortium size and the corresponding phenotypes is shown here.

Trait name	Consortium	Sample size	PMID	Publish year	Website for Consortium or Data
Coronary artery disease	CARDIoGRAM-plusC4D	184,305	26343387	2015	<a href="http://www.cardiogramplusc4d.org">http://www.cardiogramplusc4d.org</a>
LDL cholesterol	GLGC	188,577	24097068	2013	<a href="http://csg.sph.umich.edu/abecasis/public/lipids2013/">http://csg.sph.umich.edu/abecasis/public/lipids2013/</a>
HDL cholesterol					
Triglycerides					
Total cholesterol					

Body mass index	GIANT	339,224	25673413	2015	<a href="http://portals.broadinstitute.org/collaboration/giant/index.php/Main_Page">http://portals.broadinstitute.org/collaboration/giant/index.php/Main_Page</a>
Ever vs never smoked	TAG	74,053	20418890	2010	<a href="https://www.med.unc.edu/pgc/results-and-downloads">https://www.med.unc.edu/pgc/results-and-downloads</a>
Cigarettes smoked per day					

## 2. Phenotypic association analysis in UK Biobank

### 2.1 Definition of phenotypes

All conditions were defined by either self-reported, hospital episode and/or death registry data. In UK Biobank self-reported data, CAD cases were defined if they reported having ‘vascular/heart problems diagnosed by doctor’ or ‘non-cancer illnesses’ as angina or heart attack. Self-reported operation included PTCA, or coronary artery bypass grafting (CABG). In hospital episode data and death registry data including primary and secondary diagnoses and operations, MI was defined as hospital admission or cause of death due to ICD9 410–412, ICD10 I21–I24, I25.2; PTCA was defined as hospital admission for PTCA (OPCS-4 K49, K50.1, K75); CABG was defined as hospital admission for CABG (OPCS-4 K40–K46); and angina or chronic IHD was defined as hospital admission or death due to ICD9 413, 414.0, 414.8, 414.9, ICD10 I20, I25.1, I25.5–I25.9. Exclusions were made for aneurysm and atherosclerotic cardiovascular disease using hospital admissions or cause of death codes ICD9 414.1, ICD 10 I25.0, I25.3, I25.4 (and not having MI, PTCA, CABG, Angina or chronic IHD as defined above). Controls were defined as patients who were not a CAD case after exclusions.

Individuals were classified as hypertensives if their mean SBP  $\geq 140$  mm Hg or mean DBP  $\geq 90$  mm Hg (from the two blood pressure measurements from initial assessment), or if they were reported

taking blood pressure lowering medication; otherwise, they were classified as non-hypertensive. In detail, ICD 10 and ICD 9 codes used to define cases of CAD, type 2 diabetes, stroke, peripheral arterial disease, and chronic obstructive pulmonary disease, and lung cancer are given in the table below. For each disease, individuals who were not identified as disease cases were defined as controls. Smoking status was defined using self-reported data – current or ex-smokers were defined as ever smokers (cases), while individuals who reported no smoking were classified as non-ever smokers (controls). BMI was taken from initial assessment data only.

Hypersholesterolemia was defined using self-reported data, i.e, individuals who reported either having high cholesterol or taking cholesterol lowering medication were defined as cases. Individuals with familial hypercholesterolemia (codes ICD10 E78.0, ICD9 272.0) were excluded. Controls were defined as individuals who were not a hypercholesterolemia case after exclusions. Phenotypically, educational attainment was measured as length of school education (EduYears) using the same methods that were used in the report that led to the identification of the EduYear-SNPs<sup>13</sup>, that is, a continuous variable measuring the number of years of schooling completed. Briefly, using the mapping shown in Supplementary Table 1.2. of Okbay et al. *years of schooling / years-of-education equivalent for each ISCED category* were calculated as: pre-primary education 1/0; primary education or first stage of basic education 7/1; lower secondary or second stage of basic education 10/2; (upper) secondary education 13/3; post-secondary non-tertiary education 15/4; first stage of tertiary education (not leading directly to an advanced research qualification) 19/5; second stage of tertiary education (leading to an advanced research qualification, e.g. a Ph.D.) 22/6.

