
Supplementary information

***FNIP1* variants are associated with favourable metabolism in 1 million humans**

In the format provided by the
authors and unedited

Supplementary Information

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Supplementary Notes

Supplementary Note 1. Supplementary results for the genome-wide association analysis of common variants.

Leveraging genomic data on 1,032,116 people from 11 cohorts (**Fig. 1, Supplementary Table 1, Methods**), we performed a genome-wide association study (GWAS) of TG-HDL ratio. We considered 10,753,791 common variants (minor allele frequency $\geq 1\%$), imputed using the TOPMed panel,¹ that passed our quality control filters (**Methods**). Using REGENIE v3.4, we fitted linear whole-genome regression models to estimate the association of each variant with TG-HDL ratio. Association estimates were generated for each cohort separately using a multi-ancestry framework and then pooled across cohorts by inverse-variance weighted fixed-effect meta-analysis (**Methods**). We also performed a sensitivity analysis where, for each cohort, we performed a GWAS separately in each ancestry and then meta-analyzed across all cohort-ancestry sets of results.

Association statistics for the meta-analysis across cohort results (main analysis), meta-analysis across cohort-ancestry results (sensitivity analysis) and for the UK Biobank (UKB) all-ancestry (ALL) analysis (main analysis of the UKB dataset) and UKB European-ancestry (EUR) only analysis (sensitivity analysis of the UKB dataset) were all consistent with appropriate control of genetic confounding (**Supplementary Table 3**), as expected for the REGENIE approach.² Using default EUR LD-scores and fitting the LD-score regression baseline LD model on a subset of ~ 1.2 million HapMap common variants, we obtained LD-score regression intercepts of 1.18, 1.19, 1.36 and 1.37 for the UKB EUR, UKB ALL, meta-analysis of cohort-ancestry results and meta-analysis of cohort results (**Supplementary Table 3**). These are similar to or lower than what was observed in analyses of similar size across multiple traits.³ Deviations of LD-score regression intercept from 1 (up to 1.5 in UK Biobank and even higher in studies larger than UKB) are expected and have been observed in large studies in the absence of confounding and population stratification, since deviations from the theoretical model (e.g., attenuation bias) are proportional to the level of true signal and polygenicity in the study.³ The attenuation ratio statistic, calculated as $(\text{LDSC intercept} - 1) / (\text{mean } \chi^2 \text{ statistic} - 1)$, calibrates the intercept against the overall shift in χ^2 statistic due to true polygenic associations.³ Attenuation ratio values < 0.2 have been observed in UK Biobank in optimally controlled analyses³ and are considered reflective of adequate control for population stratification and genetic confounding.⁴ We observed attenuation ratio values of ~ 0.11 across all the various analyses (**Supplementary Table 3**), consistent with optimal control of inflation in the context of our massive sample size and the high polygenicity of TG-HDL ratio.

We next performed fine-mapping to identify independent common variant signals associated with TG-HDL ratio. To define fine-mapping regions, we first identified variants with $P < 1 \times 10^{-6}$ and separated them into regions at least 100kb apart. Only regions containing at least one genome-wide significant variant ($P < 5 \times 10^{-8}$) were retained. Each region was then extended to the nearest recombination hotspot, with extensions ranging from 25-250kb. Finally, a 100kb buffer was applied around each region and regions with overlapping buffers were merged into a single region to form the final loci for causal variant identification. This exercise yielded 801 physical loci for fine-mapping (**Supplementary Table 4**). Next, for each locus, we computed exact linkage disequilibrium (LD) based on the exact set of individuals included in the association analysis, followed by fine-mapping using the SuSiE software (**Methods**).⁵ Fine-

mapping identified 1,617 independent common sentinel variants, each of which was the variant with the highest posterior inclusion probability (PIP) for each independent credible set in each locus. Manhattan plot and QQ plots for the multi-ancestry meta-analysis are in **Supplementary Fig. 8**.

In parallel, we also performed ancestry-specific GWAS meta-analyses for five ancestry groups represented in our dataset (i.e. European, Admixed American, African, East Asian, South Asian). First we performed GWAS analyses within each cohort and ancestry group. For each ancestry, we then combined cohort-specific results into an ancestry-specific meta-analysis using inverse-variance weighted fixed-effect meta-analysis. We then performed fine-mapping separately in each ancestry using the same approach as described above and in **Methods**. This yielded 1,406 credible sets in the European analysis, 209 in the Admixed American analysis, 63 in the South Asian analysis, 44 in the African analysis and 9 in the East Asian analysis (**Supplementary Table 5 and Supplementary Figs. 9-13**).

Supplementary Note 2. Supplementary results for the exome-wide association analysis of rare coding variants.

We performed an exome-wide association analysis of TG-HDL ratio, estimating the association of rare coding variants (minor allele frequency < 1%) in each gene in the genome. In the exome-wide analysis, 60 genes were associated with TG-HDL ratio at the exome-wide level of statistical significance ($P < 1.04 \times 10^{-7}$; **Extended Data Table 1, Fig. 3a-b**), in an analysis adjusted for the 1,617 common variant signals identified in the same individuals (**Methods**). The exome-wide level of statistical significance was a Bonferroni correction for 20,000 genes in the genome and 24 gene-burden exposures tested for each gene (**Methods**).

We next assessed whether linkage disequilibrium between rare coding variants affected the 60 associations, noting that there were some gene-burden associations clusters (e.g. for the *APOC3*, *APOA5* and *APOA1* cluster on chromosome 11). We performed gene-burden conditional analyses adjusting the association of each of the 60 gene-burden exposures for other rare variant signals in the same chromosome (**Methods**). Of the 60 genes, 59 showed an independent association when adjusting for other gene-burden signals, whereas the association of the *AC126283.2* gene disappeared in the conditional analysis, reflecting the sequence overlap with *PLA2G12A* (**Supplementary Table 6**). The *AC126283.2* is annotated as a novel protein with no known characterization or functional details available. It is classified as a readthrough gene and tagged as a novel protein based on RNA-Seq evidence of transcription spanning the readthrough region between the *CFI* and *PLA2G12A* genes. The coding sequence (CDS) coordinates for this gene overlap with those of both *CFI* and *PLA2G12A* (Ensembl 114). Notably, *PLA2G12A* is one of the 60 genes associated with TG-HDL ratio (per-allele beta, 0.56 ratio units; 95% CI, 0.51, 0.61 ratio units; $P = 4 \times 10^{-109}$). In addition to the conditional analysis, accounting for *PLA2G12A*-*AC126283.2* sequence overlap clearly shows that *PLA2G12A* is responsible for the signal, whereas *AC126283.2* rare coding variants not shared with *PLA2G12A* have no associations with TG-HDL ratio (**Supplementary Table 8**). Therefore, *AC126283.2* cannot be considered to have an independent association with TG-HDL ratio based on our current data.

Of the 59 independent genes, 15 (25%) had been identified in the previous largest analysis of TG-HDL ratio in ~170,000 people,⁶ while the remaining 44 (75%) were novel rare coding variant associations with TG-HDL ratio (**Supplementary Table 7**). In addition to the 15 overlapping genes, the previous effort⁶ had reported rare coding variant associations for *APOE* and *TMEM136* (encoded by the *TLCD5* gene), which do not appear in the list of 59 independent rare variant associations from our discovery analysis (**Extended Data Table 1**). We evaluated why *APOE* and *TMEM136* (encoded by the *TLCD5* gene) were not associated in our large discovery analysis. We found that *APOE* rare variants were associated with TG-HDL ratio in our data *before* adjusting for common variants ($P = 1.1 \times 10^{-11}$; **Supplementary Table 9**), but this association was attenuated to below the exome-wide significance threshold *after* adjusting for common variants ($P = 0.0091$; **Supplementary Table 9**). It is important to note that the previous AJHG 2022 study did *not* adjust for common variants in their main analysis, causing the common-variant driven *APOE* signal to come through. *TMEM136* (encoded by *TLCD5*) showed no association in our exome-wide discovery analysis ($P = 0.69$; **Supplementary Table 9**), nor in the common variant unadjusted sensitivity analysis ($P = 0.80$; **Supplementary Table 9**). This is in spite of the fact that our analysis had over 3,400 rare variant carriers compared to the 157 of the AJHG 2022 paper. Therefore, it is possible that this association was a false positive in the 2022 effort.

To assess the robustness of the 59 gene-burden associations, we performed 4 sensitivity analyses using different common variant adjustment, ancestry adjustment and phenotype definition approaches. In our main analysis, gene-burden associations were adjusted for 1,617 common variant peaks identified in multi-ancestry GWAS and fine-mapping analyses. To assess the robustness of the 59 gene-burden associations to our choice of common variant adjustment approach, in the first sensitivity analysis we adjusted for common variant peaks identified in the ancestry-specific GWAS and fine-mapping instead. In this sensitivity analysis, associations were near identical as those from the main analysis (**Supplementary Table 10 and Supplementary Fig. 16a**). In the second sensitivity analysis, we did not perform any adjustment for common variants. Also here, associations were near identical as those from the main analysis (**Supplementary Table 10 and Supplementary Fig. 16b**), demonstrating robustness to the approach of common variant adjustment. In our main analysis, gene-burden associations were estimated in a multi-ancestry analysis framework. In the third sensitivity analysis, we estimated gene-burden associations in each ancestry separately and then meta-analyzed ancestry-specific association results. In this sensitivity analysis, associations were near identical as those from the main analysis (**Supplementary Table 11 and Supplementary Fig. 16c**), demonstrating the robustness of the 59 associations to the approach used to account for ancestry. In our main analysis, most TG and HDL measurements used to define the TG-HDL ratio phenotype were taken at the same time but we did allow instances where median values of TG and HDL used to define ratios were taken at different time points, which allowed for a larger discovery sample size. In the fourth sensitivity analysis, we required that measurements were taken at the same time. In this sensitivity analysis, associations were near identical as those from the main analysis (**Supplementary Table 12 and Supplementary Fig. 16d**), demonstrating robustness across different approaches to define the phenotype.

We next assessed how associations differed by ancestry for the 59 gene-burden signals. We first estimated associations separately by ancestry (**Supplementary Table 11**). We next estimated whether associations were consistent between the larger European ($N = 718,681$; 70.3%) vs a meta-analysis of non-European datasets ($N = 302,958$; 29.7%). We found that 58 of 59 genes (98%) had the same direction of association in European vs pooled non-European ancestry estimates (**Supplementary Table 11**). The only exception was the *AICF* gene, where there was a strong association in European analyses ($P = 5.5 \times 10^{-27}$), but no association in the non-European subsets ($P = 0.97$), which we demonstrate is driven by a gain-of-function variant⁷ that is specifically enriched in the European populations (p.Gly390Ser; **Supplementary Table 11 and Supplementary Fig. 19**). We further investigated how allelic heterogeneity and frequency differences across ancestries contributed to our signal discovery. We looked for genes where (i) P value in the European ancestry analysis was $> 1.04 \times 10^{-7}$, (ii) P value in any non-European ancestry analysis was < 0.05 and (iii) the minor allele frequency of the gene-burden exposure was 50% larger in that same non-European ancestry compared to the European ancestry. We found three such instances (a) *PCSK9*, showing enriched frequency in African and Admixed American ancestry; (b) *LIPE*, showing enriched frequency in Admixed American ancestry; and (c) *GALNT2*, showing enriched frequency in South Asian ancestry. There were also multiple other examples using a more lenient cutoff for enriched frequency (**Supplementary Table 11**).

We assessed whether there were sex-interactions for the 59 gene-burden associations, noting that TG-HDL ratio is associated with body fat distribution, a phenotype exhibiting strong evidence of sex-interaction.⁸ Association results were generally very consistent in men and women (effect size correlation

between men and women, $r = 0.98$, $P = 2.3 \times 10^{-41}$; **Supplementary Table 13 and Supplementary Fig. 17**), we detected an interesting interaction for *PDE3B*, where rare variants showed stronger association with lower TG-HDL ratio in women vs men ($I^2 = 93\%$; $P_{\text{interaction}} = 1.8 \times 10^{-4}$; β_{women} , -0.40 vs β_{men} , -0.28 SD units per allele). *PDE3B* is a known fat distribution gene showing stronger association with waist-to-hip ratio in women vs men.⁹ The only other statistically significant interaction ($P < 8.5 \times 10^{-4}$, a Bonferroni correction for 59 genes, and $I^2 > 75\%$) was for *APOC3*, which had strong associations in both sexes in the same direction, but with different effect estimates in the context of extremely precise estimates (SD units β_{women} , -0.99 vs β_{men} , -1.13; $I^2 = 97\%$; $P_{\text{interaction}} = 1.0 \times 10^{-9}$).

As lipid levels may be affected by fasting state, we assessed whether there were interactions with fasting state for the 59 gene-burden associations and the 1,617 common fine-mapped variants. Most measures used in our discovery analysis were collected in the frame of very large epidemiological cohorts or clinical practice, where fasting state information was not collected. However, fasting state information was available in the UK Biobank subset ($N = 409,602$; $\sim 40\%$ of our discovery analysis). In UK Biobank, 104,276 samples (25%) were collected in fed state (i.e. ≤ 2 hours since last meal), 46,550 samples (11%) samples were collected in fasted state (i.e. ≥ 6 hours since last meal) and the remaining samples were collected between 2-6 hours since last meal. To estimate whether fasting state influenced our findings, we estimated associations in the fasted vs fed state subsets of UKB and tested for interaction. In this analysis, none of the 1,617 common fine-mapped variants or the 59 gene-burden signals met a Bonferroni correction for interaction ($P_{\text{interaction}} > 3.1 \times 10^{-5}$ for common variants and $P_{\text{interaction}} > 8.5 \times 10^{-4}$ for gene-burden signals), consistent with the absence of strong interactions with fasting state (**Supplementary Tables 15 and 16**).

Among the 59 genes, there was a remarkable over-representation of genes with enriched expression in liver and adipose tissues (**Fig. 3c**), which was consistent with the common variant analysis (**Supplementary Fig. 14**). The level of enrichment was far greater for the rare variant analysis compared to the common variant one, reflecting the higher confidence in causal gene identification afforded by the rare coding variant analysis.

