

1                   **The causal effects of lipid traits on kidney function in Africans:**  
2                   **bidirectional and multivariable Mendelian-randomization study**

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40 **Abstract**

41

42 **Background:** Observational studies have investigated the effect of serum lipids on  
43 kidney function, but these findings are limited by confounding, reverse causation and  
44 have reported conflicting results. Mendelian randomization (MR) studies address this  
45 confounding problem. However, they have been conducted mostly in European ancestry  
46 individuals. We, therefore, set out to investigate the effect of lipid traits on the estimated  
47 glomerular filtration rate (eGFR) based on serum creatinine in individuals of African  
48 ancestry.

49

50 **Methods:** We used the two-sample and multivariable Mendelian randomization (MVMR)  
51 approaches; in which instrument variables (IVs) for the predictor (lipid traits) were derived  
52 from summary-level data of a meta-analyzed African lipid GWAS (MALG, n=24,215) from  
53 the African Partnership for Chronic Disease Research (APCDR) (n = 13,612) & the Africa  
54 Wits-IN-DEPTH partnership for Genomics studies (AWI-Gen) dataset (n=10,603). The  
55 outcome IV's were computed from the eGFR summary-level data of African-ancestry  
56 individuals within the Million Veteran Program (n=57,336). A random-effects inverse  
57 variance method was used in our primary analysis, and pleiotropy was adjusted for using  
58 robust and penalized sensitivity testing. The lipid predictors for the MVMR were high-  
59 density lipoprotein (HDL) cholesterol, low-density lipoprotein (LDL) cholesterol, and  
60 triglycerides (TG).

61

62 **Results:** We found a significant causal association between genetically predicted low-  
63 density lipoprotein (LDL) cholesterol and eGFR in African ancestry individuals  $\beta = 1.1$   
64 (95% CI [0.411-1.788]; p=0.002). Similarly, total cholesterol (TC) showed a significant  
65 causal effect on eGFR  $\beta = 1.619$  (95% CI [0.412-2.826]; p=0.009). However, the IVW  
66 estimate showed that genetically predicted HDL-C  $\beta = -0.164$ , (95% CI = [-1.329-1.00]; p  
67 = 0.782), and TG  $\beta = -0.934$  (CI = [-2.815-0.947]; p = 0.33) were not significantly causally  
68 associated with the risk of eGFR. In the multivariable analysis inverse-variance weighted  
69 (MVIWV) method, there was evidence for a causal association between LDL and eGFR  
70  $\beta = 1.228$  (CI = [0.477-1.979]; p=0.001). A significant causal effect of Triglycerides (TG)

71 on eGFR in the MVIVW analysis  $\beta = -1.283$  (95% CI = [-2.605-0.038];  $p=0.057$ ) was  
72 observed as well. HDL showed no evidence of a significant causal association with eGFR  
73 in the MVIVW method ( $\beta = -0.117$  (95% CI [-1.252-0.018];  $p=0.840$ ). We found no  
74 evidence of a reverse causal impact of eGFR on serum lipids. All our sensitivity analyses  
75 indicated no strong evidence of pleiotropy or heterogeneity between our instrumental  
76 variables.

77

78 **Interpretation:** In this African ancestry population, genetically predicted higher LDL-C  
79 and TC are causally associated with higher eGFR levels, which may suggest that  
80 the relationship between LDL, TC and kidney function may be U-shaped. And as such,  
81 lowering LDL\_C does not necessarily improve risk of kidney disease. This may also imply  
82 the reason why LDL\_C is seen to be a poorer predictor of kidney function compared to  
83 HDL. In addition, this further supports that more work is warranted to confirm the potential  
84 association between lipid traits and risk of kidney disease in individuals of African  
85 Ancestry.

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87 **Keywords:** Serum lipids; eGFR; Chronic Kidney Disease; Kidney function; Two-sample  
88 Mendelian Randomization

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103 **Introduction**

104 Chronic kidney disease (CKD) is defined as a reduction in kidney function indicated by  
105 estimated glomerular filtration rate (eGFR) <60 ml/min per 1.73 m<sup>2</sup> or kidney damage  
106 markers or both that persist for at least three months[1]. It has a significant impact  
107 worldwide, with an estimated prevalence of 10-15% globally as a direct cause of mortality,  
108 morbidity, and comorbidity in other complex traits[2]. The prevalence of CKD in Africa is  
109 equally high with most sub-Saharan African countries showing generally a >10%  
110 prevalence. Managing CKD in its advanced stages requires huge amounts of resources,  
111 and this is quite cumbersome on most sub-Saharan Africa (SSA) economies.

112

113 Serum lipids: high-density lipoprotein (HDL) and low-density lipoprotein (LDL) cholesterol,  
114 rank among the highest commonly measured biomarkers in clinical medicine[3]. Most  
115 epidemiological studies have reported an association between these lipids and kidney  
116 function, indicating that low HDL cholesterol is associated with poor kidney function and  
117 CKD progression[4-6]. In a well-powered study of 2 million United States veterans who  
118 were followed up for a median of 9 years, *Bowe et al.*, [7] reported on the association  
119 between HDL cholesterol concentrations and various CKD end points. The authors  
120 reported individuals with low HDL cholesterol concentrations (<30 mg/dL) have the  
121 highest risk for CKD or CKD progression [5]. Other studies have found that higher levels  
122 of blood total cholesterol (TC), LDL, TC: HDL ratio, TG: HDL ratio, and lower levels of  
123 blood HDL cholesterol, are associated with a higher risk of incident CKD [8]. However,  
124 evidence from these epidemiological and observational studies is limited by its inability to  
125 demonstrate a causal relationship and inconsistencies between several studies [9-12].  
126 Further still, most of such high-powered studies have not only been limited by sample  
127 selection bias towards majorly European ancestries, but also confounding from  
128 environmental factors.