Disease	ICD 10 codes	ICD 9 codes	Operation codes
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Coronary artery disease	I20 - 25  (excluding I25.0, I25.3, I25.4)	410 - 414  (excluding 414.1)	K40 – K46, K49,  K50.1, K75
Type 2 diabetes	E11	25000, 25010	-
Stroke	I60, I61, I63	430, 431, 435	-
Peripheral arterial disease	I73.9	443.9	-
Chronic obstructive pulmonary disease	J44	491.2, 496.9	-
Chronic obstructive pulmonary disease – extended	J43.9, J40, J44, J45.9, J46, J47	430, 431, 435, 491.2, 496	-
Lung cancer	C34	162	-

## 2.2 phenotypic association

Regression analyses were performed to evaluate the phenotypic association between EduYears and risk of CAD and its risk factors (in section 2.1). Prior analysis real years of school education were standardized into Z-scores (centred and scaled to have a mean of 0 and standard deviation (SD) of 1).

## 2.3 ‘genetic CAD score’ and EduYears

Based on the 50 CAD SNPs reported by Khera et al<sup>24</sup> ([Extended Data Table 2](#)) a weighted genetic risk score was calculated to evaluate the cumulative genetic effect of CAD risk on EduYears. Genetic risk score for CAD was estimated in the same way as the EduYear-wGRS. We gave a value from minimum 0 to maximum 2 for every SNP for every individual according to the sum of the posterior probabilities from the imputation files to indicate the number of CAD-increasing alleles and multiplied the number of alleles by

the reported effect sizes. Then we totalled these values for each individual across all 50 SNPs to generate a weighted genetic risk score of CAD.

Linear regression was performed to evaluate the effect size of the weighted CAD genetic risk score on real EduYears. The genetic risk score was modelled as a continuous variable and standardized into Z-scores (centred and scaled to have a mean of 0 and standard deviation (SD) of 1). The top five principle components based on autosomal genotypes and the genotyping array were included in the regression model as covariates.

### **3. Processing of individual-level genotypes**

#### **3.1 Genotyping and imputation**

Genotyping was performed using a range of common, commercially available genotyping arrays. The 1000 Genomes Phase I integrated variant (v3) set released in NCBI build 37 (hg19) coordinates with reference data from March 2012 (updated August 2012) was utilized as the reference panel for imputation in all nine case-control studies of coronary disease.

UK Biobank released genotypes imputed to the 1000 Genomes panel for 152,249 participants profiled with a SNP array harboring 820,967 variants comprising common variants optimized for imputation, validated rare coding variants and sets of phenotype-associated variants or their proxies (e.g. GWAS catalogue).

#### **3.2 Quality control**

The following pre-imputation QC criteria were taken in all nine case-control studies of coronary disease: individual call rate  $\geq 0.98$ , SNP call rate  $> 0.98$ , minor allele frequency (MAF)  $> 0.01$ , concordant recorded and genotype-derived gender, population outliers excluded (deviate beyond mean  $\pm 5 \times \text{SD}$  for top two principle components), IBD PI\_HAT  $< 0.125$  ( individuals distant away than third-degree relatives), heterozygosity rate within mean  $\pm 3 \times \text{SD}$ , and deviation from Hardy-Weinberg Equilibrium(HWE)  $p > 1e-6$ . As an essential statistical technique to estimate genotypes that were not directly assayed, and in order to harmonize our cohort data collected from different genotyping array platforms we imputed the data prior to the meta-analysis. After genotype QC, haplotypes were then pre-phased from genotypes with SHAPEIT2 haplotype estimation tool to generate the best guess haplotypes based on the given genotypes. Then the best guess haplotypes were forwarded to IMPUTE2 for imputation. For each bi-allelic variant [A/B] for each individual, the main output of IMPUTE2 reported the three genotypes AA, AB and BB in the form of their probabilities accounting for the genotype imputation uncertainty, instead of giving an fixed designation. Finally the following post-imputation QC criteria were taken: SNP call rate  $> 0.98$ , MAF  $> 0.05$ , Hardy-Weinberg  $p > 1e-5$ .

#### **4. Selection of genetic variants**

##### **4.1 Genetic variants for educational attainment**

A list of 74 lead SNPs of each genetic locus for educational attainment (EduYear-SNPs) was obtained from Okbay et al. of the latest GWAS publication for educational attainment<sup>13</sup>, where the authors have generated a list of 74 variants, and their effect-alleles, frequencies, and corresponding effect sizes and p-values from meta-analyses analyses. For each SNP two alleles were extracted



from the 1000G Reference Genome. Then for all SNPs the reported effects were aligned to the EduYear-increasing alleles. The detailed list is compiled and shown in [Extended Data Table 1](#).

#### **4.2 Genetic variants for coronary artery disease**

A list of 50 lead SNPs of each genetic locus for CAD risk was compiled from Khera et al.<sup>14</sup> where the authors have used to compose the genetic risk score of CAD. Effect-alleles, frequencies, and corresponding effect sizes were obtained from Supplementary Table 1 of Khera et al. The detailed list is compiled and shown in [Extended Data Table 2](#). For each SNP two alleles were extracted from the 1000G Reference Genome. Then for all SNPs the reported effects were aligned to the CAD risk increasing alleles.