We performed pathway enrichment analyses using DEPICT,¹⁰ which revealed 761 enriched pathways ($P < 5.9 \times 10^{-6}$; **Supplementary Table 18**). There was an overwhelming representation of energy metabolism pathways including lipid and glucose homeostasis, oxygen and energy consumption, lipoprotein metabolism, insulin resistance, liver fat accumulation, lipolysis regulation, fat storage and more (**Supplementary Table 18**). For these pathways, an average of 16 (interquartile range, 11 to 19) of our 59 genes contributed to the pathway enrichment association (**Supplementary Tables 18**), reflecting an extremely high concentration of true biological signal. To dissect the contribution of different lipid fractions to TG-HDL associations and pathway enrichment, we evaluated associations with TG and HDL for the 59 genes and defined effect size balance as $|\beta_{\text{triglycerides}}| / (|\beta_{\text{triglycerides}}| + |\beta_{\text{HDL}}|)$, where genes with balance ≥ 0.75 were classified as “TG-dominant”, genes with balance ≤ 0.25 classified as “HDL-dominant” and genes with balance < 0.75 and > 0.25 classified as “TG-HDL balanced” (**Methods**). As expected from our discovery approach, most genes (39 genes, 66%) were TG-HDL balanced, while 7 (12%) genes were HDL-dominant and 13 (22%) genes were TG-dominant (**Supplementary Table 19**). Genes with predominant triglyceride or HDL association showed enrichment for the respective lipoprotein particle pathways (i.e. HDL for HDL-dominant genes and VLDL and chylomicrons for triglyceride-dominant genes; **Supplementary Tables 20 and 21**), among various other pathways.

Supplementary Note 3: Mendelian disease symptom analysis for *FNIP1* and *FLCN*.

Biallelic loss-of-function variants in *FNIP1* cause *recessive* immunodeficiency-93 and hypertrophic cardiomyopathy (MIM: 619705), a syndromic immunodeficiency characterized by B-cell lymphopenia, agamma/hypogammaglobulinemia, multiple cardiac anomalies (hypertrophic cardiomyopathy, congenital cardiac disease, Wolff-Parkinson White pre-excitation syndrome), neurodevelopmental differences, muscle disease, and several other findings.¹¹⁻¹³

To estimate associations between heterozygous *FNIP1* predicted loss-of-function (pLOF) variants and the features of this Mendelian syndrome, we aligned the set of clinical features reported in patients affected by *FNIP1*-related immunodeficiency syndrome¹³ to our internal database of clinical phenotypes, which are derived from the structured data available in electronic health records (i.e. diagnostic/procedure codes, prescribed medications, and laboratory results). The specific *FNIP1*-related immunodeficiency syndrome features included in this study, along with their aligned EHR-derived phenotypes, are provided in **Supplementary Table 23**. We then constructed a composite phenotype of the core clinical features of the syndrome, where a core feature was any finding present in at least 20% of reported cases (**Supplementary Table 23**).¹¹⁻¹³ Similar to our composite cardiometabolic phenotype, individuals diagnosed with at least one of the core features were defined as cases of the composite Mendelian phenotype, whereas individuals without each of the core features were defined as controls. In the association analyses, *FNIP1* heterozygous pLOF variant carriers did not show a statistically significant association with the composite Mendelian phenotype (**Supplementary Fig. 23**). There were some nominally significant associations with individual features of the syndrome, particularly lower neutrophil counts and some electrocardiographic features (**Supplementary Fig. 24**), possibly reflecting the impact of partial *FNIP1* loss-of-function in immune and cardiac cells.

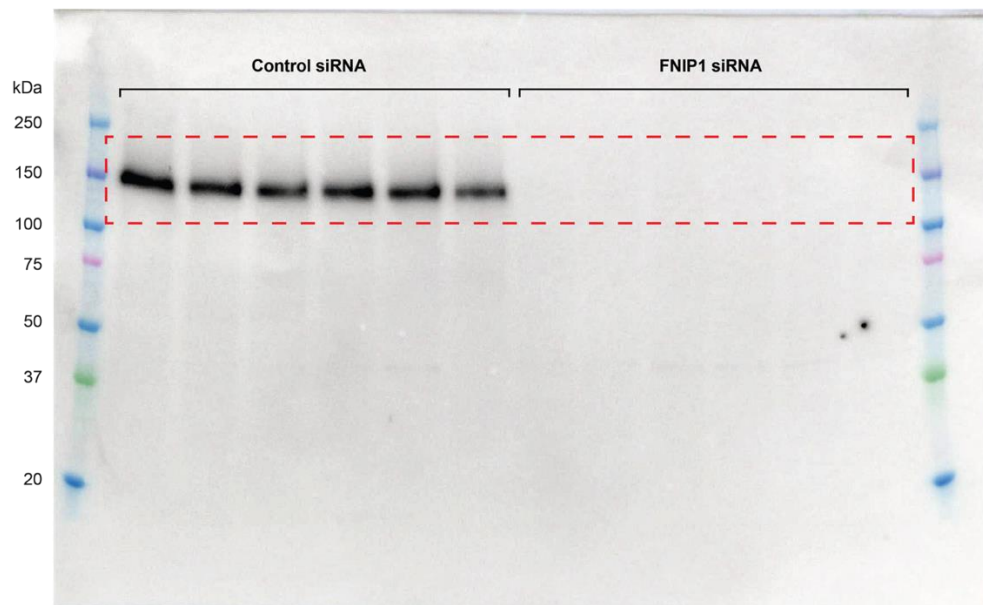
In contrast to *FNIP1*, the *FLCN* gene is associated with an autosomal *dominant* genetic disorder driven by haploinsufficiency, Birt–Hogg–Dubé syndrome (BHDS; MIM: 607273). Therefore, we hypothesized that *FLCN* heterozygous rare variant carriers in our dataset may be at higher risk for the reported clinical features of this disease.¹⁴ To test this hypothesis, we aligned the documented clinical features of BHDS to our internal database of EHR-derived phenotypes (**Supplementary Table 24**). Also in this case, we constructed a composite phenotype of the core clinical features of BHDS, where a core feature was any finding present in at least 20% of reported cases.¹⁴ Individuals diagnosed with at least one of the core features of BHDS were defined as cases of the composite Mendelian phenotype, whereas individuals without each of the core features were defined as controls. In the association analysis, heterozygous *FLCN* variants were associated with higher odds of the composite Mendelian phenotype (**Supplementary Fig. 23**) and were also at increased risk for several BHDS features (**Supplementary Fig. 26a**), particularly pneumothorax and renal malignancy.

In addition to the Mendelian phenotypes, we investigated associations with hepatic cancer for rare variants in *FLCN* and *FNIP1*, given the recent report of enhanced susceptibility to liver injury and carcinogenesis in mice with a hepatic knockout of *Flcn*.¹⁵ Heterozygous variants in *FLCN* or *FNIP1* were not associated with hepatic cancer (**Supplementary Fig. 26b**).

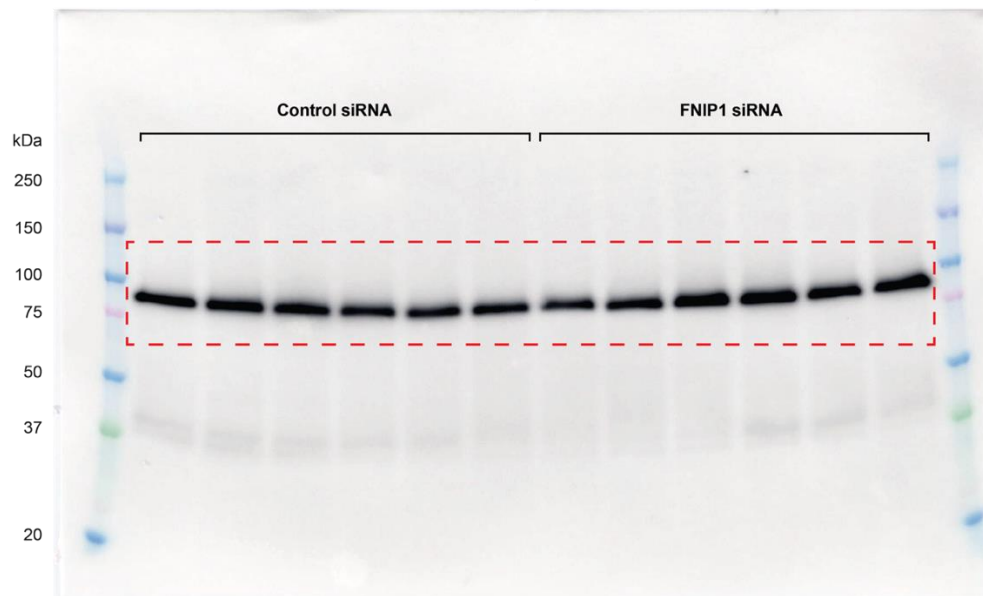
Supplementary Figures

Supplementary Figure 1. Full scans of immunoblots on primary human hepatocytes.

a FNIP1 immunoblot on primary human hepatocytes

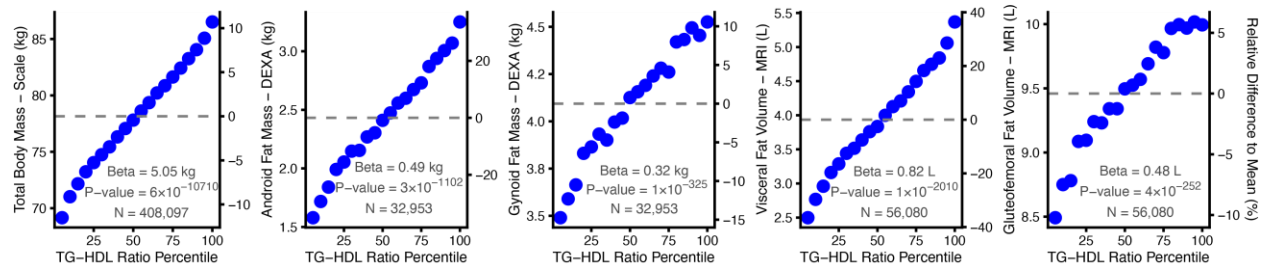


b HSP90 immunoblot on primary human hepatocytes (loading control)



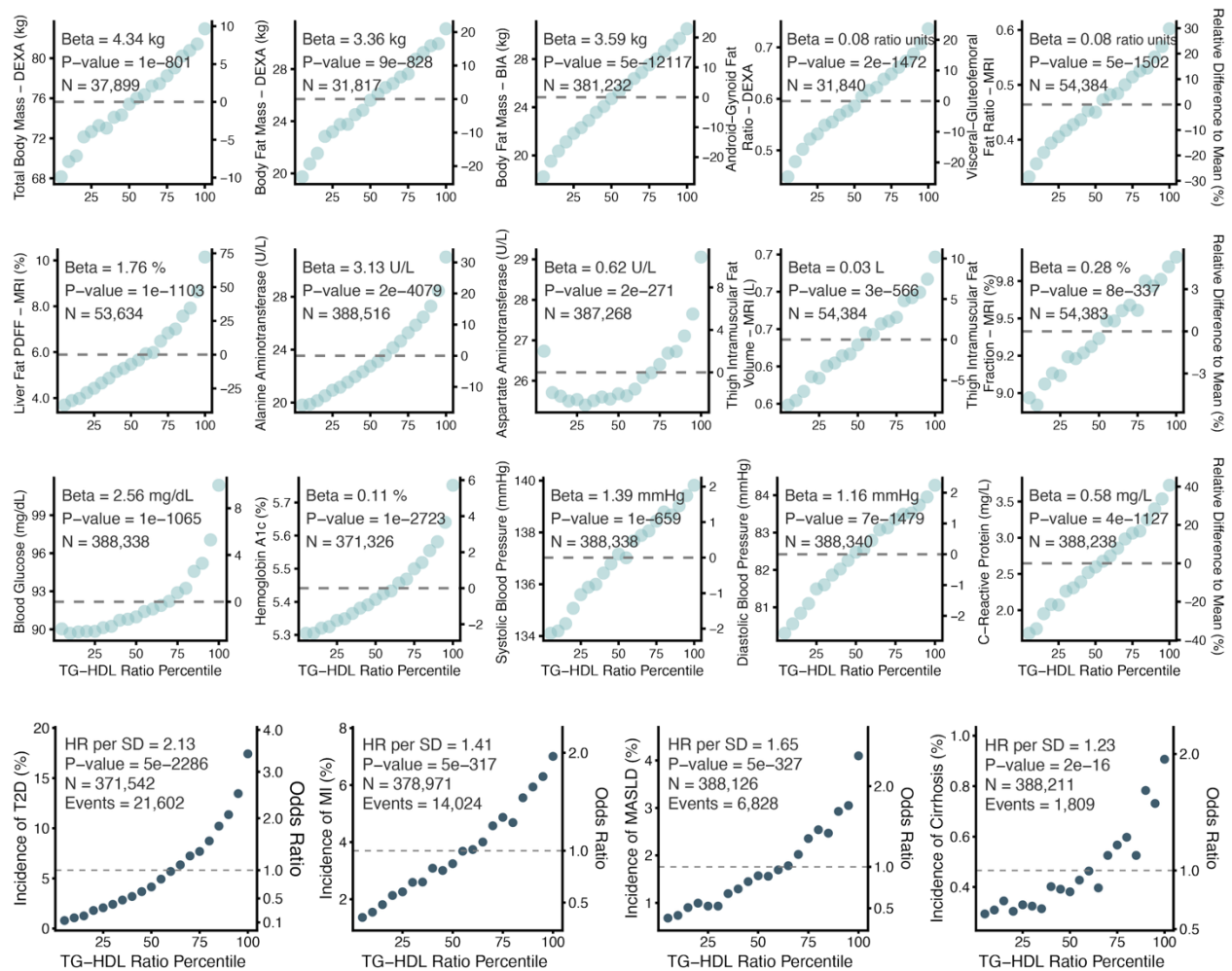
a, Immunoblot of primary human hepatocytes probed with anti-FNIP1 antibody. **b**, Immunoblot of primary human hepatocytes probed with anti-HSP90 (loading control) antibody. The loading control was run on a separate gel. Red boxes are crops included in Extended Data Fig. 5d. See also Methods.

Supplementary Figure 2. Association of TG-HDL ratio with additional anthropometric phenotypes.