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130 Mendelian randomization studies can enable us to conduct causal inferences by dealing  
131 better with environmental confounding and reverse causation[3, 13, 14].[15]. However,  
132 similar to observational studies, the association of serum lipids and eGFR has been  
133 conflicted, even in the MR studies. Studies like that by *Coassin et al.*, indicated that HDL

134 cholesterol does not influence eGFR, and they further proposed pleiotropic effects on  
135 eGFR for some of the associated SNPs [8]. Other findings elsewhere conflicted these  
136 findings and reported a genetically higher HDL concentration being associated with higher  
137 eGFR[16, 17]. Such studies, however, have been subject to sample selection bias due to  
138 the lack of ethnic diversity in the Genome-Wide Association Studies (GWASs) used which  
139 are primarily based on European ancestry individuals[18, 19]. A two-sample Mendelian  
140 randomization analysis of data from the most extensive lipid and CKD cohorts supported  
141 genetically higher HDL cholesterol concentration as causally associated with better  
142 kidney function[20]. This analysis and several others were performed on European  
143 ancestry individuals, and the results cannot be confidently generalized to non-European  
144 ancestry individuals.

145

146 In this study, therefore, we set out to use bi-directional and multivariable MR methods to  
147 investigate the causal relationship between serum lipids profile and kidney function using  
148 estimated glomerular filtration rate based on serum creatinine (eGFR<sub>crea</sub>) as a marker  
149 among individuals of African-ancestry selected from the Million veteran program (MVP)  
150 and Meta-analysed of continental African Lipid GWASs (APCDR and AWI-Gen), which  
151 we called MALG (n=24,215).

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153

## 154 **Methods**

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### 156 **GWAS data sources**

157 We selected eGFR instruments from GWAS summary statistics of all individuals of  
158 African ancestry within the U.S. Veteran's Administration million veteran program, MVP  
159 (N=57336) [21]. Genetic instruments for lipid traits were obtained from summary statistics  
160 of MALG (n=24,215) - 13,612 African-ancestry participants from the African Partnership  
161 for Chronic Disease Research (APCDR) & the Africa Wits-IN-DEPTH partnership for  
162 Genomics studies (AWI-Gen) [22]. More information about the African cohorts (AWI-  
163 Gen+APCDR) from which the lipids instrumental variables were obtained are detailed  
164 elsewhere [21-23].

165

### 166 **Univariable Mendelian Randomization**

167 After instrument harmonization and selection, the inverse-weighted variance (IVW)  
168 method was used to perform the bi-directional MR analysis. In the absence of directional  
169 pleiotropy and heterogeneity between exposure and outcome, the estimates from this  
170 method have been reported to be reasonably accurate [23]. We checked for the possible  
171 presence of horizontal pleiotropy between instrumental variables by including the MR-  
172 Egger regression method and MR-PRESSO. Evidence of horizontal pleiotropy was based  
173 on the MR-Egger intercept value deviating significantly from zero with a P-value  $\leq 0.05$   
174 [23, 24]. The weighted median method was used as the method of choice in case of  
175 observed pleiotropy [25].

176

### 177 **Multivariable Mendelian Randomization**

178 The Multivariable Mendelian Randomization method can be applied for multiple genetic  
179 instruments regardless of their association with the exposure [26]. In this MVMR method,  
180 the instrumental variables may be associated with more than one risk factor but they must  
181 fulfill the equivalent instrumental-variable assumptions [27]. Thus, we applied this method  
182 by considering all the instrumental variables for HDL, LDL, and TG to determine their  
183 independent effects on eGFR.

184

### 185 **Sensitivity analyses**

186 We performed a sensitivity analysis using the penalization method in which the  
187 contribution of some of the instrumental variables (e.g., heterogeneous or outlying IVs) to  
188 the analysis is down-weighted (or penalized) [25]. We performed the systematic leave-  
189 one-out approach to determine potential pleiotropy per SNP. The resultant effect was  
190 assessed using the robust penalized IVW estimate. The change in results before and  
191 after SNP removal was then assessed. We also checked for heterogeneity between  
192 instrumental variables determined by Q statistics at P-value  $\leq 0.05$ .

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196 **Ethics statement**

197 The parent studies; MVP, and MALG obtained participant consent with respective ethical  
198 approvals, and consequently, this work is exempt from seeking further ethics approval.

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200 **Statistical analysis**

201 We performed the MR analyses using the two-sample random-effects inverse-variance  
202 weighted (IVW) method implemented in the Mendelian Randomization R package [28].

203 This method determines the causal estimates for instruments that meet the instrumental  
204 variable assumptions reported elsewhere [14]. To account for the documented horizontal

205 pleiotropy between lipids, we conducted a multivariable MR (MVMR) including  
206 instrumental variables from HDL, LDL, and TG at  $P < 5 \times 10^{-8}$ . We further checked for

207 reverse causality by conducting an MR analysis considering eGFR<sub>crea</sub> from MVP as  
208 exposure and lipid traits from MALG as outcome. The genetic instruments included in this

209 study for all analyses were selected as those significantly associated with the risk of lipid  
210 traits at  $p < 5 \times 10^{-8}$  in the MALG dataset with clumping at 500kb. We controlled for the

211 false discovery rate in multiple testing using the Bonferroni method [29]. Statistical  
212 significance for causal associations was considered at  $p\text{-value} < 0.005$ . All analyses were

213 performed using Mendelian Randomization packages in R.

214

215 **Role of funding source**

216 Funding sources had no role in the conduct or reporting of the research.

217

218 **Results**

219 The bi-directional MR analysis was performed as shown in **figure1**. Further details on the  
220 instrumental variables chosen can be found in **supplementary data**.

221

222 **Association of estimated glomerular filtration rate with lipid levels**

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224 **Univariable MR**

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226 The associations between genetically predicted lipid traits and eGFR are shown in  
227 **Table1, figure 2, supplementary figure s2**. We found no evidence of a statistically  
228 significant causal association between genetically predicted HDL-C and eGFR ( $\beta = -$   
229  $0.164$ ,  $95\%$  CI =  $-1.329-1.00$ ;  $p = 0.782$ ). The effect estimates ( $\beta$ ) [ $95\%$  confidence  
230 intervals (CIs)] for the other lipid traits on eGFR were  $1.1$ ([ $0.411-1.788$ ];  $0.002$ ),  
231  $1.619$ ([ $0.412-2.826$ ];  $0.009$ ) and  $-0.934$ ([ $-2.815-0.947$ ];  $0.33$ ) for LDL, TC, and TG  
232 respectively. There was evidence of a significant causal association between genetically  
233 predicted LDL cholesterol and eGFR. Similarly, TC showed a significant causal effect on  
234 eGFR (**Figure 2**). Genetically predicted Triglycerides (TG) were not significantly  
235 associated with eGFR as well.