#### **4.3 Genetic variants proxies for risk factors**

In Mendelian Randomization analysis summary statistics were extracted for CAD and each trait respectively for 74 EduYear-SNPs in the corresponding genome-wide association studies. However, most of these GWAS meta-analysis were originally performed based on HapMap-imputed genotypes, thus not for all of these EduYear-SNPs summary statistics for various traits were reported. Therefore, for SNPs not available in the reported summary statistics we identified SNP proxies with an LD  $r^2 > 0.5$  in the reference European genomes (both 1000G pilot 1 and Phase I v3). [Extended Data Table 3](#) is showing the full SNP availability in each reported trait and their proxies used in the analyses.

## Supplementary reference

- 1 Samani, N. J. *et al.* Genomewide association analysis of coronary artery disease. *N Engl J Med* **357**, 443-453, doi:10.1056/NEJMoa072366 (2007).
- 2 Erdmann, J. *et al.* New susceptibility locus for coronary artery disease on chromosome 3q22.3. *Nat Genet* **41**, 280-282, doi:10.1038/ng.307 (2009).
- 3 Erdmann, J. *et al.* Genome-wide association study identifies a new locus for coronary artery disease on chromosome 10p11.23. *Eur Heart J* **32**, 158-168, doi:10.1093/eurheartj/ehq405 (2011).
- 4 Consortium, C. D. A comprehensive 1000 Genomes-based genome-wide association meta-analysis of coronary artery disease. *Nat Genet* **47**, 1121-1130, doi:10.1038/ng.3396 (2015).
- 5 Stitzel, N. O. *et al.* Inactivating mutations in NPC1L1 and protection from coronary heart disease. *N Engl J Med* **371**, 2072-2082, doi:10.1056/NEJMoa1405386 (2014).
- 6 Nelson, C. P. *et al.* Association analyses based on false discovery rate implicate new loci for coronary artery disease. *Nature genetics*, doi:10.1038/ng.3913 (2017).
- 7 Consortium., W. T. C. C. Genome-wide association study of 14,000 cases of seven common diseases and 3,000 shared controls. *Nature* **447**, 661-678, doi:10.1038/nature05911 (2007).
- 8 Consortium, C. A. D. *et al.* Large-scale association analysis identifies new risk loci for coronary artery disease. *Nat Genet* **45**, 25-33, doi:10.1038/ng.2480 (2013).
- 9 Kathiresan, S. *et al.* Genome-wide association of early-onset myocardial infarction with single nucleotide polymorphisms and copy number variants. *Nat Genet* **41**, 334-341, doi:10.1038/ng.327 (2009).
- 10 Tryka, K. A. *et al.* NCBI's Database of Genotypes and Phenotypes: dbGaP. *Nucleic Acids Res* **42**, D975-979, doi:10.1093/nar/gkt1211 (2014).
- 11 Locke, A. E. *et al.* Genetic studies of body mass index yield new insights for obesity biology. *Nature* **518**, 197-206, doi:10.1038/nature14177 (2015).
- 12 Consortium, T. a. G. Genome-wide meta-analyses identify multiple loci associated with smoking behavior. *Nat Genet* **42**, 441-447, doi:10.1038/ng.571 (2010).
- 13 Okbay, A. *et al.* Genome-wide association study identifies 74 loci associated with educational attainment. *Nature* **533**, 539-542, doi:10.1038/nature17671 (2016).
- 14 Khera, A. V. *et al.* Genetic Risk, Adherence to a Healthy Lifestyle, and Coronary Disease. *N Engl J Med* **375**, 2349-2358, doi:10.1056/NEJMoa1605086 (2016).

## Extended Data Figure and Legends

### Genetically modulated educational attainment and coronary disease risk

A.