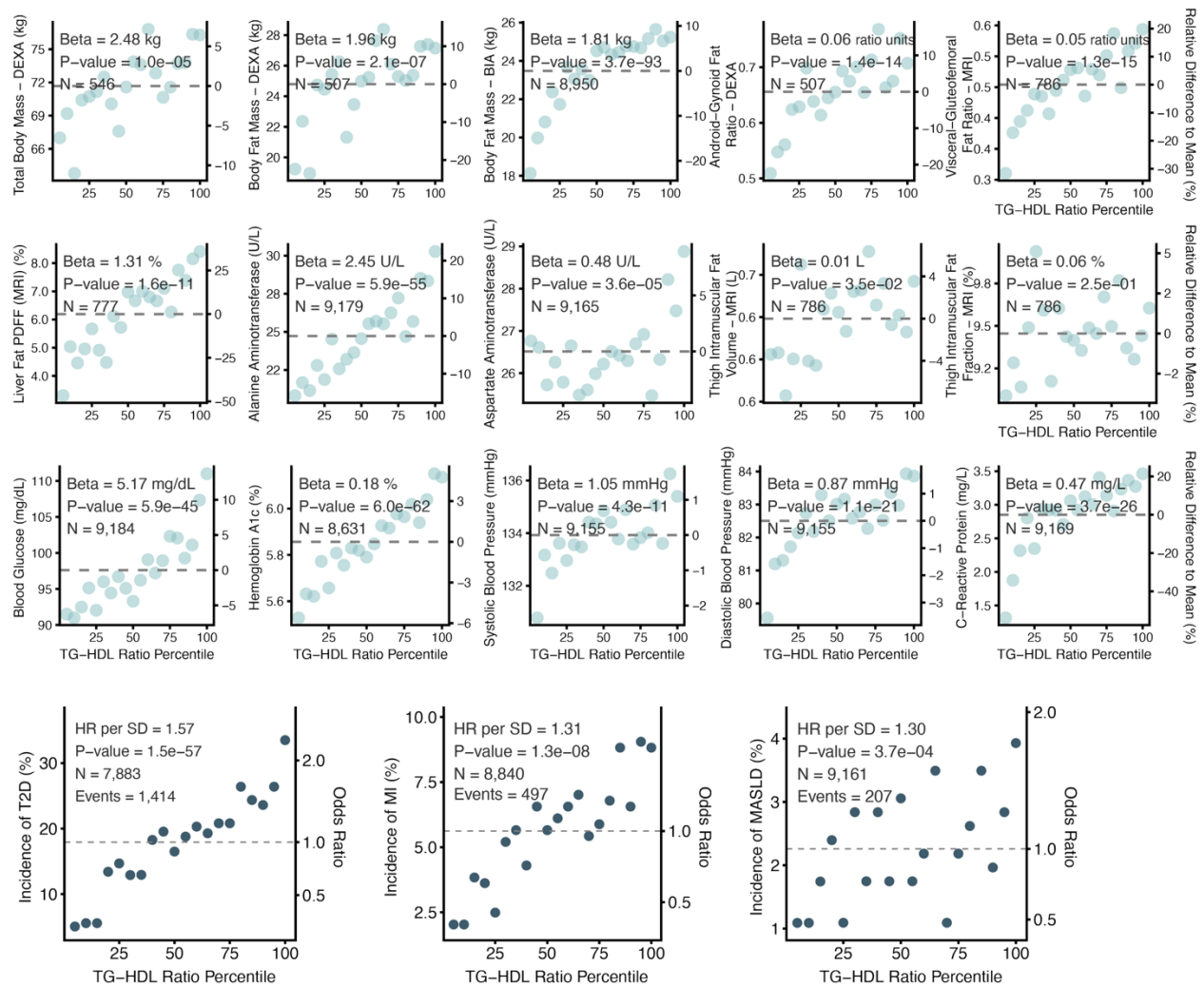
Body and fat distribution phenotypes were measured in the UKB cohort by dual-energy X-ray absorptiometry (DEXA) and magnetic resonance imaging (MRI). Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. No adjustment was made for multiple comparisons.

Supplementary Figure 3. Association of TG-HDL ratio with cardiometabolic phenotypes and disease risk in individuals of European ancestry.



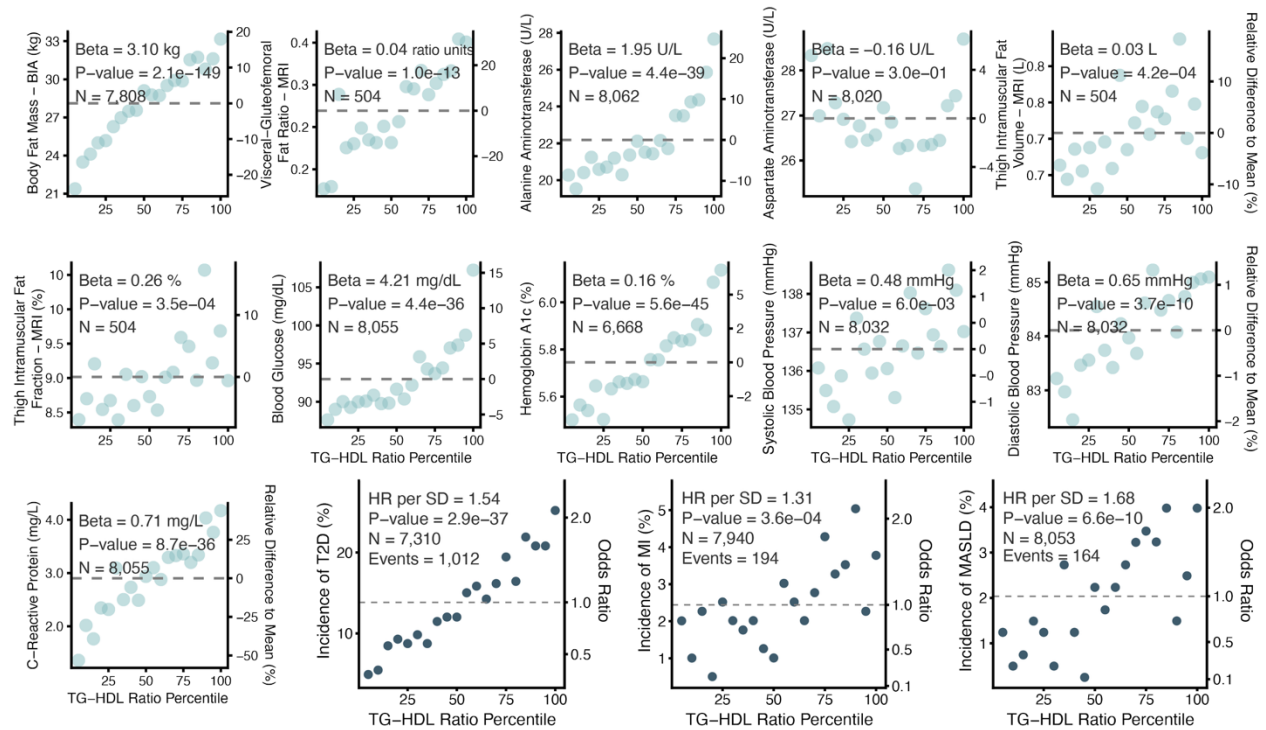
Associations were estimated in the UKB cohort. Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. Associations between the TG-HDL ratio (per 1 SD increase) and incident events were estimated using Cox proportional hazards models adjusted for age and sex; hazard ratios (HR) are shown with two-sided *P* values. No adjustment was made for multiple comparisons.

Supplementary Figure 4. Association of TG-HDL ratio with cardiometabolic phenotypes and disease risk in individuals of South Asian ancestry.



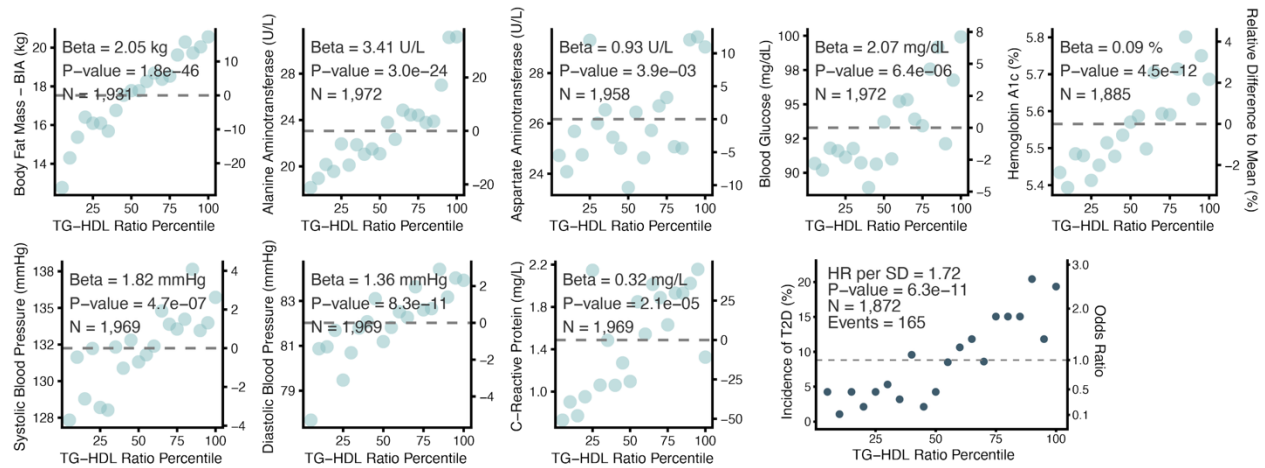
Associations were estimated in the UKB cohort. To allow sufficient statistical power to estimate associations, phenotypes available in less than 500 individuals or binary outcome phenotypes with less than 100 incident cases in South Asian ancestry participants were not analyzed. Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. Associations between the TG-HDL ratio (per 1 SD increase) and incident events were estimated using Cox proportional hazards models adjusted for age and sex; hazard ratios (HR) are shown with two-sided *P* values. No adjustment was made for multiple comparisons.

Supplementary Figure 5. Association of TG-HDL ratio with cardiometabolic phenotypes and disease risk in individuals of African ancestry.



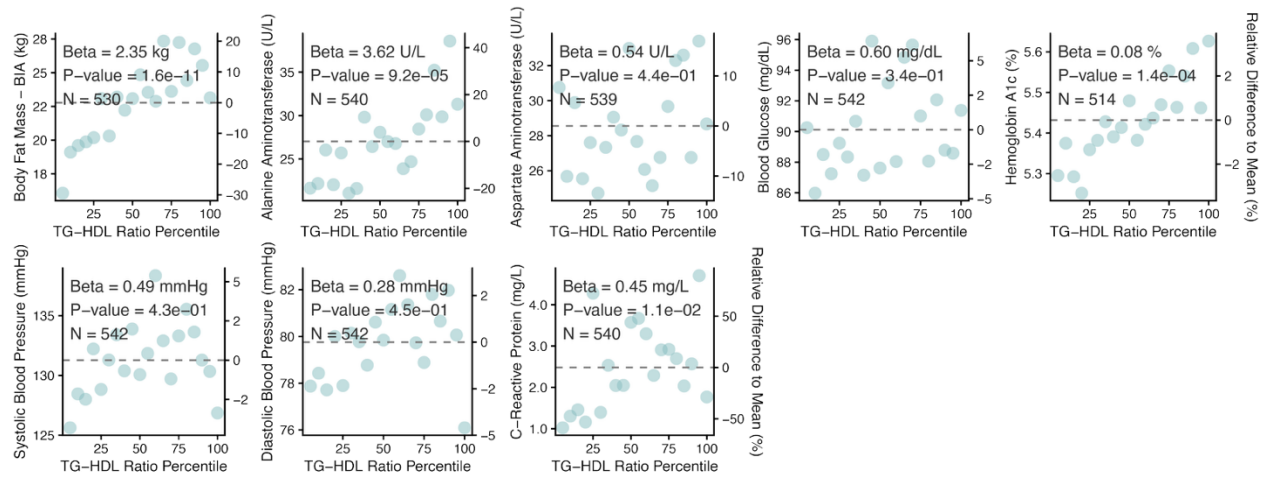
Associations were estimated in the UKB cohort. To allow sufficient statistical power to estimate associations, phenotypes available in less than 500 individuals or binary outcome phenotypes with less than 100 incident cases in African ancestry participants were not analyzed. Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. Associations between the TG-HDL ratio (per 1 SD increase) and incident events were estimated using Cox proportional hazards models adjusted for age and sex; hazard ratios (HR) are shown with two-sided *P* values. No adjustment was made for multiple comparisons.

Supplementary Figure 6. Association of TG-HDL ratio with cardiometabolic phenotypes and disease risk in individuals of East Asian ancestry.



Associations were estimated in the UKB cohort. To allow sufficient statistical power to estimate associations, phenotypes available in less than 500 individuals or binary outcome phenotypes with less than 100 incident cases in East Asian ancestry participants were not analyzed. Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. Associations between the TG-HDL ratio (per 1 SD increase) and incident events were estimated using Cox proportional hazards models adjusted for age and sex; hazard ratios are (HR) shown with two-sided *P* values. No adjustment was made for multiple comparisons.

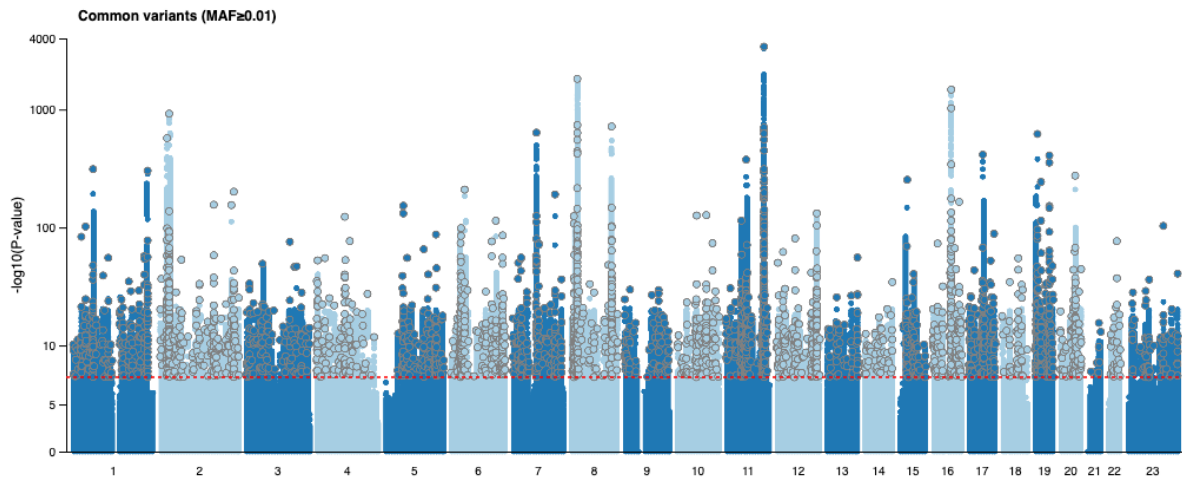
Supplementary Figure 7. Association of TG-HDL ratio with cardiometabolic phenotypes and disease risk in individuals of Admixed American ancestry.