236

237 The reverse MR analysis showed no significant causal association between eGFR and  
238 all four lipid traits, as shown in the **supplementary figure S1 & Table S1**. For the reverse  
239 MR, the effect estimate ([ $95\%$  CI]) for HDL, LDL, TC, and TG was  $0.01$ ([ $-0.011-0.012$ ];  
240  $p=0.873$ ),  $0.007$ ([ $-0.005-0.018$ ];  $p=0.265$ ),  $0.008$ ([ $-0.005-0.021$ ];  $p=0.225$ ) and  $0.00$ ([ $-$   
241  $0.011-0.011$ ];  $p=0.984$ ) respectively. eGFR showed no evidence of a reverse causal  
242 effect on this population's genetically predicted lipid traits.

243

#### 244 **Multivariable MR**

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246 The MVMR analysis showed statistically significant causal associations for genetically  
247 predicted lipid traits; LDL and TG on eGFR (**figure 3; supplementary TableS2**). LDL  
248 cholesterol had a significant positive causal effect on eGFR, consistent with that observed  
249 in the forward univariable analysis ( $\beta = 1.228$ ([ $0.477-1.979$ ];  $p=0.001$ ). There was  
250 evidence of a significant causal effect of genetically predicted TG on eGFR ( $\beta = -1.3$ ([ $-$   
251  $2.533-0.067$ ];  $p=0.039$ ). HDL was not significantly associated with eGFR, just like in  
252 prior analyses.

253

#### 254 **Sensitivity analyses**

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256 We accounted for the pleiotropic effects between instrumental variables using MR-Egger,  
257 penalized robust MREgger, leave-one-out analysis, simple median, and weighted median  
258 analyses. We found no evidence of horizontal pleiotropy between IVs using the MR-Egger  
259 regression intercept analysis. All associations had p-values > 0.005 for the MR-Egger  
260 intercept, as shown in **figure s2**. We further estimated any horizontal pleiotropy using the  
261 leave-one-out approach and found no evidence of any confounding due to pleiotropy  
262 between SNPs with all p-value > 0.05 (**Table2**).

263

## 264 **Discussion**

265 In this African-ancestry MR study, we investigated the causal effect of genetically  
266 predicted lipid traits on eGFR<sub>crea</sub> using a two-sample and multivariable MR approach. In  
267 the primary MR-IVW forward analysis, LDL-C and TC showed evidence of a significant  
268 causal association with eGFR. Therefore, we report significant evidence that genetically  
269 predicted lipids; LDL and TC are causally associated with eGFR<sub>crea</sub> in this African  
270 population. However, the reverse MR-IVW analysis indicated a non-significant causal  
271 association between eGFR<sub>crea</sub> and either of the genetically predicted lipids.

272

273 Our findings in the main analysis on HDL and TC differ from those reported on MR  
274 analyses in European ancestry cohorts by Lanktree *et al.* and other groups[16, 17, 30].  
275 They reported a significant association between higher HDL levels with higher eGFR.  
276 Here, we report no evidence of association between genetically-proxied HDL cholesterol  
277 and better kidney function in this African cohort. However, our findings tally with those  
278 from another study based on European ancestry individuals using GLCG and CKDGen  
279 consortium datasets which reported a non-significant effect of HDL on eGFR levels [8].  
280 Notably, elevated HDL has been shown to lower the mortality rate of CKD within observed  
281 ranges [31].

282

283 Our causal association between LDL and eGFR differs with findings from elsewhere [4,  
284 10]. The Chronic Renal Insufficiency Cohort Study reported no association between LDL-  
285 C levels and the change rate of eGFR in low proteinuria individuals at baseline [32]. We,  
286 therefore, suggest better powered future studies within the same African ancestry to

287 clarify the true association between serum lipids and kidney function as measured by  
288 eGFR in this ancestry.

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290 The reverse univariable analysis showed no evidence of a significant causal association  
291 between eGFR and lipid traits. Our findings from the reverse association between eGFR  
292 and serum lipids are consistent with findings elsewhere[33].

293

294 In the main univariable analysis, we report that high LDL and TC levels had a strong  
295 significant causal effect on eGFR levels. In the multivariable MR analysis, low TG levels  
296 had a protective effect on eGFR. Unlike TC, genetically predicted low TG levels showed  
297 a consistent causal effect on eGFR between the MVMR and the main forward univariable  
298 analysis, showing significance in the latter. Findings from other studies have reported a  
299 conflicting association between TG and eGFR, but these have been based on European  
300 ancestry populations [16, 33-35]. Evidence from observational studies supports a greater  
301 triglyceride to HDL cholesterol ratio as associated with a decline in eGFR [20, 36]. These  
302 observational studies are, however, limited by confounding and inability to determine  
303 direction of effect.

304

305 The respective directions of effect from the MVMR analysis were quite similar to those  
306 observed in the forward univariable MR analysis. In this MVMR analysis, both LDL and  
307 TG had protective causal effects on eGFR. The un-expected direction of effect of  
308 genetically predicted LDL and TG on eGFR reported in this study might be due to the low  
309 statistical power in this study. Noteworthy, a recent study reported an inconsistent  
310 evidence between higher atherogenic lipids including LDL-C, TG, and Apo B and weak  
311 increase in eGFR [33]. A higher eGFR association with higher LDL-C and TG has been  
312 previously associated with glomerular hyperfiltration rates that occur in individuals with  
313 cardiometabolic conditions [37]. We couldn't verify the role of underlying cardiometabolic  
314 conditions towards the observations in this study. We recommend a more powered study  
315 on African-ancestry individuals, accounting for such clinical parameters to further clarify  
316 our findings.