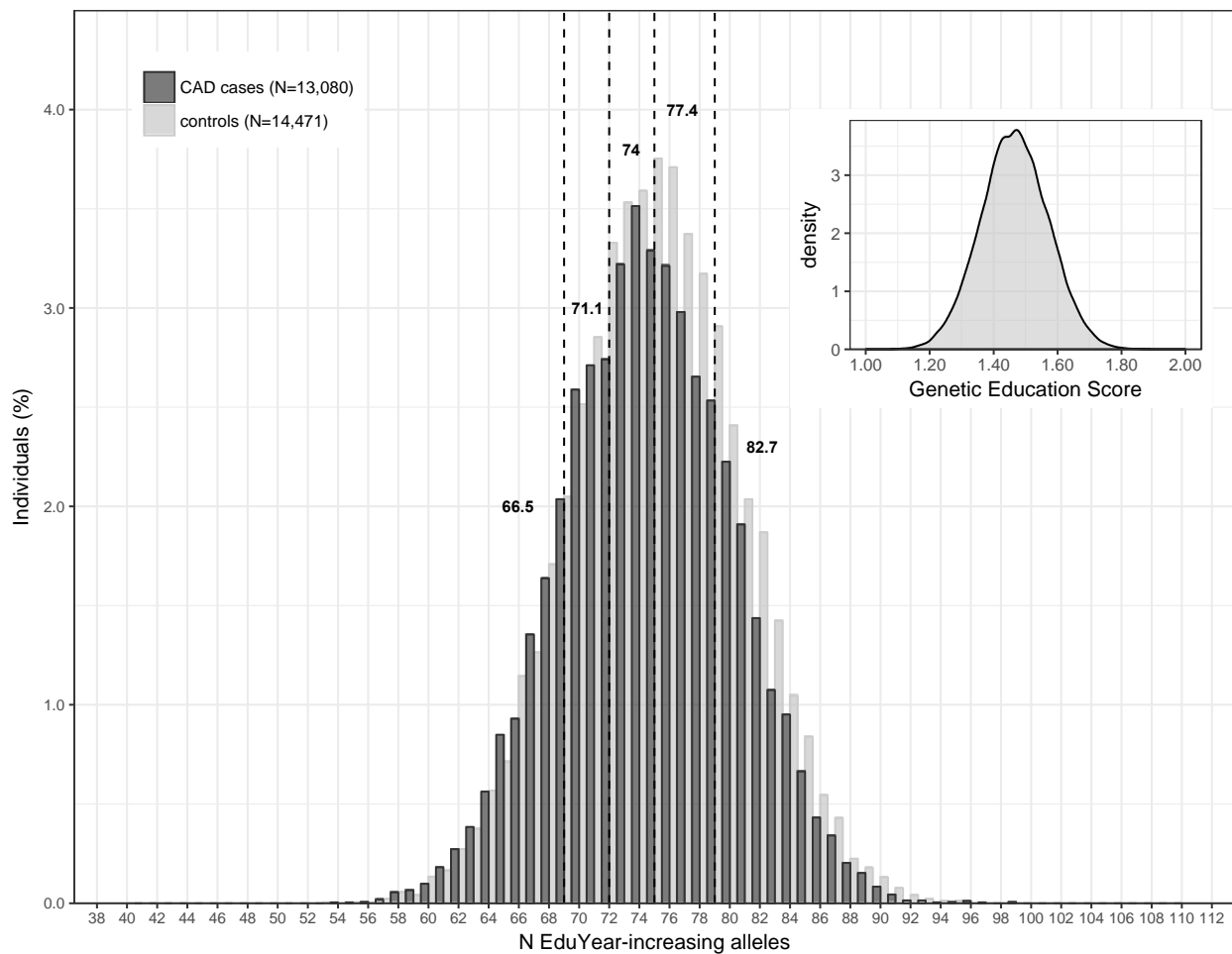
Question: whether?	Approach			Data
	Outcome	Exposure	Counfounders	
Is the genetic component of educational attainment associated with CAD?	CAD	'genetic education score'		GerMIFSI GerMIFSI GerMIFSI GerMIFSI GerMIFSV GerMIFSVI WTCCC Cardiogenics MIGen UKBB
... and even partly independent of the actual 'years of school education'?			'years of school education'	
Is the genetic component of educational attainment associated with specific lifestyle & risk factors of CAD?	lifestyle & risk factors			UKBB
... and even partly independent of the actual 'years of school education'?			'years of school education'	

B.

Question: how?	Approach			Data
	Outcome	Exposure	Counfounders	
Is the impact of the genetic component of educational attainment on CAD risk due to the intermediate impact on specific lifestyle & risk factors? - Association	CAD	'genetic education score'	'years of school education' + possible intermediate factors	UKBB
Is the impact of the genetic component of educational attainment on CAD risk due to the intermediate impact on specific lifestyle & risk factors? - Causality	Outcome	EduYear	Genetic Instrumental variables	Summary statistics obtained from various large GWAS consortia
	CAD			
	lifestyle & risk factors			
	CAD		EduYear-SNPs	
			EduYear-SNPs excluding those associated with CAD and other causal risk factors	