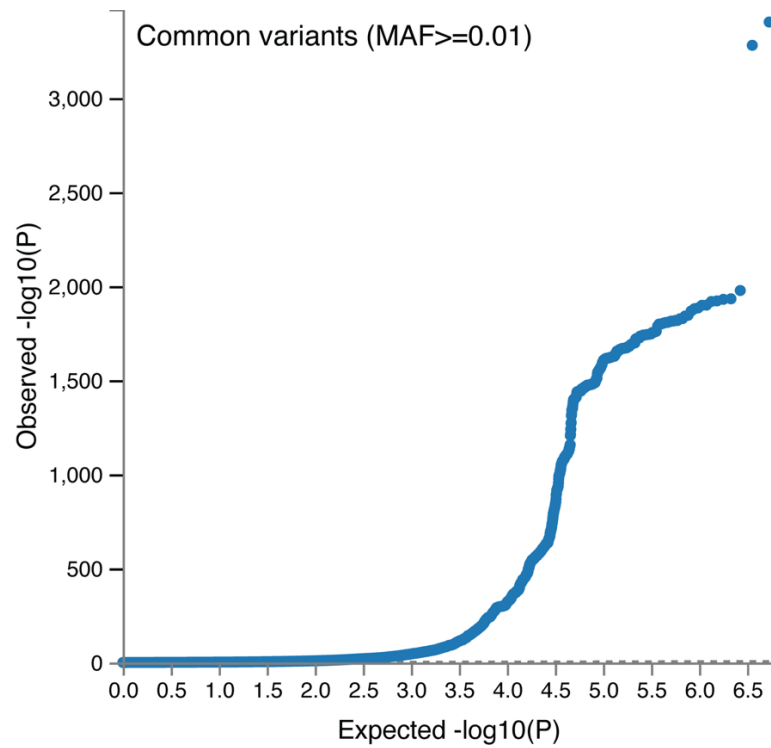
Associations were estimated in the UKB cohort. To allow sufficient statistical power to estimate associations, phenotypes available in less than 500 individuals or binary outcome phenotypes with less than 100 incident cases in Admixed American ancestry participants were not analyzed. Associations between the TG-HDL ratio (per 1 standard deviation [SD] increase) and each outcome were estimated using linear regression adjusted for age and sex; effect estimates are shown with two-sided *P* values. No adjustment was made for multiple comparisons.

Supplementary Figure 8. Association of common variants with TG-HDL ratio in the all-ancestry meta-analysis.

Panel a.



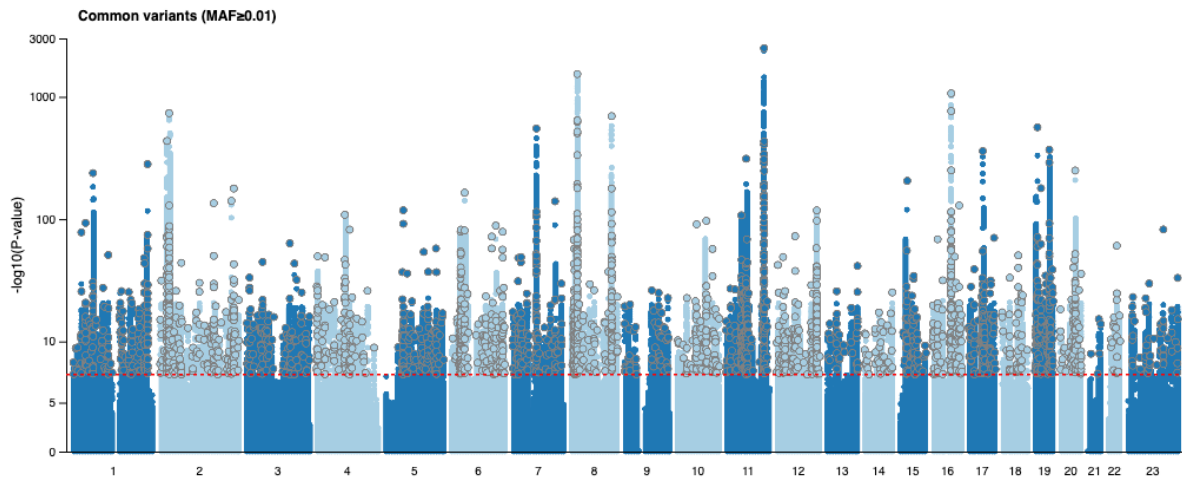
Panel b.



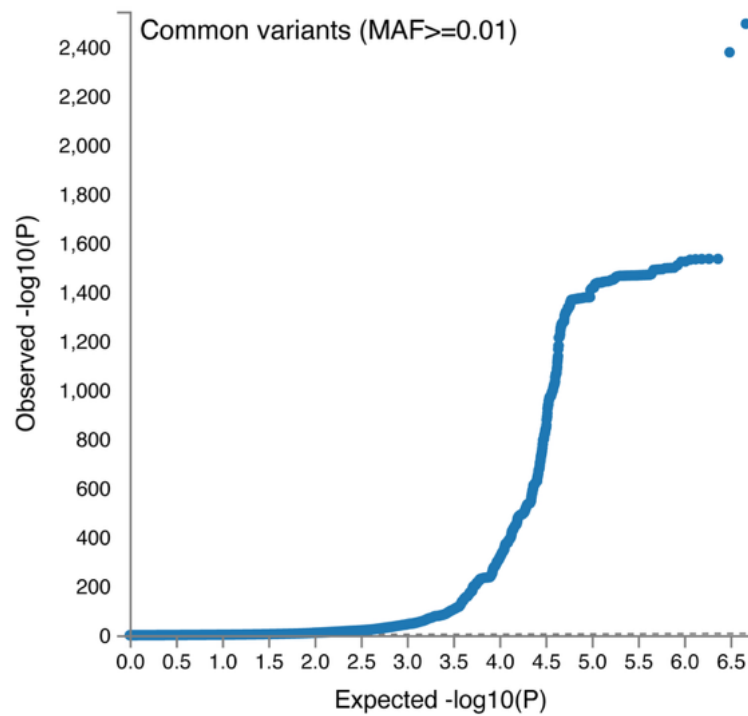
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 9. Association of common variants with TG-HDL ratio in the European ancestry meta-analysis.

Panel a.



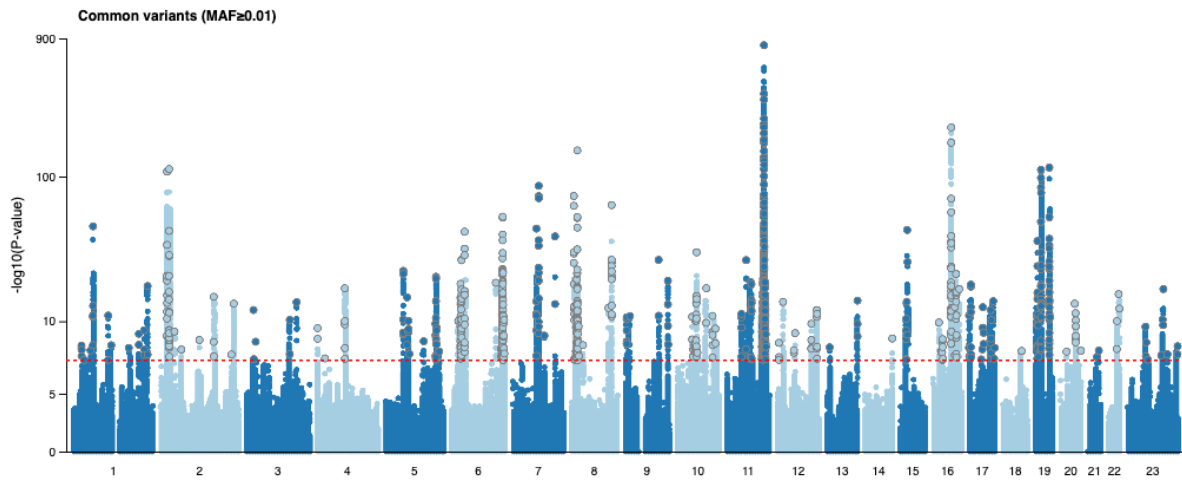
Panel b.



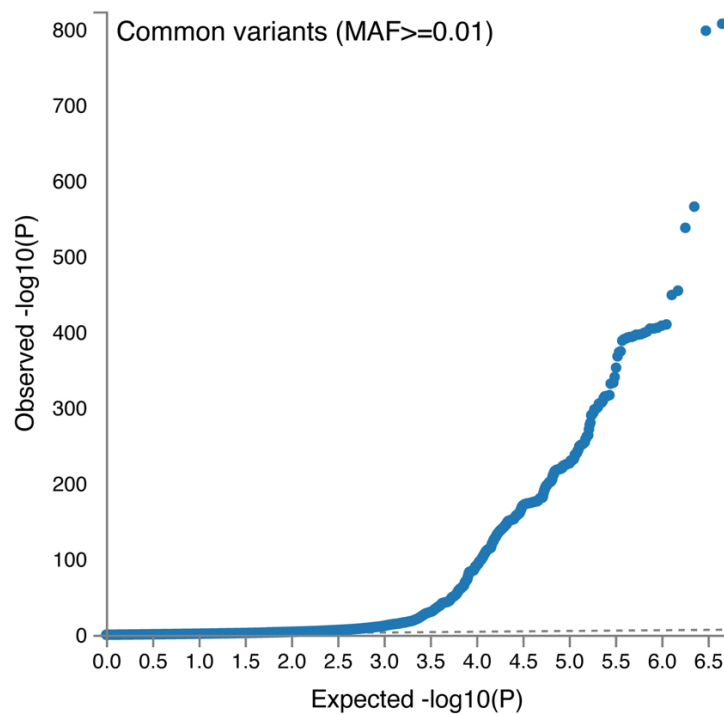
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 10. Association of common variants with TG-HDL ratio in the Admixed American ancestry meta-analysis.

Panel a.



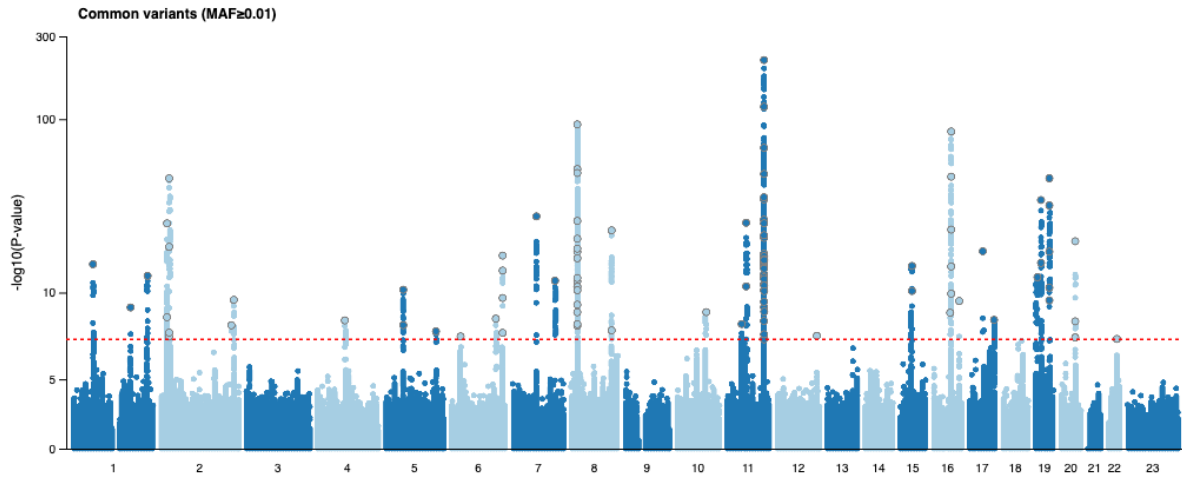
Panel b.



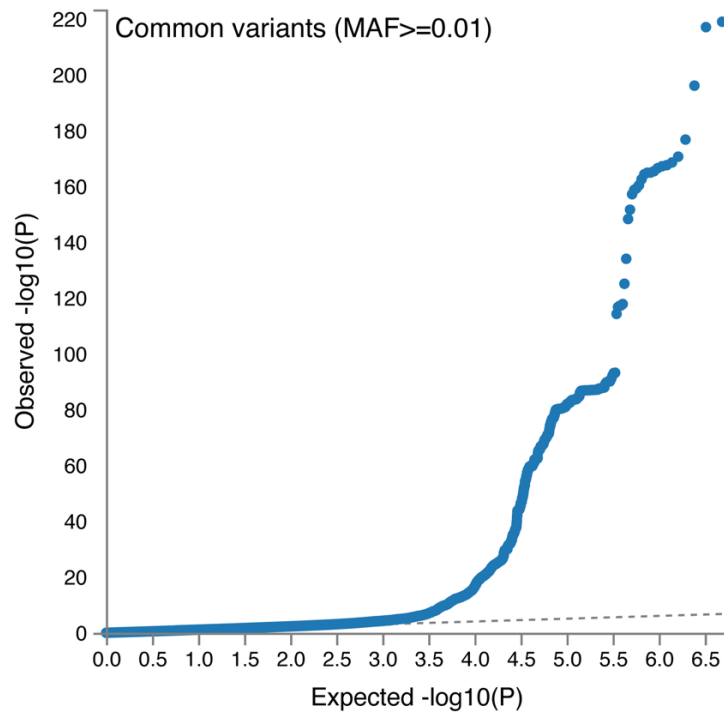
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 11. Association of common variants with TG-HDL ratio in the South Asian ancestry meta-analysis.

Panel a.



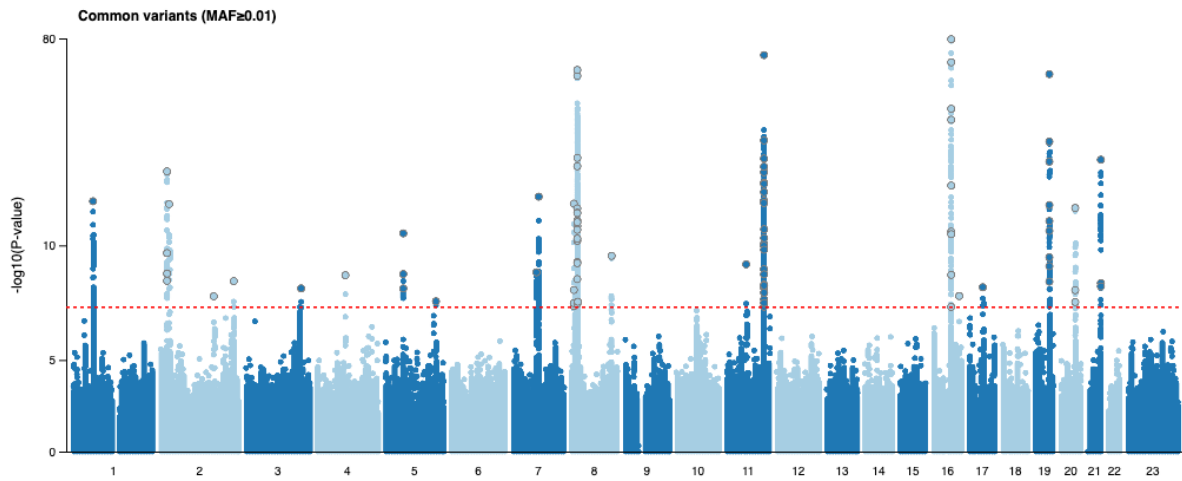
Panel b.