317

318 Our study strengths were in the use of continental African-derived GWAS summary  
319 statistics (MALG) and assessing a possibility for a reverse causation between eGFR and  
320 serum lipids. We also performed sensitivity analyses including multi-variable MR-Egger  
321 to determine reliability of our instrumental variables as detailed under the methods  
322 section.

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### 325 **Study limitations**

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327 The study was limited by a lack of access to individual-level data as we only had access  
328 to GWAS summary statistics. This meant that the strength of the instruments used  
329 couldn't be measured directly. Therefore, we couldn't measure a possible bias caused by  
330 weak instruments. In our case, weak instruments would lead to an estimate of the causal  
331 effect that is biased toward the observational effect estimate. The study was also limited  
332 by power, and we also didn't correct for sample overlap. We also did not assess for  
333 ancestral differences in the instrumental variables with other ancestries, as suggested by  
334 Graham et al. [38].

335

### 336 **Conclusions**

337 This Mendelian Randomization study suggests a causal association between LDL  
338 cholesterol and higher eGFR, but not HDL cholesterol. We report that genetically  
339 elevated LDL cholesterol levels are associated with developing higher eGFR. Our findings  
340 suggest that the relationship between non-HDL cholesterol and kidney function may be  
341 U-shaped. This may be a reason why LDL is seen to be a poor predictor of renal  
342 function compared to HDL, and as such lowering LDL does not necessarily improve risk  
343 of kidney disease. Therefore, our findings highlight the need for bigger MR studies  
344 focused on African ancestry individuals to accurately determine the association between  
345 serum lipid traits and kidney function measured by eGFR<sub>crea</sub> in continental Africans.

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350 **Data sharing statement**

351 All scripts for the analysis are available from the authors upon request.

352

353 **Contributors**

354 SF conceptualised the study. CK performed the analyses. OS verified the underlying  
355 data. CK, OS, TC and SF wrote the first draft of the manuscript. All authors read and  
356 approved the final version of the manuscript.

357

358 **Declaration of interests**

359 DG is employed part-time by Novo Nordisk and has received consultancy fees from  
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361 all other authors.

362

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376 MVP is Gaziano, J.M. et al. Million Veteran Program: A mega-biobank to study genetic  
377 influences on health and disease. *J Clin Epidemiol* 70, 214-23 (2016). This research is  
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381

382 Dr. Segun Fatumo is the guarantor of this work and, as such, had full access to all the  
383 data in the study and takes responsibility for the integrity of the data and the accuracy of  
384 the data analysis.

385

## 386 Tables and figures

387

### 388 Tables

389

390 **Table1: Univariable IVW Mendelian Randomization results.** LDL-C: low-density lipoprotein cholesterol; HDL-C:  
391 high-density lipoprotein cholesterol; TC: Total Cholesterol; TG: Triglycerides; IVW: Inverse Variance Weighted; SE,  
392 standard error. \*statistically significant ( $p < 0.05$ )

Exposure	Outcome	BETA	SE	95%CI	P-value
HDL	eGFR	-0.164	0.594	-1.329-1	0.782
LDL	eGFR	1.1	0.351	0.411-1.788	0.002*
TC	eGFR	1.619	0.616	0.412-2.826	0.009*
TG	eGFR	-0.934	0.96	-2.815-0.947	0.33

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**Table2: Leave-one-out sensitivity analyses for all SNPs in the Multivariable MR**

SNP	MR-Egger intercept	SE	95% CI	P-value
rs1800588	-0.058	0.084	-0.222-0.107	0.493
rs17111732	-0.038	0.098	-0.229-0.153	0.698
rs116513376	-0.061	0.085	-0.227-0.106	0.476
rs59523416	-0.056	0.084	-0.220-0.108	0.503
rs12740374	-0.028	0.073	-0.171-0.115	0.703
rs143375141	-0.070	0.085	-0.236-0.097	0.413
rs35804417	-0.057	0.084	-0.221-0.107	0.497
rs75143493	-0.073	0.075	-0.220-0.075	0.334
rs73015020	-0.095	0.079	-0.250-0.060	0.229
rs10416720	-0.076	0.089	-0.251-0.099	0.393
rs7412	-0.084	0.095	-0.271-0.102	0.375
rs3810308	-0.107	0.083	-0.270-0.056	0.199
rs326	-0.073	0.088	-0.246-0.100	0.406
rs2070895	-0.054	0.088	-0.227-0.119	0.538

rs12721054	-0.035	0.069	-0.170-0.101	0.613
rs114139997	-0.054	0.077	-0.204-0.096	0.477

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**Supplementary material**

**Supplementary tables**

**Table S1: Reverse Mendelian Randomization results.** \*LDL: low-density lipoprotein cholesterol; HDL: High-density lipoprotein cholesterol; TC: Total Cholesterol; TG: Triglycerides

Exposure	Outcome	BETA	SE	95%CI	P
eGFR	HDL	0.001	0.006	-0.011-0.012	0.873
eGFR	LDL	0.007	0.006	-0.005-0.018	0.265
eGFR	TC	0.008	0.007	-0.005-0.21	0.225
eGFR	TG	0	0.006	-0.011-0.011	0.984

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**Table S2: Multivariable Mendelian Randomization results.** \*LDL: low-density lipoprotein cholesterol; HDL: High-density lipoprotein cholesterol; TG: Triglycerides; SE: standard error; CI: confidence interval

Exposure Trait	Outcome	BETA	SE	95%CI	P
HDL	eGFRcrea	-0.117	0.579	-1.252-0.018	0.84
LDL	eGFRcrea	1.228	0.383	0.477-1.979	0.001
TG	eGFRcrea	-1.3	0.629	-2.533-0.067	0.039