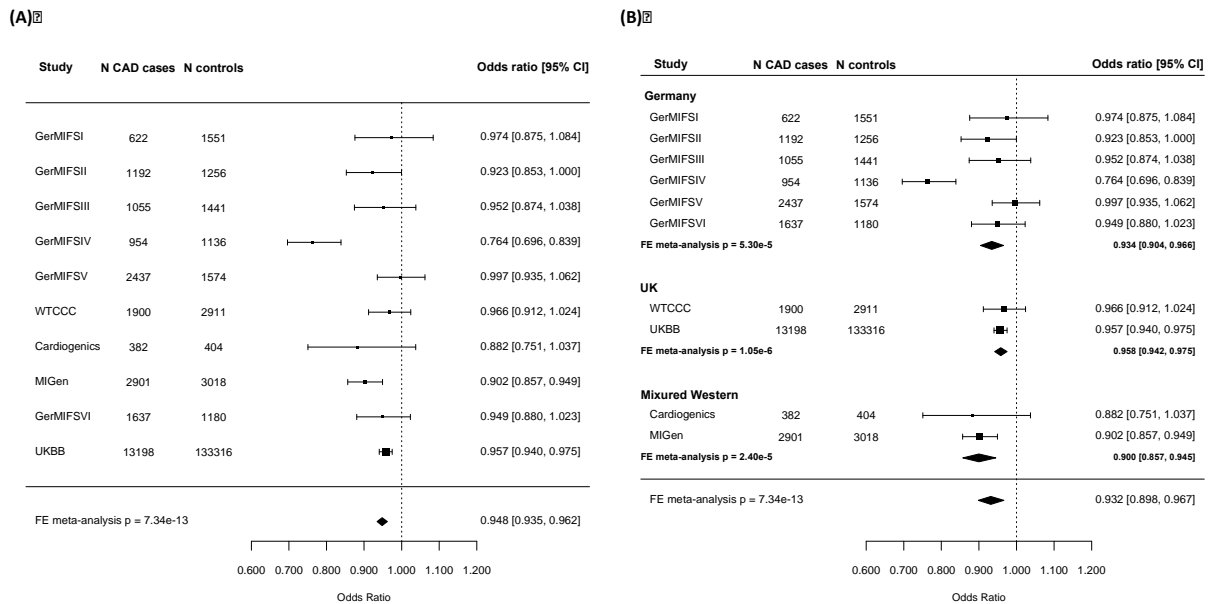
**Extended Data Figure 1. Study design. (A).** We studied the genetic component underlying the relationship between higher educational attainment and lower CAD risk (blue block) in multiple cohort data (GerMIFS I-VI, WTCCC, Cardiogenics, MIGen at discovery stage and UK Biobank (UKBB) at replication stage) and associated the 'genetic education score' with the susceptibility of CAD and other traits, which allowed to estimate the respective effect sizes. As the 'genetic education score' certainly affects the (exogenous) phenotype 'years of school education' (real EduYears) further adjustment for this phenotype (which is only available in the UKBB cohort) was needed to examine effects of the 'genetic education score' that are not directly mediated by school education. **(B).** With the aim to further characterize the interplay between the genetic basis of educational attainment, the prevalence of CAD and its related lifestyle risk factors (green

block), we performed similar regression analysis with additional inclusion of possible intermediate lifestyle and risk factors, to check the (inter)dependence of the ‘genetic education score’, lifestyle risk factors and CAD risk. Furthermore, we employed genetic Mendelian randomization approach to investigate the causality of educational attainment on CAD and/or its related risk factors.