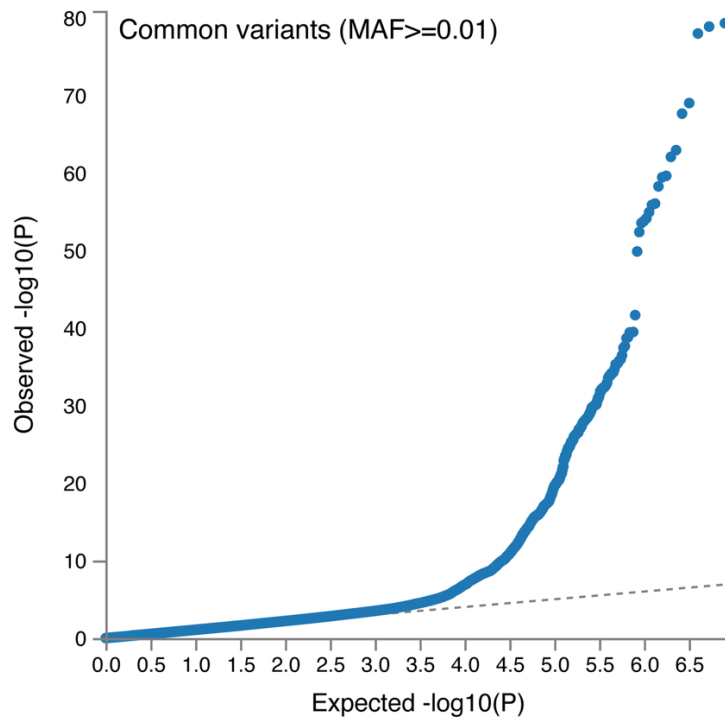
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 12. Association of common variants with TG-HDL ratio in the African ancestry meta-analysis.

Panel a.



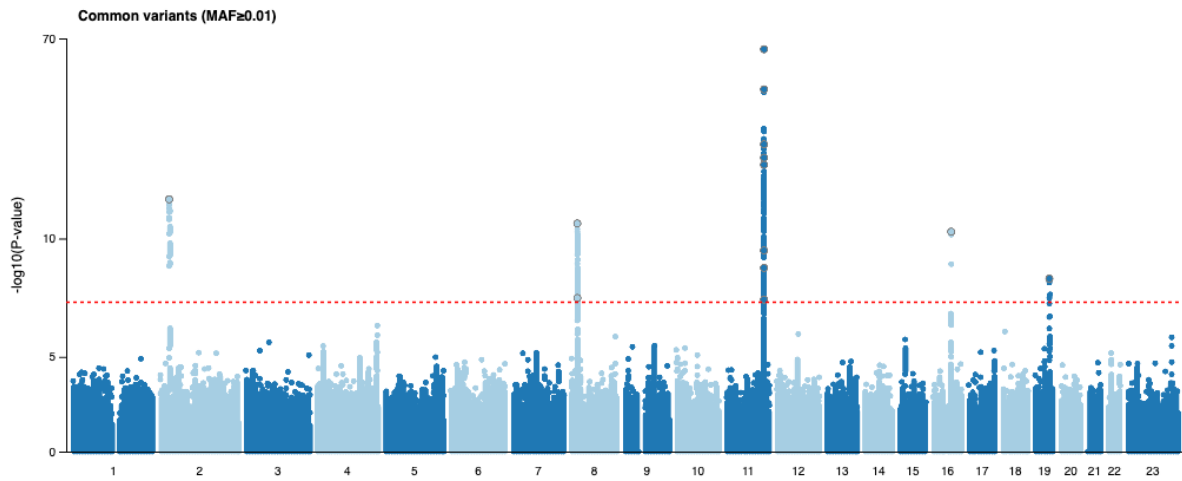
Panel b.



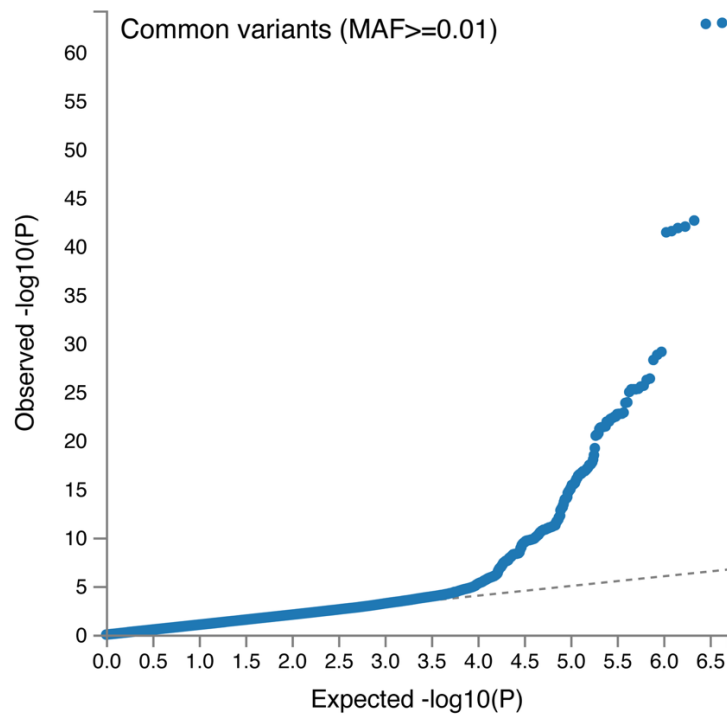
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 13. Association of common variants with TG-HDL ratio in the East Asian ancestry meta-analysis.

Panel a.

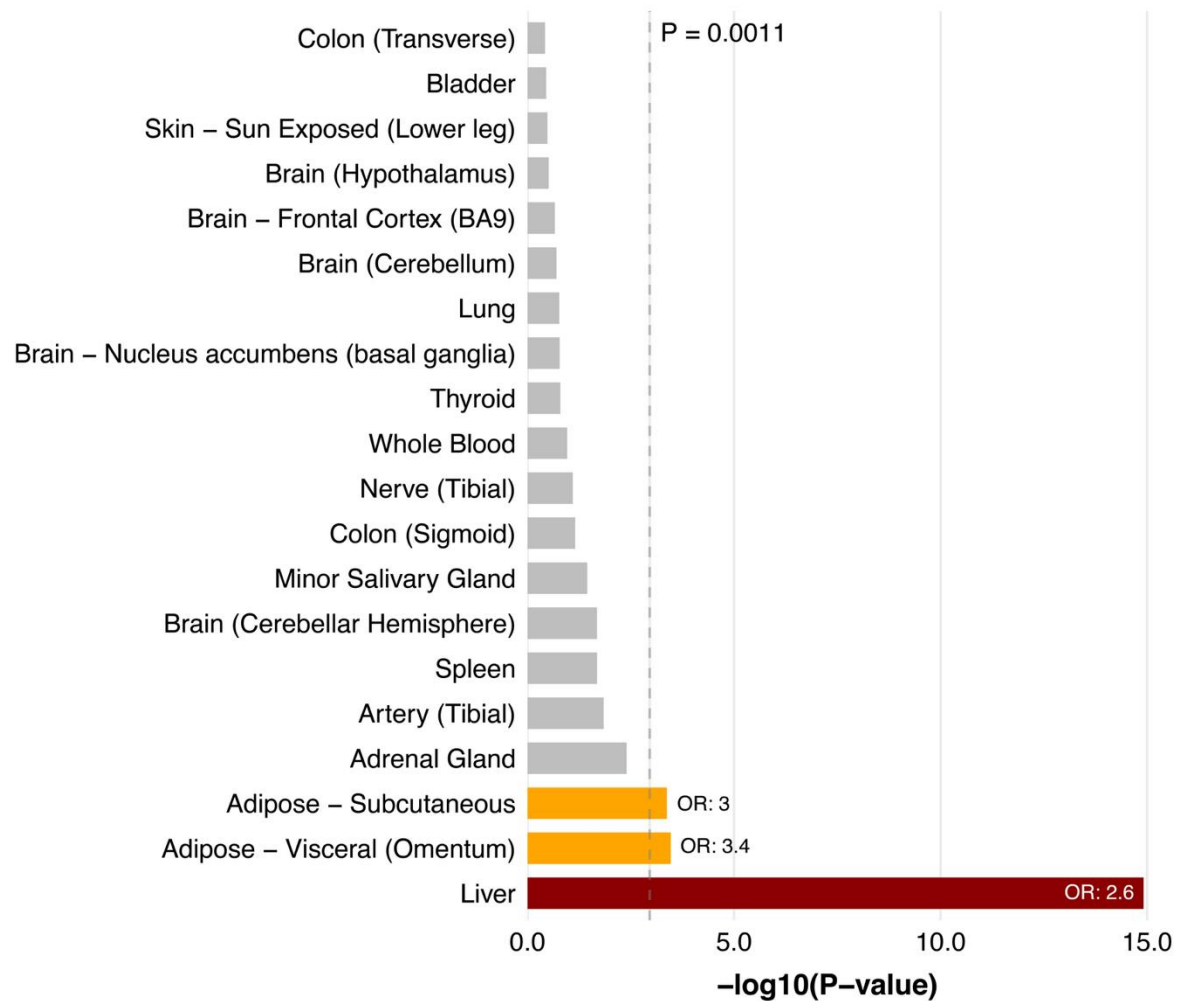


Panel b.



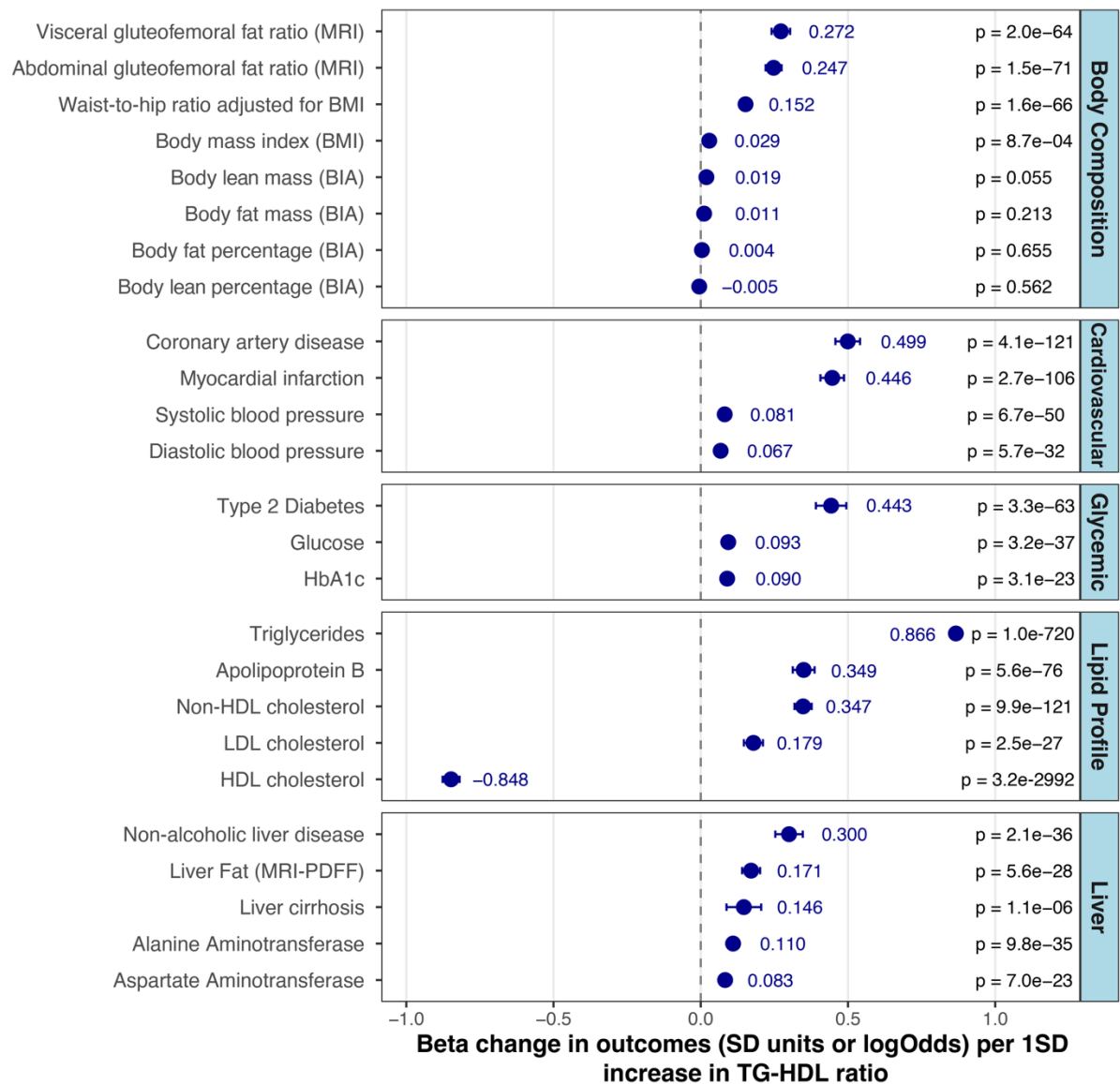
a, Manhattan plot. **b**, QQ plot. Associations are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests for variants with minor allele frequency (MAF) higher than 1%.

Supplementary Figure 14. Tissue enrichment analysis for the common variant genome-wide analysis of TG-HDL ratio.



Each tissue-specific enrichment odds ratio (OR) represents the likelihood of being a GWAS-prioritized gene exhibiting expression enrichment in a given tissue, relative to genes lacking such enrichment in that tissue (see Methods for full details). The plot shows the top 20 tissues. The enrichment ORs and P values were obtained a one-sided penalized likelihood ratio test from the Firth-corrected logistic model.

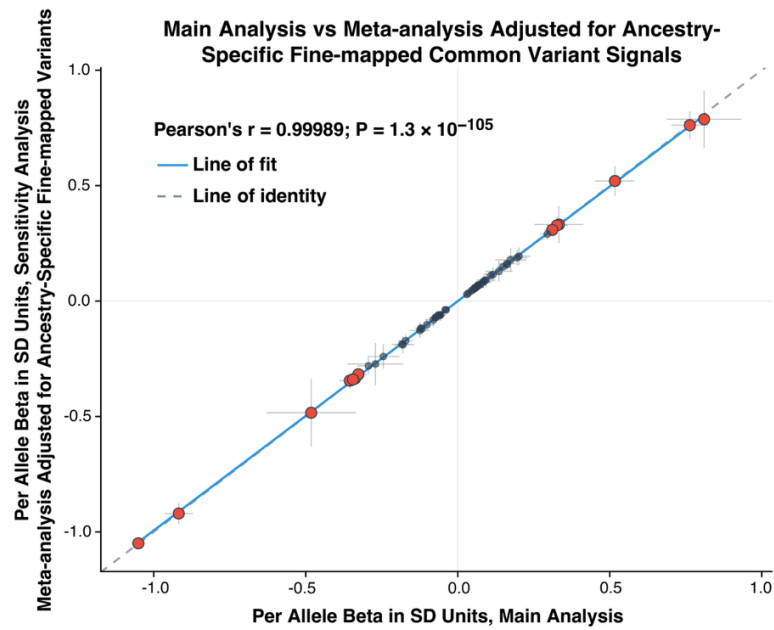
Supplementary Figure 15. Association with cardiometabolic phenotypes of a polygenic risk score for TG-HDL ratio, built with common fine-mapped variants identified in our study.