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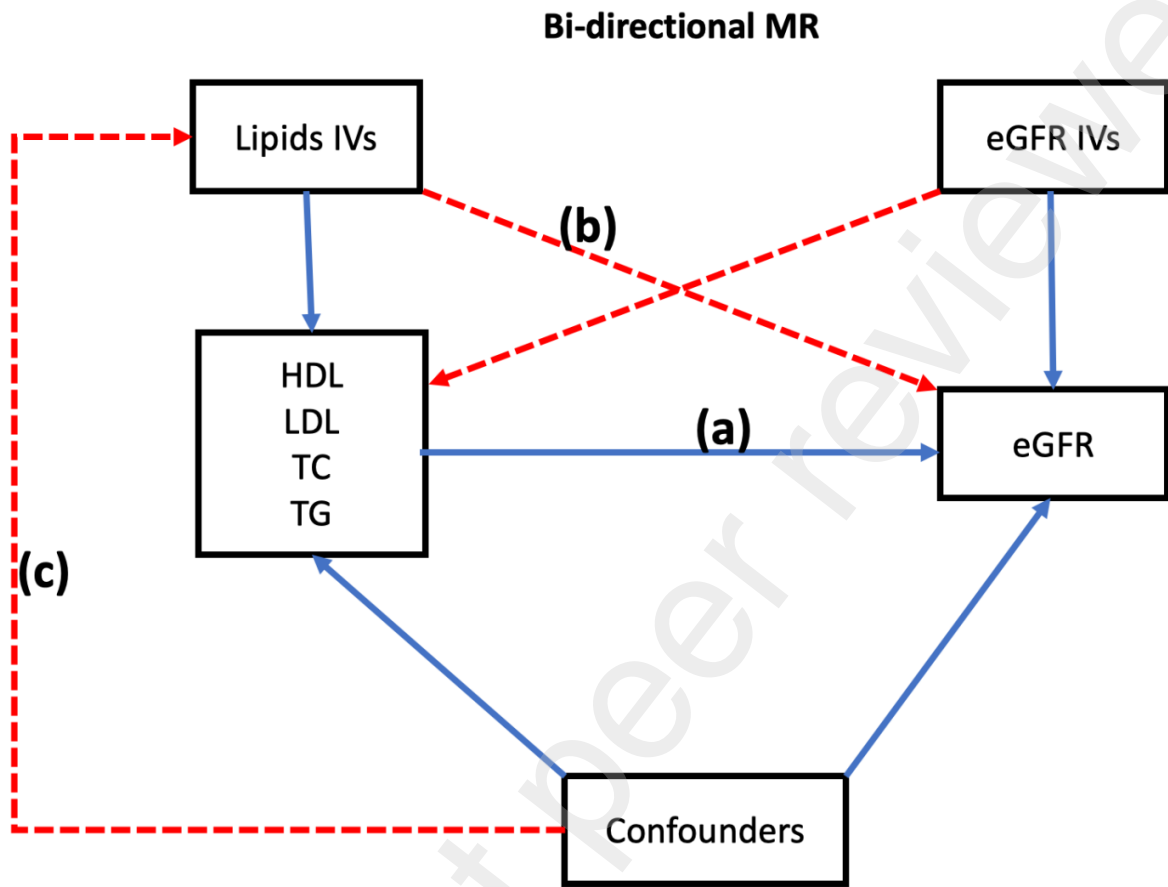
**Table S3: Heterogeneity Tests.** LDL: low-density lipoprotein cholesterol; HDL: High-density lipoprotein cholesterol; TG: Triglycerides; TC: total cholesterol

Exposure trait	Cochran's Q	I <sup>2</sup> (%)	p-value
HDL	2.3129	56.8	0.1283
LDL	11.5815	22.3	0.2379
TC	9.5642	47.7	0.0886
TG	7.4009	59.5	0.0602

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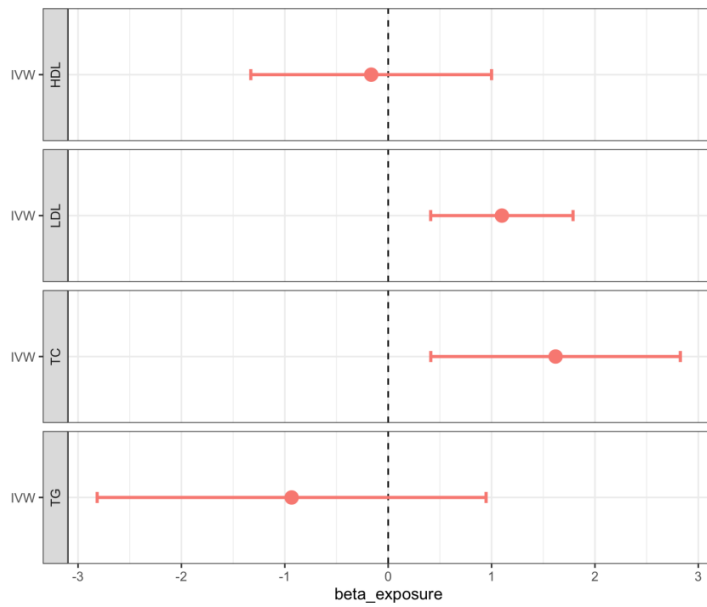
**Figures**