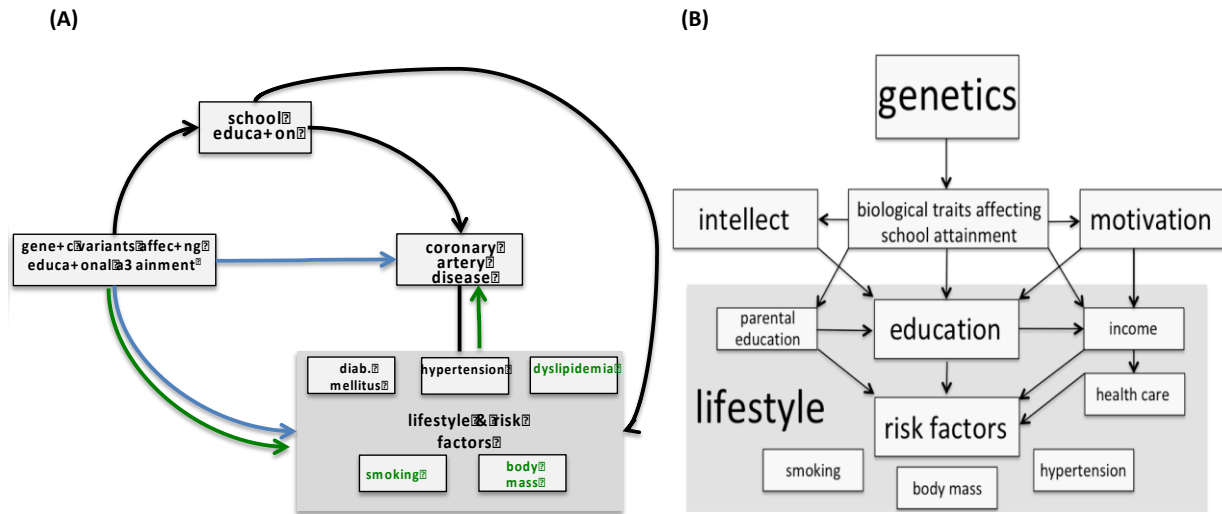


**Extended Data Figure 2. Distribution of genetic risk score of EduYear in participants from nine case-controls studies for coronary artery disease.**

Gaussian distribution showing the number of EduYear-increasing alleles in a group of 13,080 cases with coronary disease and 14,471 controls from nine large case-control studies. Individuals were divided in quintiles (dashed lines) in each study based on their 'genetic education score'. The number above each quintile represents the average number of EduYear-increasing alleles in each quintile.



**Extended Data Figure 3. Forest plot for meta-analysis including all studies.** In addition to the nine studies from which we have initially identified the inverse association between the 'genetic education score' and risk of CAD, a consistent inverse correlation with similar logistic regression was also found in UK Biobank for replication. Afterwards a meta-analysis was performed to combine the effects across all ten studies including UK Biobank. (A) The same effect is replicated and obtained with an even more significant fixed-effect meta-analysis p-value ( $p=7.34 \times 10^{-13}$  compared to  $p=1.52 \times 10^{-8}$  in the discovery studies). (B) We also categorized all studies according to countries, and observed directionally identical effects ( $p=1.05 \times 10^{-6}$  for the UK;  $p=5.30 \times 10^{-5}$  for Germany;  $p=2.40 \times 10^{-5}$  for the mixture of several Western countries).