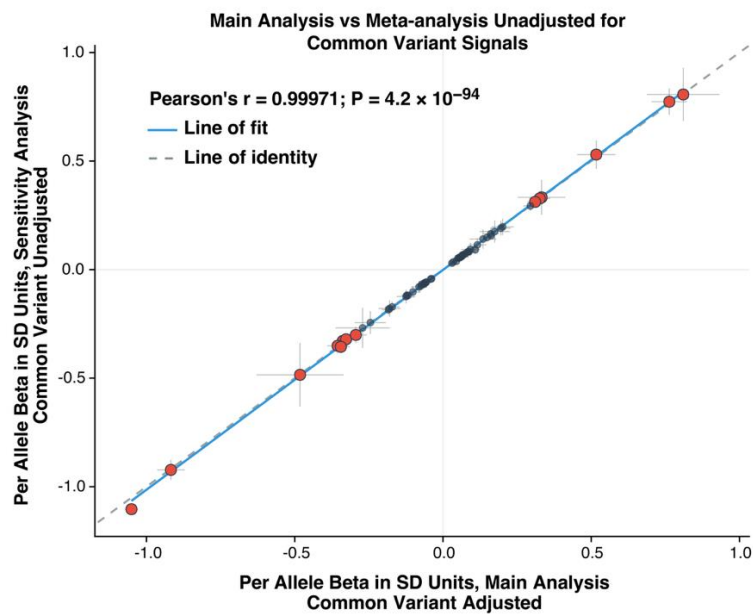
Associations ($\text{Beta} \pm 95\% \text{ CI}$) and two-sided P values were obtained from inverse-variance weighted Mendelian randomization analysis using estimates from 1,617 finemapped TG-HDL ratio variants on TG-HDL in standard deviation (SD) units as exposure and on several cardiometabolic outcomes in SD units for quantitative traits and logOdds units for binary traits. BIA, bioimpedance; BMI, body mass index; HbA1c, hemoglobin A1c; MRI, magnetic resonance imaging; PDFF, proton density fat fraction.

Supplementary Figure 16. Robustness of main analysis associations after sensitivity analyses.

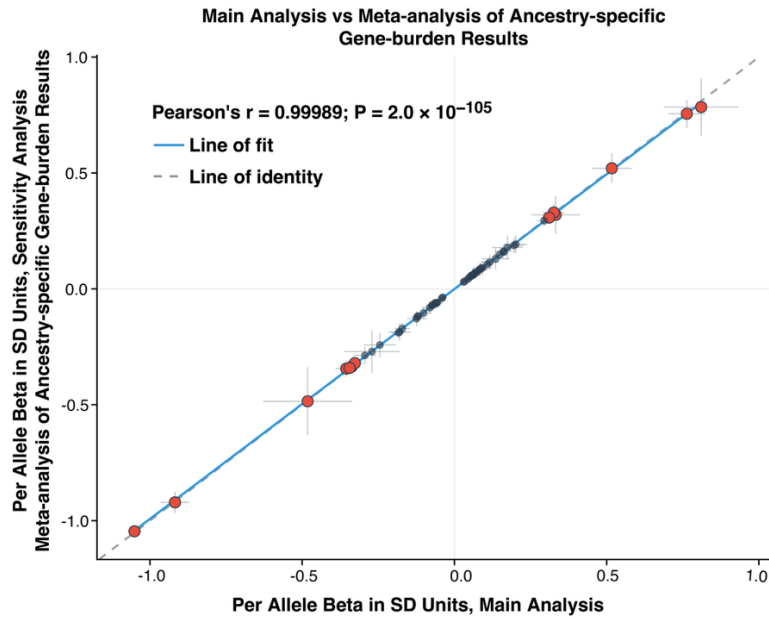
Panel a.



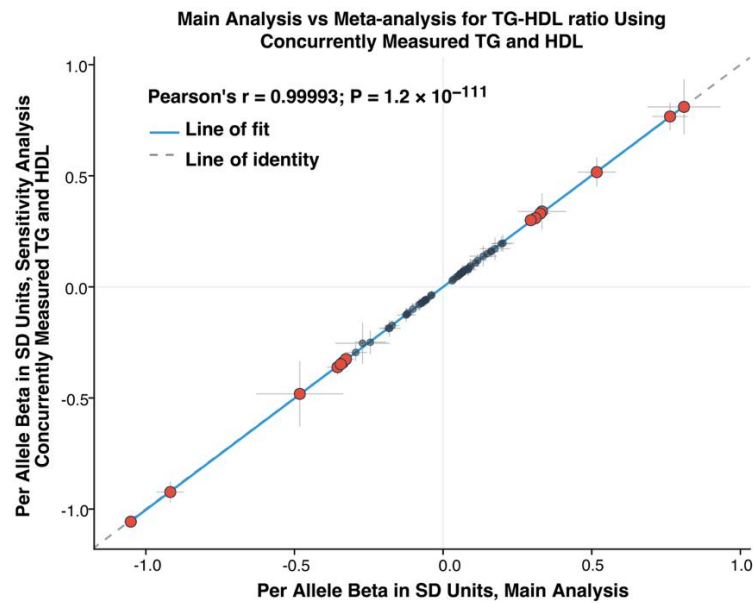
Panel b.



Panel c.

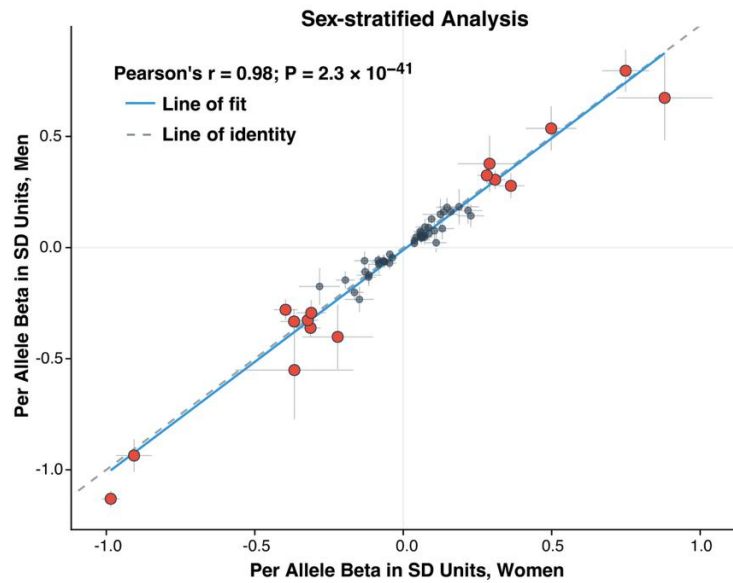


Panel d.



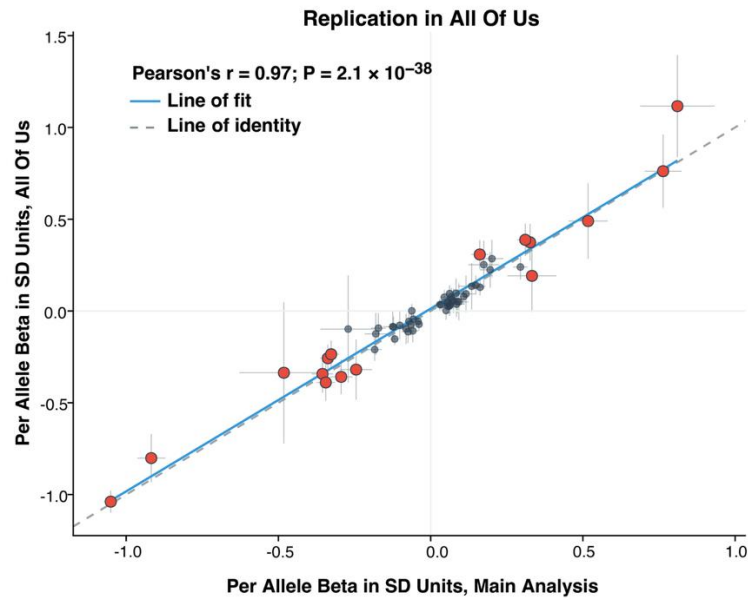
Concordance of per-allele effect estimates for the top 59 rare variant gene masks between main meta-analysis and **a**, meta-analysis of ancestry-specific results adjusted for common ancestry-specific fine-mapped variants, **b**, meta-analysis unadjusted for common variants, **c**, meta-analysis of ancestry-specific results adjusted for 1,617 common fine-mapped variants from multi-ancestry meta-analysis, and **d**, meta-analysis of TG-HDL ratio with TG and HDL measured from same blood draw. Pearson's correlation coefficients and two-sided P values are shown for each comparison.

Supplementary Figure 17. Concordance of TG-HDL ratio associations between men and women.



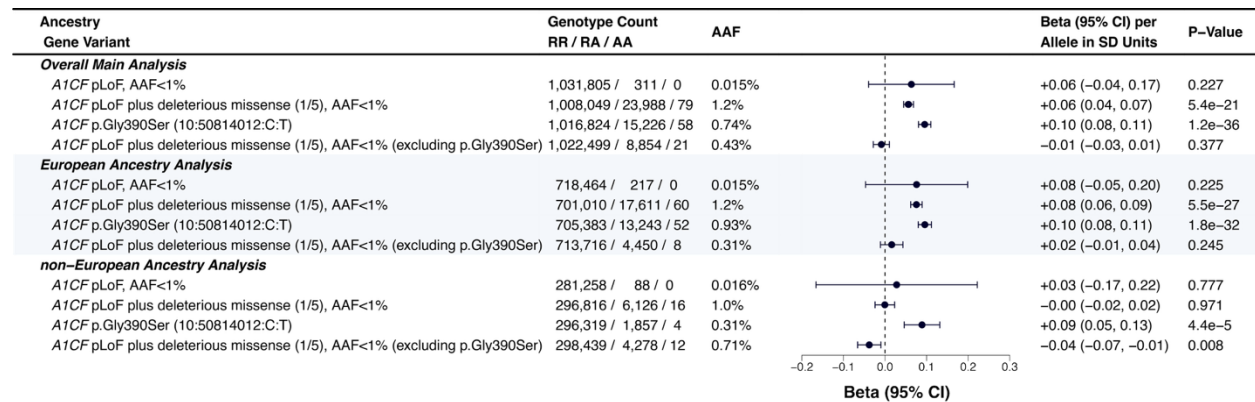
Concordance of per-allele effect estimates for the top 59 rare variant gene masks between sex-stratified meta-analyses in men versus women. Pearson's correlation coefficient and two-sided P value are shown.

Supplementary Figure 18. Replication of TG-HDL ratio associations in the All of Us cohort.



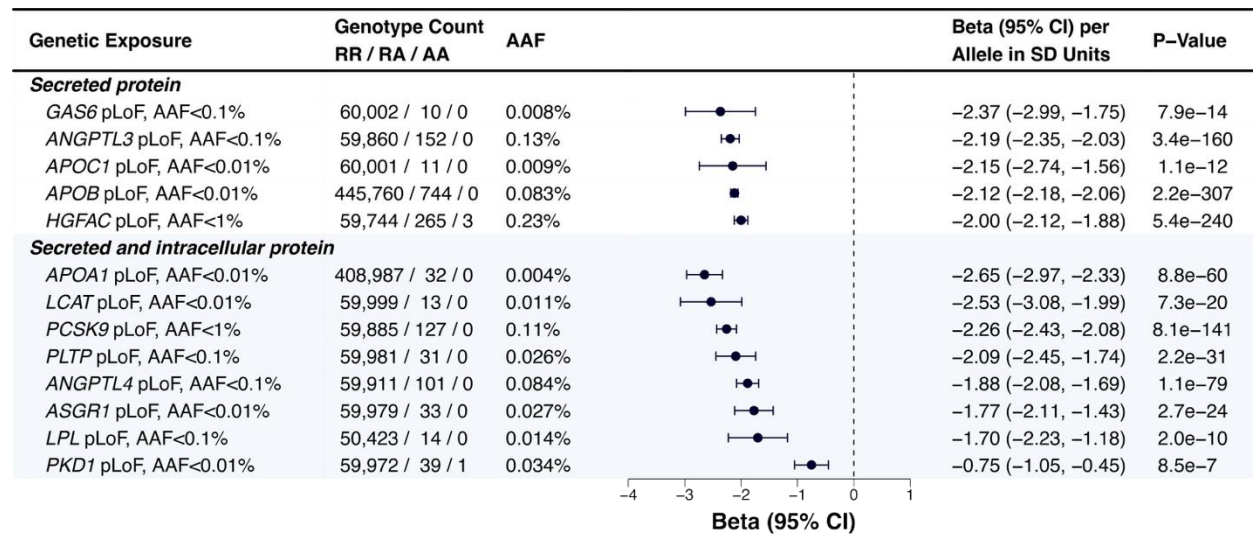
Concordance of effects for the top 59 rare variant gene masks between main meta-analysis and analysis with TG-HDL ratio in the All of Us cohort. Pearson's correlation coefficient and two-sided P value are shown.

Supplementary Figure 19. Association of *A1CF* rare loss-of-function plus deleterious missense variants with TG-HDL ratio by ancestry reveals that overall signal is driven by p.Gly390Ser variant.



Associations are shown in per-allele change in standard deviation (SD) units (Beta $\pm$ 95% CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 20. Association of predicted loss-of-function variants in 13 genes with the respective protein levels.