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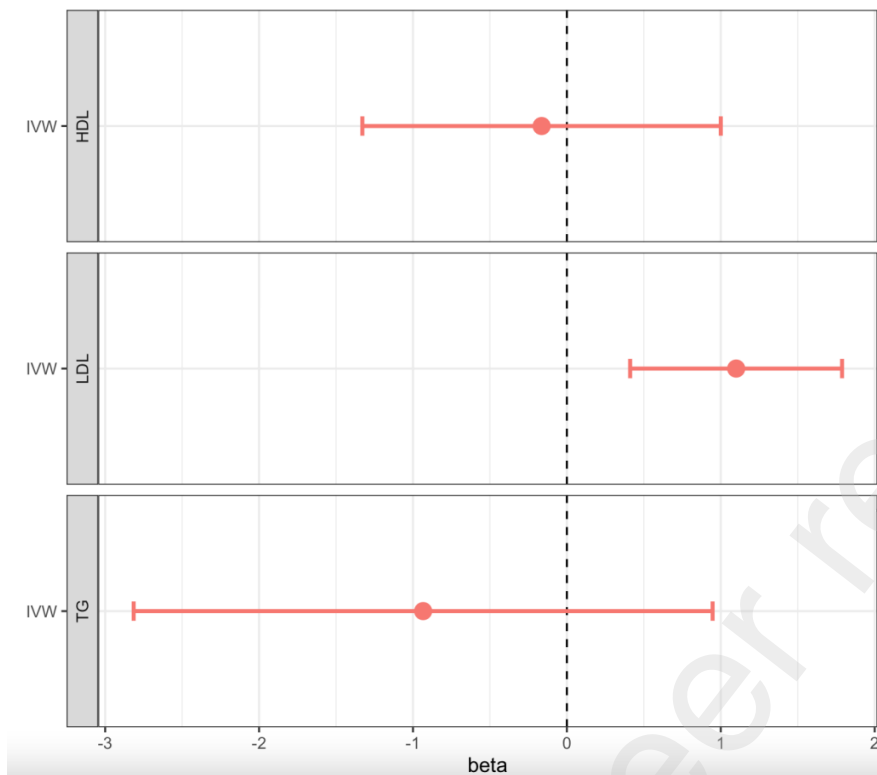
**Figure 1:** A schematic representation of bi-directional MR analyses: (a) Forward univariable MR; (b) IVs for lipid traits should not have an association with eGFR; (c) IVs for lipid traits are not related to measured or unmeasured confounding. HDL, high-density lipoprotein; LDL, low-density lipoprotein; TG, triglycerides; eGFR, estimated glomerular filtration rate; SNP, single-nucleotide polymorphism; MR, Mendelian Randomization; F/R, Forward/Reverse; IVs, Instrumental variables.



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**Figure2:** Forest plot of the beta estimates and their 95% confidence intervals between genetically predicted lipid traits and eGFR using the IVW univariable MR method. IVW, inverse-variance weighted; HDL, high-density lipoprotein cholesterol; LDL, low-density lipoprotein cholesterol, TC: total cholesterol