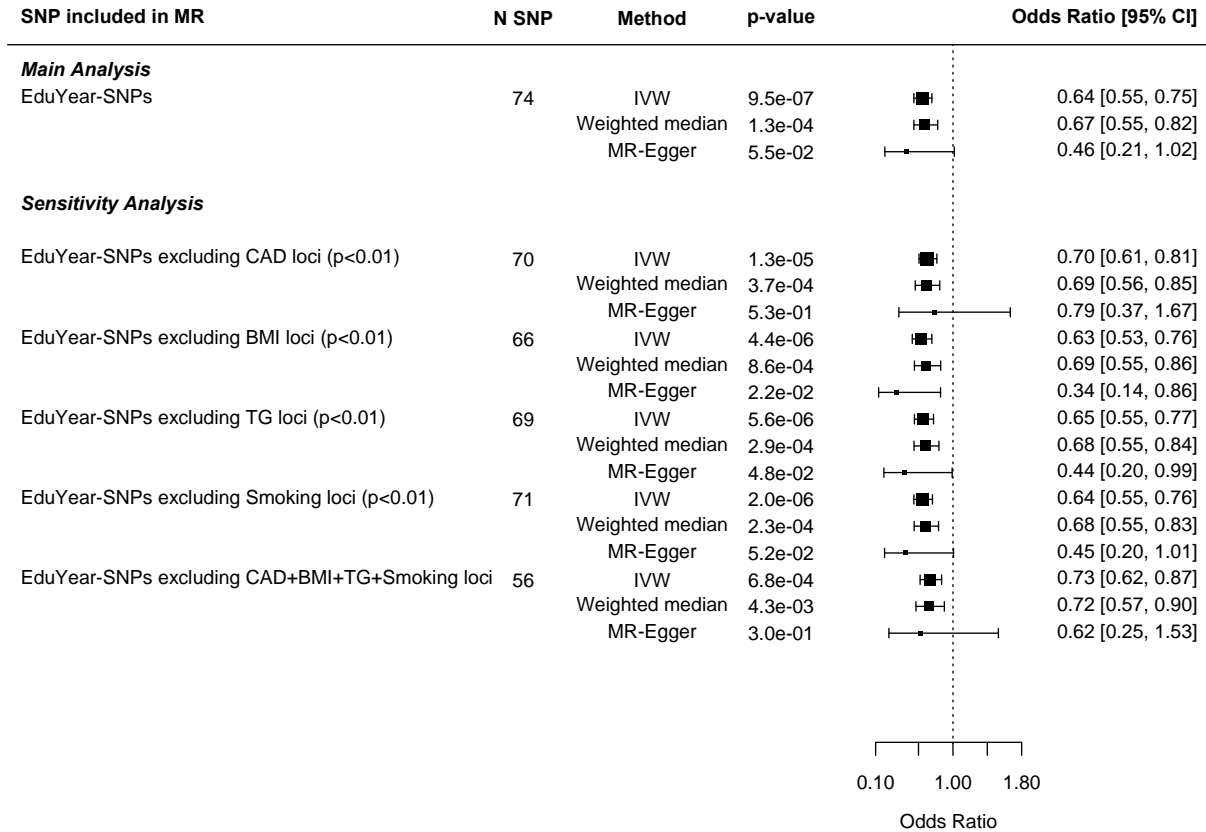


#### Extended Data Figure 4. Interpretation of findings.

**A.** It has been known that educational attainment is partially modulated by common genetic variants and inversely associated with cardiovascular diseases (black lines). In the present study, we have firstly found that the common genetic variants that influence length of school education are associated with the manifestation of CAD (straight blue line in the middle). Further analyses indicated the common genetic variants that influence length of school education are in parallel associated with specific lifestyle and risk factors (blue line in the lower part) (e.g. BMI, smoking status, and triglycerides). Importantly, these associations (blue lines) are partly independent on the actual length of education (black lines). Finally, several lifestyle related factors were deduced as intermediate factors that mediate the genetic component increasing in CAD risk (green elements and lines). In summary, genetic factors may also influence decision making for a health-conscious lifestyle later in life and affect thereby the prevalence of CAD through its risk factors.

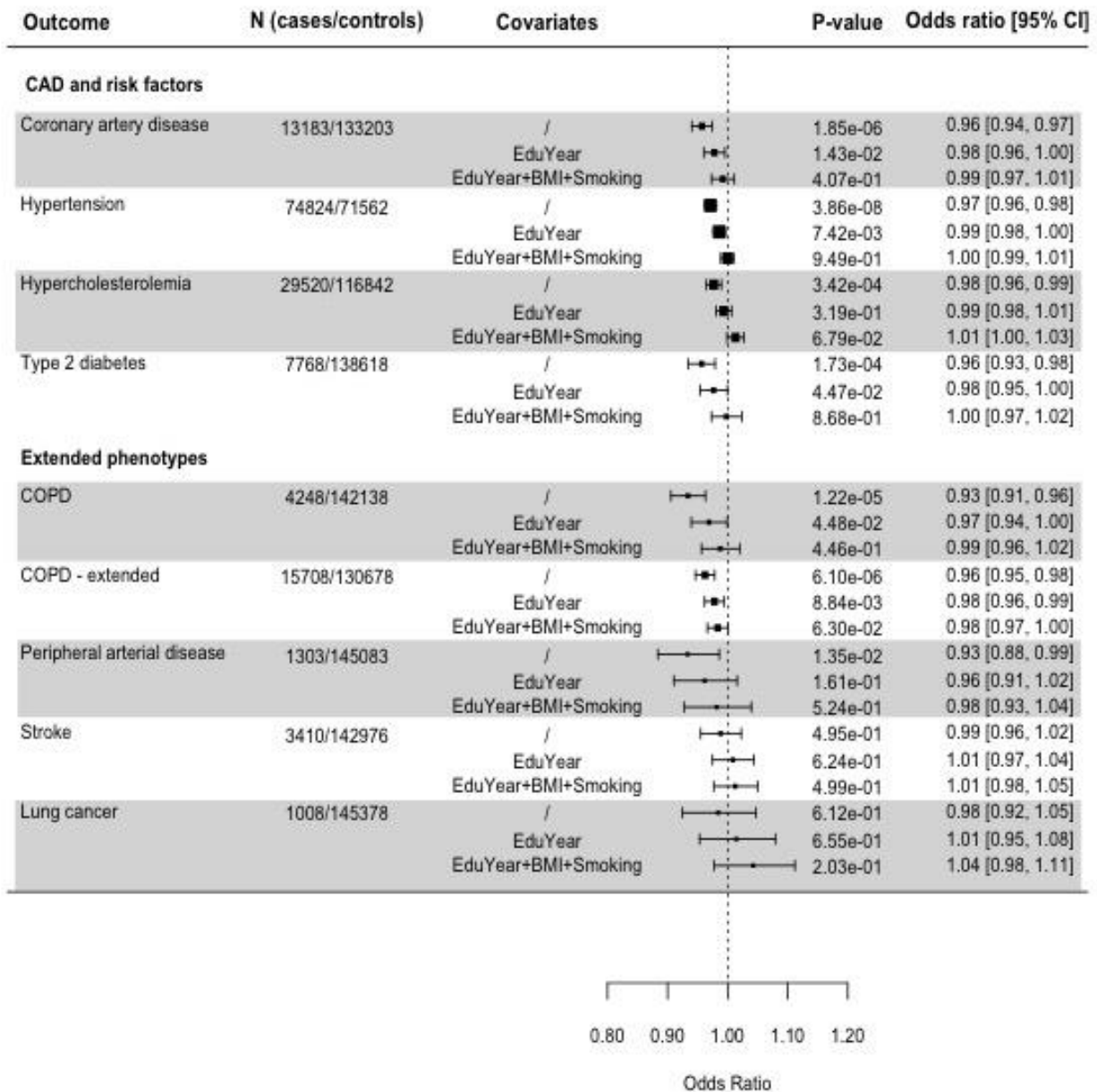
**B.** We are well aware of that despite of our observation that the signal between the ‘genetic education score’ and CAD risk decreases when smoking and BMI are included as co-variables, we can only demonstrate plausible deductions (the green elements and lines in Panel A) instead of causality, due to the fact that the ‘genetic education score’ may have broader implications. It is likely that a number of confounders such as intelligence, behaviour patterns, socioeconomic factors in respective individuals as