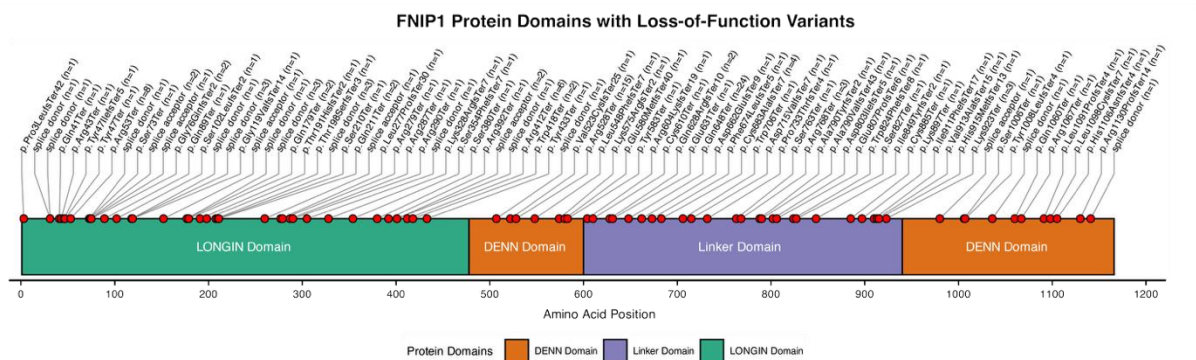


Out of the 59 proteins encoded by top TG-HDL ratio genes, 13 were annotated as “secreted” in Human Protein Atlas and were measured by Olink proteomics in UK Biobank and the Geisinger Health System or by immunoassay (for APOB and APOA1) in the UK Biobank. Associations are shown in per allele change in standard deviation (SD) units (Beta $\pm$ 95% CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

30

Supplementary Figure 22. Rare predicted loss-of-function variants contributing to the *FNIP1* gene-burden association with TG-HDL ratio.

Panel a.



Panel b.

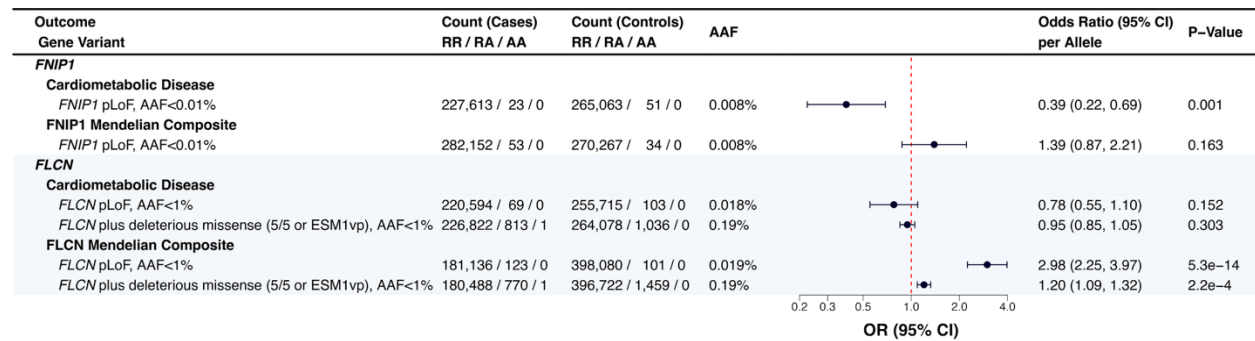
FNIP1 pLoF, AAF<0.01%

Gene Variant	Genotype Count RR / RA / AA	AAF		Beta (95% CI) per Allele in Clinical Units	P-Value	Heterogeneity P-Value
All Variants	1,031,961 / 155 / 0	0.008%		-1.66 (-2.17, -1.16) ratio	1.1e-10	
NMD classification						
NMD Variants	1,031,511 / 126 / 0	0.006%		-1.62 (-2.18, -1.06) ratio	1.5e-8	0.81
Non-NMD/splice site Variants	931,010 / 29 / 0	0.002%		-1.88 (-3.05, -0.71) ratio	0.002	
Location of pLoF mutation						
N-Terminus Variants	1,026,423 / 68 / 0	0.003%		-1.96 (-2.72, -1.20) ratio	4.4e-7	0.32
C-Terminus Variants	1,031,549 / 87 / 0	0.004%		-1.43 (-2.11, -0.76) ratio	3.1e-5	

Beta (95% CI) in SD Units per Allele

a, Predicted loss-of-function (pLoF) variants in *FNIP1* identified by exome sequencing mapped to the respective protein domains. **b**, Gene-burden analyses for subgroups of pLoF variants annotated according to variant position (N- versus C- terminus) or predicted non-sense mediated decay (NMD) status. We estimated heterogeneity in genetic associations between variant groups, showing that *FNIP1* pLoF variants with different annotations (N- vs C-terminus or NMD vs non-NMD) were robustly and consistently associated with lower TG-HDL ratio ($P_{\text{heterogeneity}} > 0.32$ for each comparison). Variants located at or before the transcript midpoint (amino acid position ≤ 583) were classified as N-terminal variants; the remainder were classified as C-terminal variants. Association estimates are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests. Heterogeneity P values are based on Cochran's Q statistic, evaluated with a chi-squared distribution with 11 degrees of freedom. See Methods for NMD variant definition. AAF, alternative allele frequency; CI, confidence interval; NMD, non-sense mediated decay; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

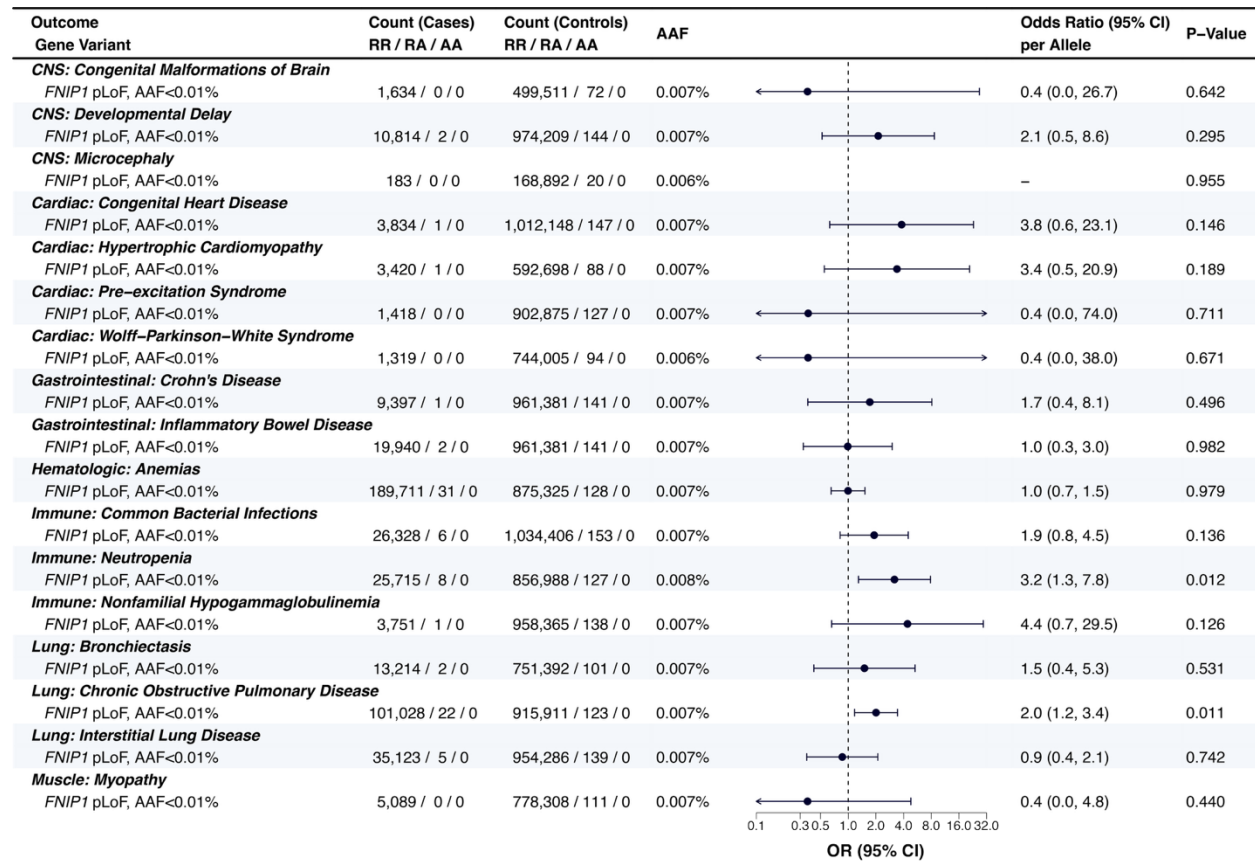
Supplementary Figure 23. Association of *FNIP1* and *FLCN* variants with cardiometabolic and Mendelian composite phenotypes.



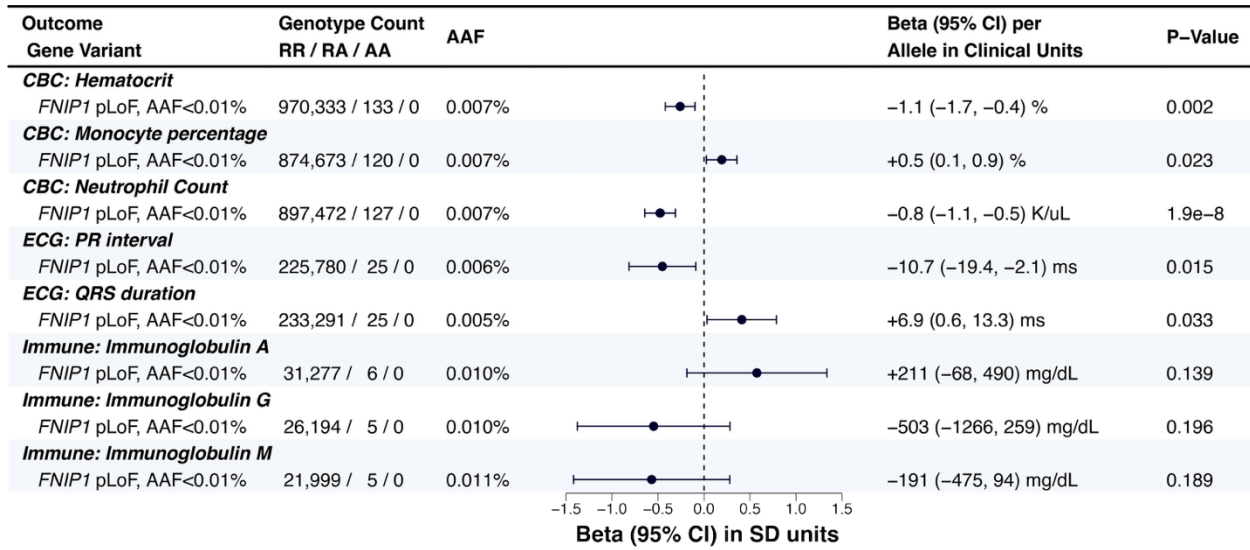
For the composite cardiometabolic phenotype, case status was defined as being a case of coronary artery disease, type 2 diabetes or liver disease (i.e. MASLD or liver cirrhosis), while control status was defined as being a control for each of those diseases. The *FNIP1* Mendelian composite phenotype was a combination of the key clinical features of immunodeficiency-93 and hypertrophic cardiomyopathy (see Supplementary Note 3 and Supplementary Table 23), whereas the *FLCN* Mendelian composite phenotype was a combination of the key clinical features of Birt–Hogg–Dubé syndrome (see Supplementary Note 3 and Supplementary Table 24). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; OR, odds ratio; pLOF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 24. Association of heterozygous pLOF variants in *FNIP1* with individual phenotypes described in autosomal recessive *FNIP1*-related immunodeficiency syndrome.

Panel a.



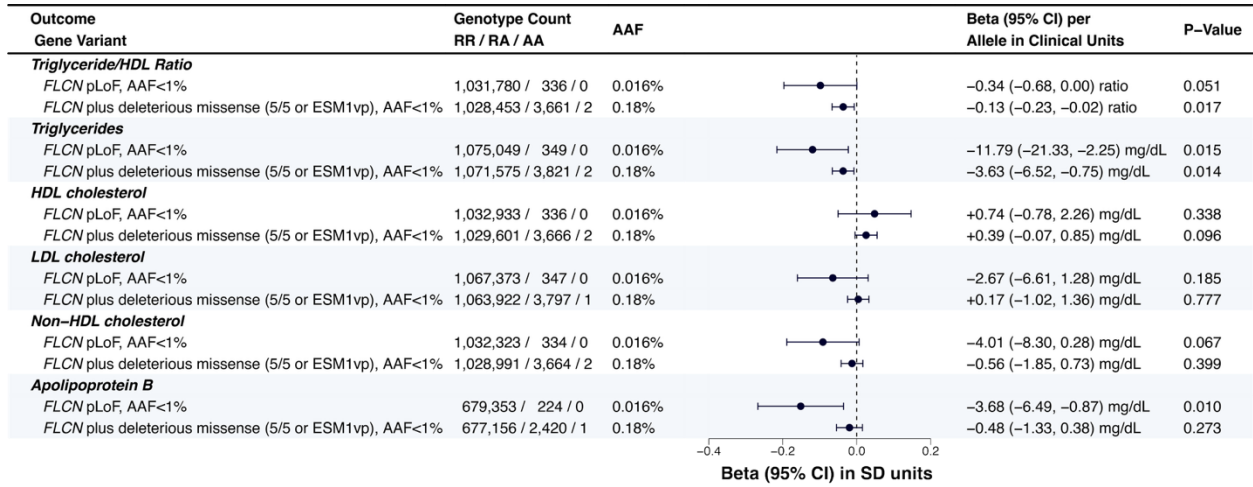
Panel b.



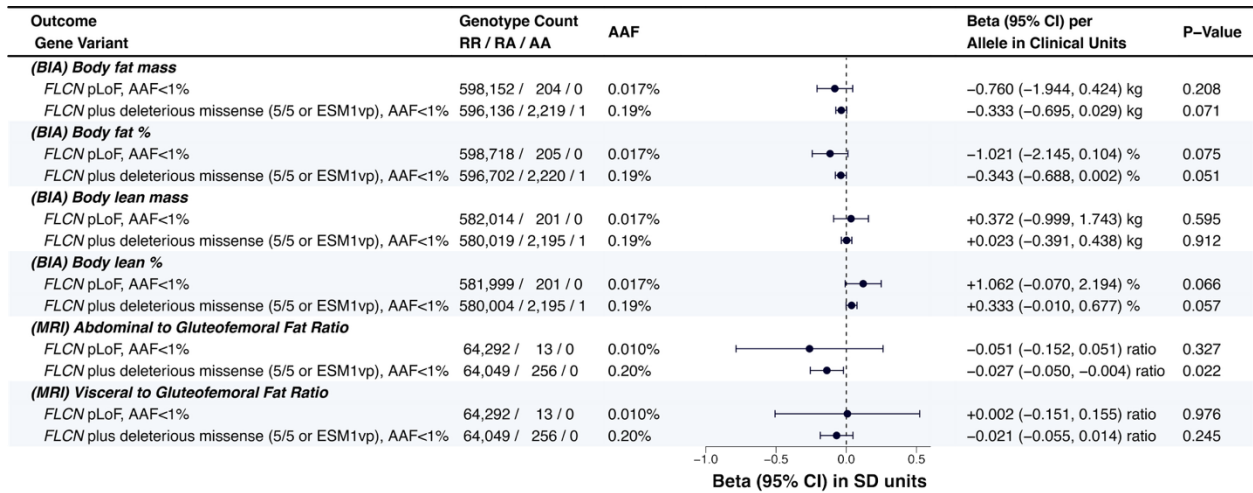
a, Associations of pLoF variants in *FNIP1* with binary traits ($OR \pm 95\%$ CI), and **b**, quantitative traits ($Beta \pm 95\%$ CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and P values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; OR, odds ratio; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 25. Association of variants in *FLCN* with cardiometabolic phenotypes.