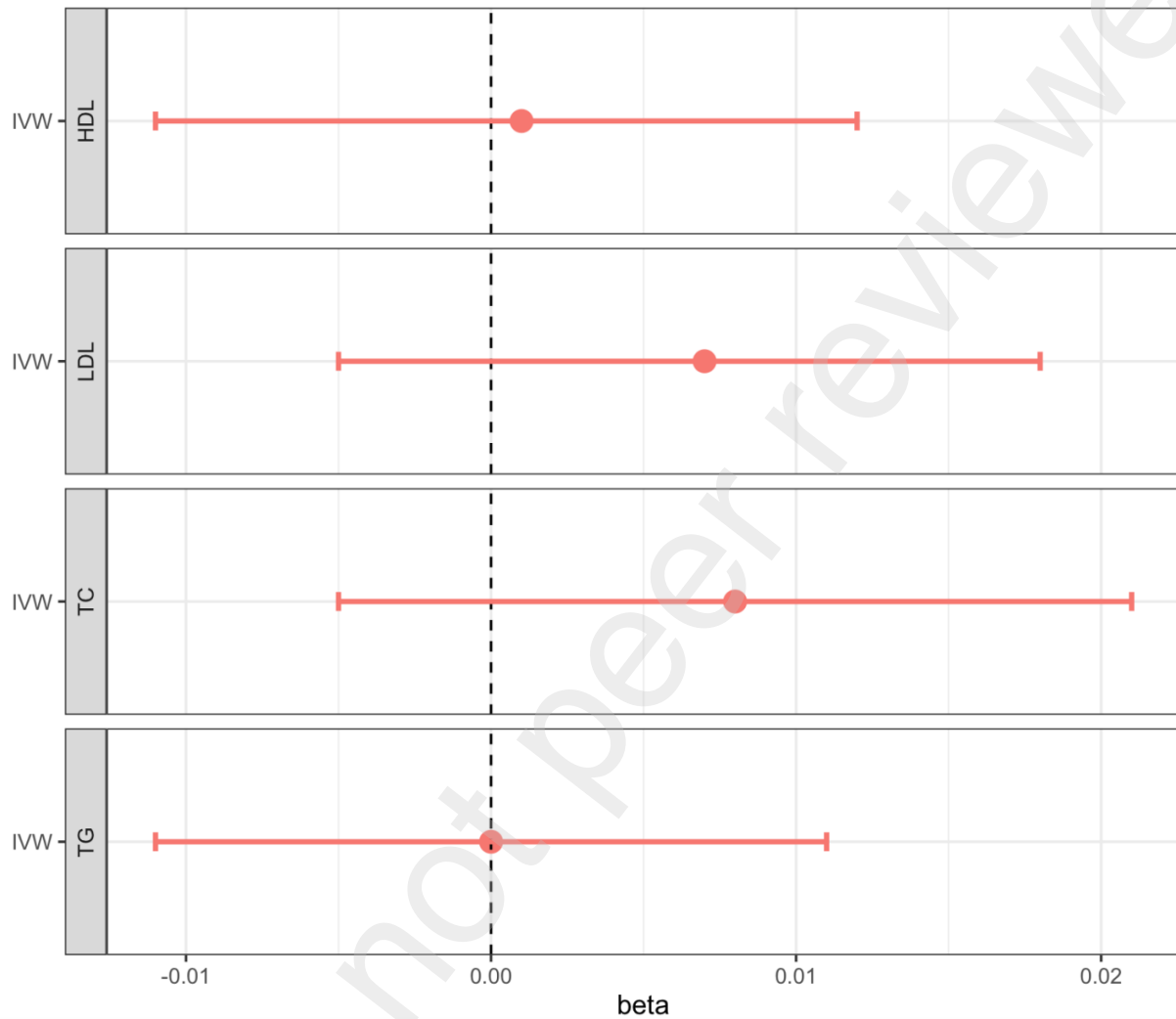




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 464 **Figure 3:** Forest plot showing the beta estimates and 95% confidence intervals of Multivariate MR of lipids vs eGFR  
 465 traits. HDL-C: high-density lipoprotein cholesterol; LDL-C: low-density lipoprotein cholesterol; TG: Triglycerides  
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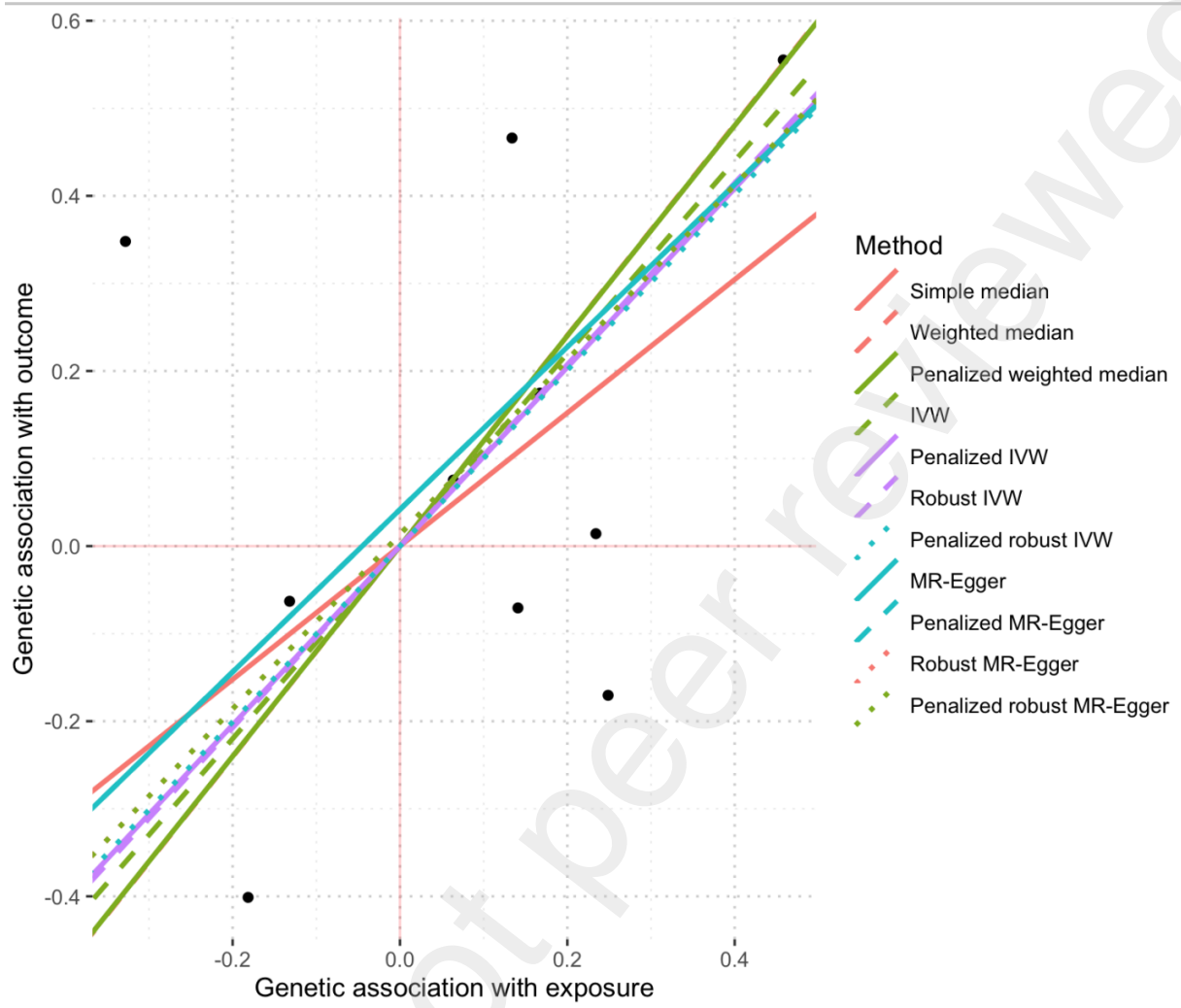
488 **Supplementary figures**