well as the parental generation are involved in the interplay of educational attainment, CAD factors and prevalence of CAD. Here in Panel B we illustrate these potential and plausible links.



### Extended Data Figure 5. Genetic causality of educational attainment and coronary artery disease as well as its risk factors

Mendelian randomization (MR) analysis was performed to investigate the genetic causality of educational attainment and coronary artery disease (CAD) as well as its risk factors. Several MR methods were employed to combine individual-SNP beta estimates retrieved from various genome-wide meta-analyses (details described in Methods and Supplementary Text). For sensitivity analyses we excluded from the 74 EduYear-SNPs which had marginal associations ( $p < 0.01$  in the published summary statistics) with CAD or an examined risk factor (Extended Data Table 3). A 1-SD increase in education years and 28% lower risk of CAD (odds ratio for weighted median method of 0.72, 95% CI 0.57, 0.90,  $p = 4.3 \times 10^{-3}$ ) was observed even after all confounder-influential SNPs have been excluded.



**Extended Data Figure 6. Association between the ‘genetic education score’ and extended phenotypes in UK Biobank.**

Regression models of the ‘genetic education score’ on extended phenotypes with adjustment for real years of school education completed (EduYears), BMI or smoking. In addition to the covariates shown here, all



models were also adjusted for the first 5 principal components based on autosomal genotypes plus genotype array platform.

Manuscripts (including legend for main displaying items) : 4876

References: 5725 (several Consortium papers have very long author list)

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**Abstract**

**Aims:** Genetic disposition and lifestyle factors are understood as independent components underlying the risk of multiple diseases. In this study, we aim to investigate the interplay between genetics, educational attainment - an important denominator of lifestyle - and coronary artery disease (CAD) risk.

**Methods and Results:** Based on the effect sizes of 74 genetic variants associated with educational attainment, we calculated a ‘genetic education score’ in 13,080 cases and 14,471 controls and observed an inverse correlation between the score and risk of CAD ( $p=1.52 \times 10^{-8}$ ; odds ratio [OR] 0.79 (95% confidence interval [CI] 0.73-0.85) for the higher compared to the lowest score quintile). We replicated in 146,514 individuals from UK Biobank ( $p=1.85 \times 10^{-6}$ ) and also found strong associations between the ‘genetic education score’ with ‘modifiable’ risk factors including smoking ( $p=5.36 \times 10^{-23}$ ), body mass index ( $p=1.66 \times 10^{-30}$ ), and hypertension ( $p=3.86 \times 10^{-8}$ ). Interestingly, these associations were only modestly attenuated by adjustment for years spent in school. By contrast, a model adjusting for BMI and smoking abolished the association signal between the ‘genetic education score’ and CAD risk suggesting an intermediary role of these two risk factors. Mendelian randomization analyses performed with summary statistics from large genome-wide meta-analyses and sensitivity analysis using 1271 variants affecting educational attainment (OR 0.68 for the higher compared to the lowest score quintile; 95% CI 0.63-0.74;  $p=3.99 \times 10^{-21}$ ) further strengthened these findings.

**Conclusion:** Genetic variants known to affect educational attainment may have implications for a health-conscious lifestyle later in life and subsequently affect the risk of coronary artery disease.

**Keywords:** atherosclerosis / school education / coronary artery disease / genome-wide association studies / genetics



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