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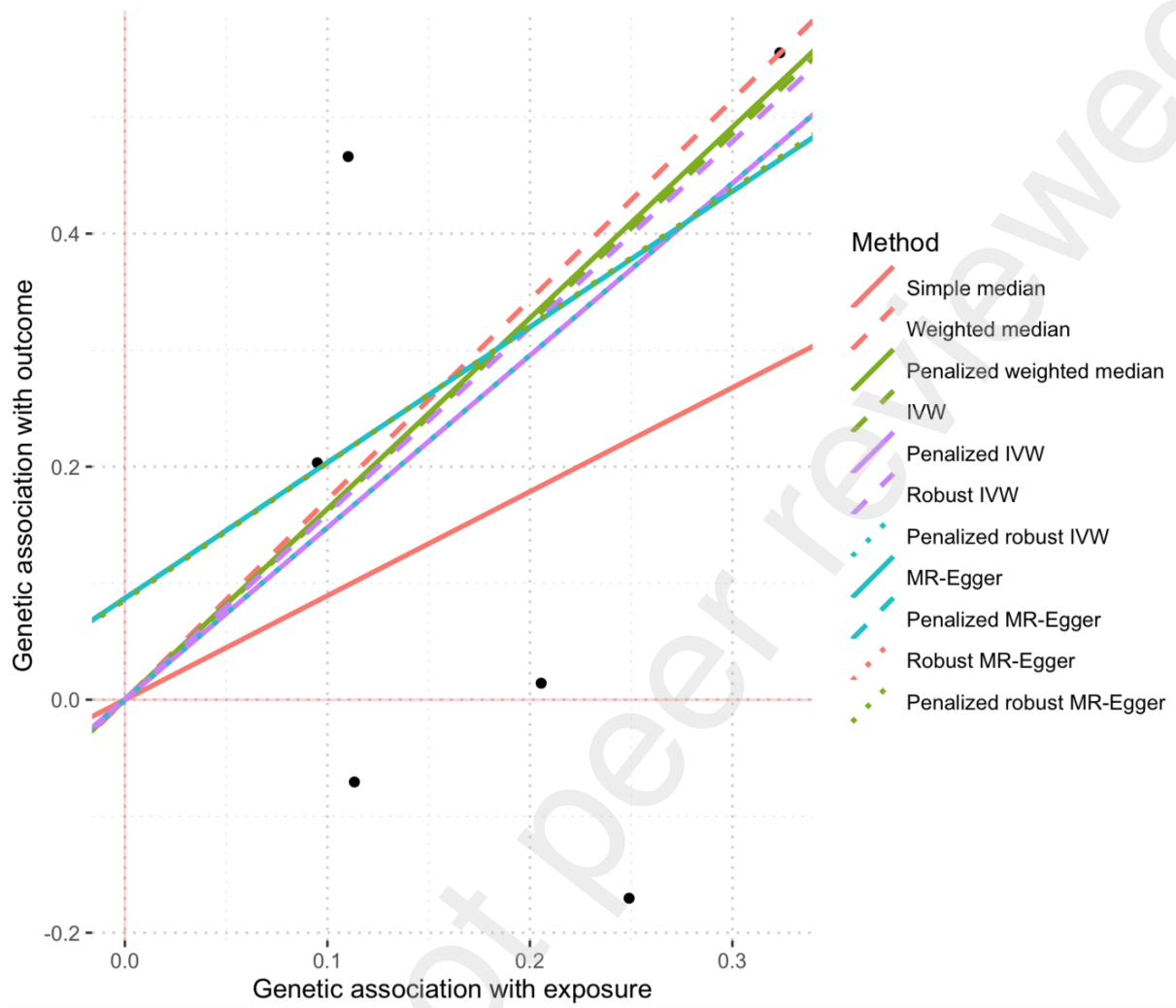
491 **Figure S1:** Forest plot showing the beta estimates and their 95% confidence intervals of reverse MR of eGFRcrea vs  
492 lipid traits. HDL-C: high-density lipoprotein cholesterol; IVW: inverse-variance weighted; LDL-C: low-density  
493 lipoprotein cholesterol; Total C: total cholesterol; TG: Triglycerides  
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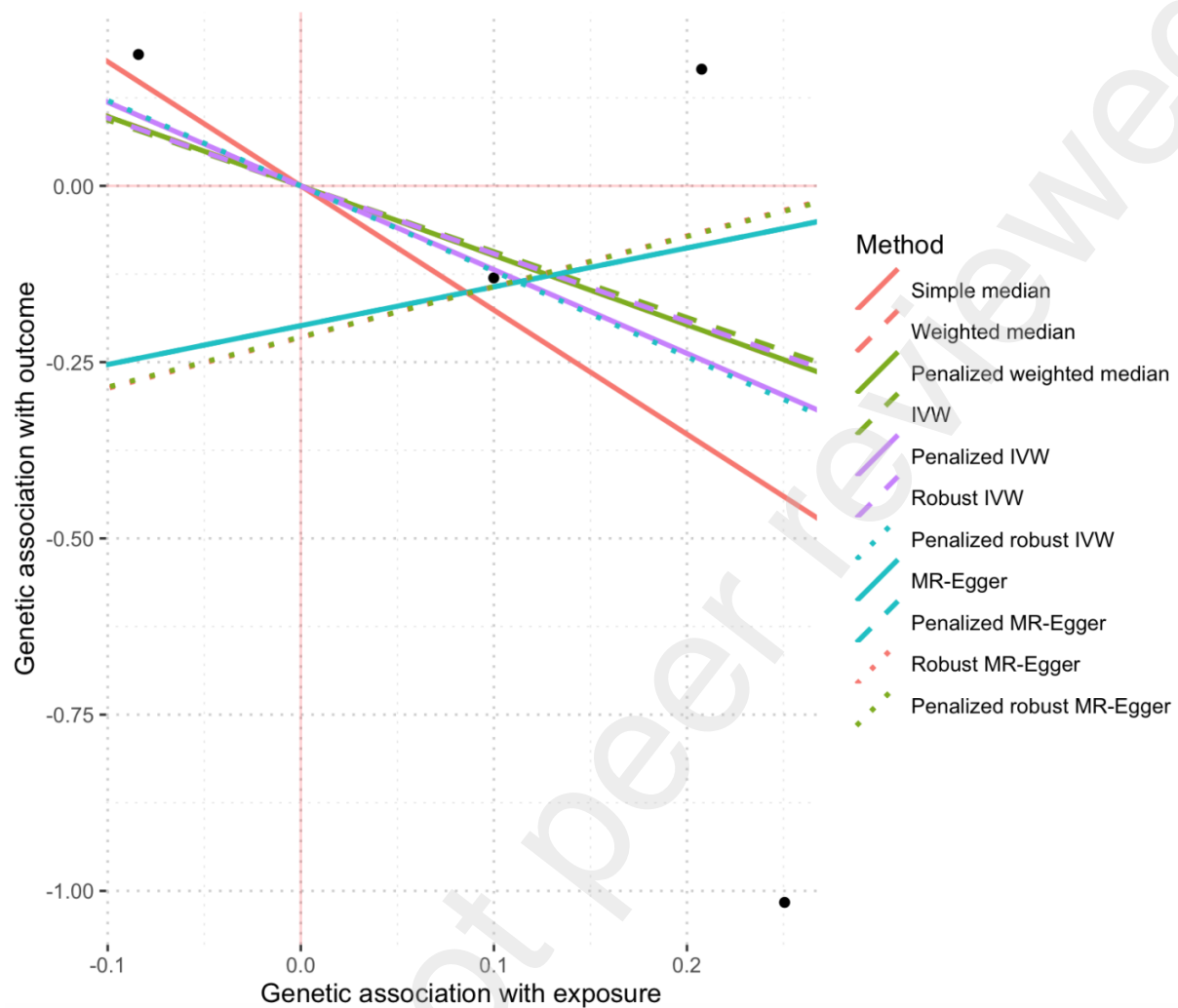
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(a)



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**Figure S2:** Estimated causal effects of lipids on eGFR using univariable MR assessed using different MR methods: (a) Causal estimates for LDL, (b) Causal estimates for TC (c) causal estimates for TG. LDL-C, low-density lipoprotein; TG, triglycerides; eGFR<sub>crea</sub>, estimated glomerular filtration rate based on creatinine measurements; IVW, inverse variance-weighted

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