Panel a.



Panel b.



Panel c.

Outcome Gene Variant	Genotype Count RR / RA / AA	AAF	Beta (95% CI) per Allele in Clinical Units	P-Value
Body Mass Index				
FLCN pLoF, AAF<1%	1,236,547 / 416 / 0	0.017%	-0.176 (-0.686, 0.335) kg/m ²	0.500
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	1,232,593 / 4,368 / 2	0.18%	-0.110 (-0.269, 0.049) kg/m ²	0.172
Waist to Hip Ratio (Adjusted for BMI)				
FLCN pLoF, AAF<1%	620,656 / 215 / 0	0.017%	-0.009 (-0.017, -0.001) ratio	0.031
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	618,570 / 2,300 / 1	0.19%	-0.002 (-0.004, 0.001) ratio	0.123
HbA1c				
FLCN pLoF, AAF<1%	952,264 / 301 / 0	0.016%	-0.132 (-0.237, -0.028) %	0.013
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	949,246 / 3,317 / 2	0.17%	-0.022 (-0.054, 0.009) %	0.166
Random glucose				
FLCN pLoF, AAF<1%	969,380 / 324 / 0	0.017%	-1.482 (-4.203, 1.239) mg/dL	0.286
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	966,091 / 3,611 / 2	0.19%	-0.560 (-1.380, 0.260) mg/dL	0.179
Liver Fat (MRI-PDFF)				
FLCN pLoF, AAF<1%	63,415 / 13 / 0	0.010%	-1.450 (-4.319, 1.420) %	0.322
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	63,176 / 252 / 0	0.20%	-0.349 (-1.002, 0.304) %	0.295
Alanine Aminotransferase				
FLCN pLoF, AAF<1%	905,351 / 295 / 0	0.016%	-1.147 (-2.812, 0.518) U/L	0.177
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	902,252 / 3,392 / 2	0.19%	-0.840 (-1.331, -0.349) U/L	8.1e-4
Aspartate Aminotransferase				
FLCN pLoF, AAF<1%	923,513 / 303 / 0	0.016%	-0.455 (-1.854, 0.943) U/L	0.524
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	920,345 / 3,469 / 2	0.19%	-0.134 (-0.549, 0.280) U/L	0.523
Systolic Blood Pressure				
FLCN pLoF, AAF<1%	1,251,818 / 422 / 0	0.017%	+1.550 (0.043, 3.056) mmHg	0.044
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	1,247,755 / 4,483 / 2	0.18%	+0.482 (0.020, 0.945) mmHg	0.042
Diastolic Blood Pressure				
FLCN pLoF, AAF<1%	1,251,799 / 422 / 0	0.017%	+0.090 (-0.794, 0.974) mmHg	0.842
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	1,247,736 / 4,483 / 2	0.18%	+0.181 (-0.092, 0.453) mmHg	0.194

Beta (95% CI) in SD units

Panel d.

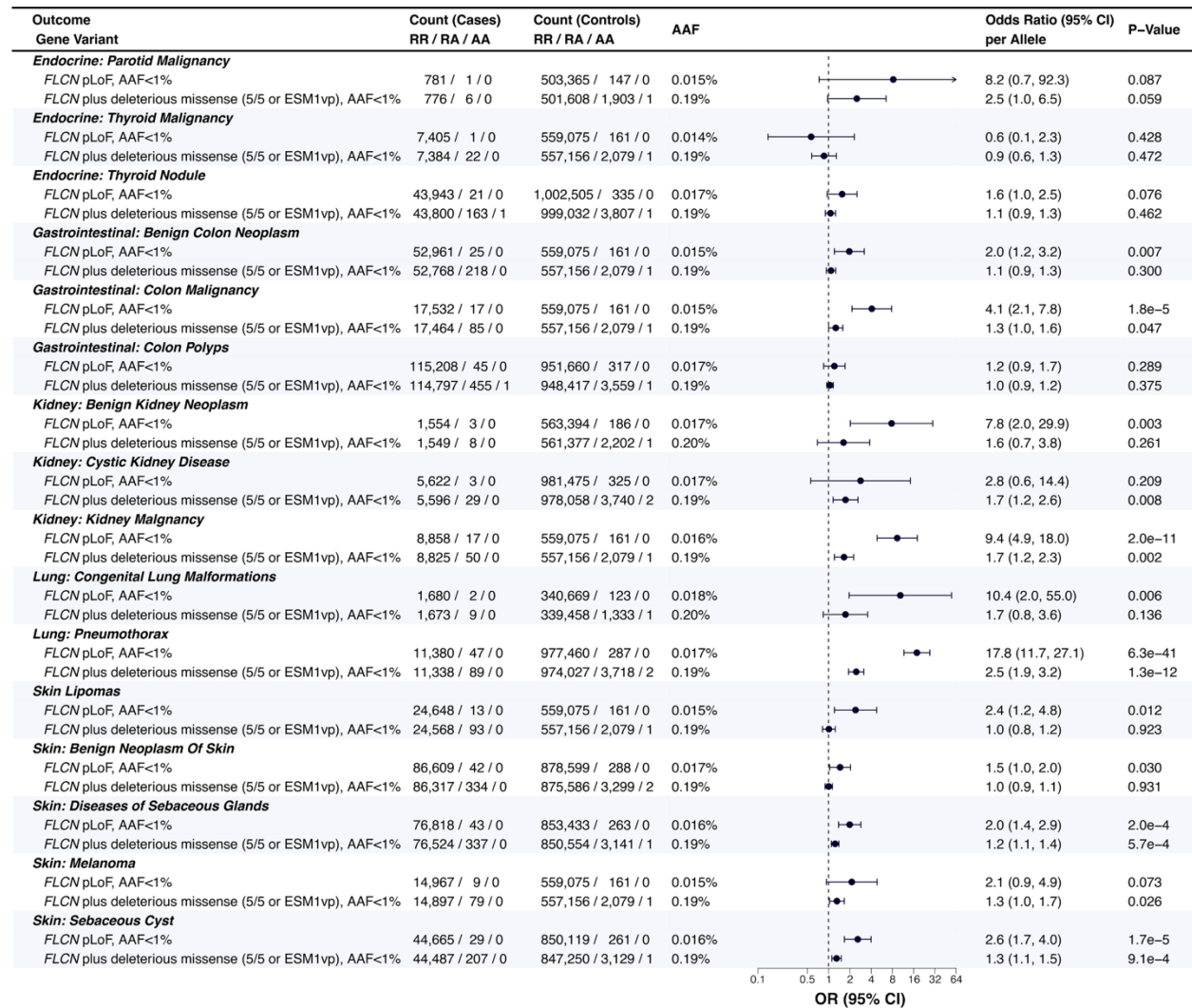
Outcome Gene Variant	Count (Cases) RR / RA / AA	Count (Controls) RR / RA / AA	AAF	Odds Ratio (95% CI) per Allele	P-Value
Coronary Artery Disease					
FLCN pLoF, AAF<1%	88,200 / 34 / 0	625,912 / 212 / 0	0.017%	1.1 (0.8, 1.7)	0.513
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	87,903 / 331 / 0	623,806 / 2,316 / 2	0.19%	1.0 (0.9, 1.1)	0.962
Myocardial Infarction					
FLCN pLoF, AAF<1%	60,956 / 24 / 0	670,637 / 223 / 0	0.017%	1.1 (0.7, 1.8)	0.620
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	60,742 / 238 / 0	668,388 / 2,470 / 2	0.19%	1.0 (0.9, 1.2)	0.766
Type 2 diabetes					
FLCN pLoF, AAF<1%	187,425 / 44 / 0	718,771 / 251 / 0	0.016%	0.7 (0.5, 0.9)	0.014
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	186,874 / 594 / 1	716,393 / 2,628 / 1	0.18%	0.9 (0.8, 1.0)	0.067
Liver Disease (Non Alcoholic)					
FLCN pLoF, AAF<1%	51,677 / 21 / 0	707,792 / 244 / 0	0.017%	1.1 (0.7, 1.9)	0.603
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	51,515 / 183 / 0	705,329 / 2,707 / 0	0.19%	1.0 (0.8, 1.1)	0.623
Liver Cirrhosis (Any)					
FLCN pLoF, AAF<1%	15,252 / 9 / 0	721,587 / 246 / 0	0.017%	2.2 (1.0, 4.9)	0.059
FLCN plus deleterious missense (5/5 or ESM1vp), AAF<1%	15,200 / 61 / 0	719,070 / 2,763 / 0	0.19%	1.2 (0.9, 1.5)	0.286

OR (95% CI)

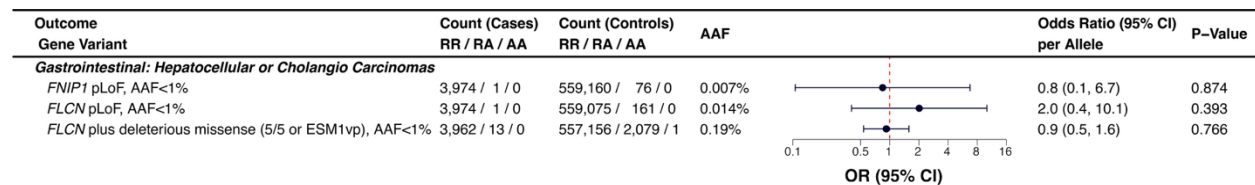
a, Associations of variants in *FLCN* with lipid traits (Beta $\pm$ 95% CI), **b**, anthropometric traits (Beta $\pm$ 95% CI), **c**, quantitative cardiometabolic traits (Beta $\pm$ 95% CI), and **d**, cardiometabolic outcomes (OR $\pm$ 95% CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; ESM1vp, Evolutionary Scale Modeling; OR, odds ratio; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 26. Association of variants in *FLCN* with Birt–Hogg–Dubé syndrome phenotypes and with risk for liver cancers.

Panel a.



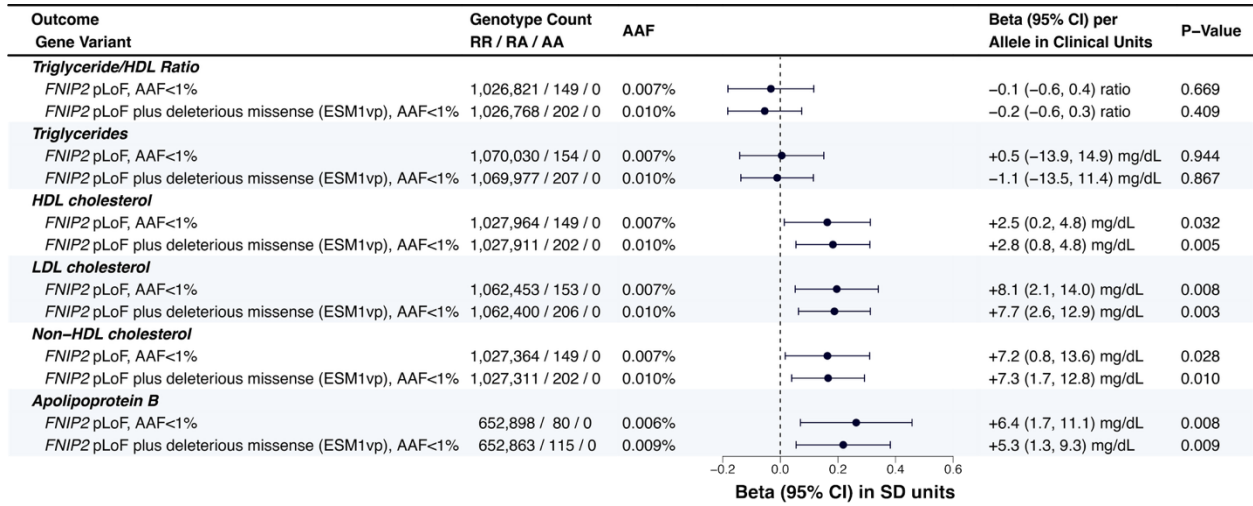
Panel b.



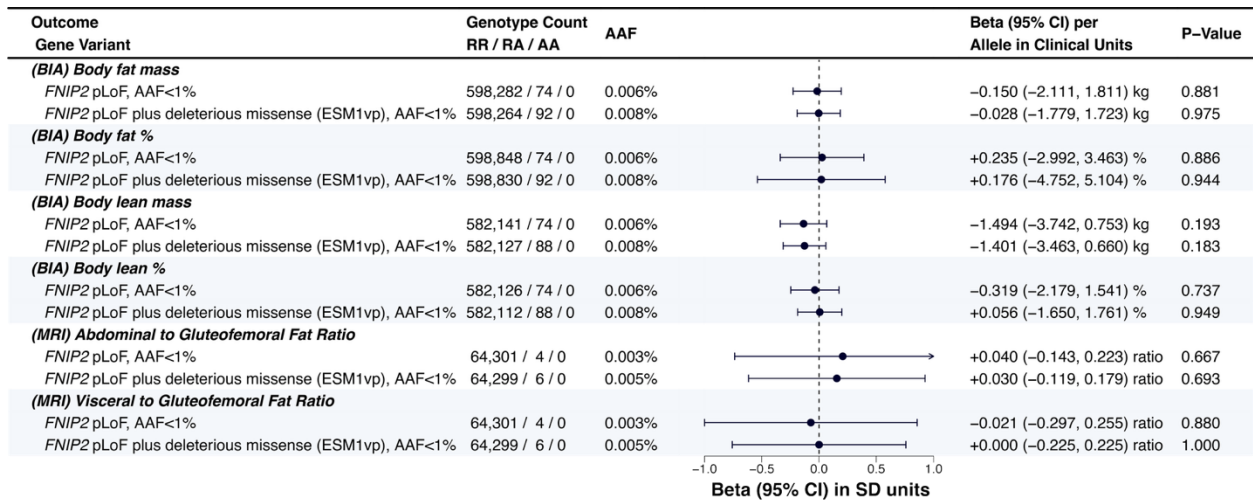
a, Associations of *FLCN* variants (i.e. pLoF or pLoF plus deleterious missense) with Birt–Hogg–Dubé syndrome phenotypes (OR ± 95% CI). **b**, Associations of *FLCN* variants with a composite phenotype of hepatocellular carcinoma and cholangiocarcinoma (OR ± 95% CI); *FNIP1* associations are shown for comparison in this panel. Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; ESM1vp, Evolutionary Scale Modeling; OR, odds ratio; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 27. Association of variants in *FNIP2* with cardiometabolic phenotypes.

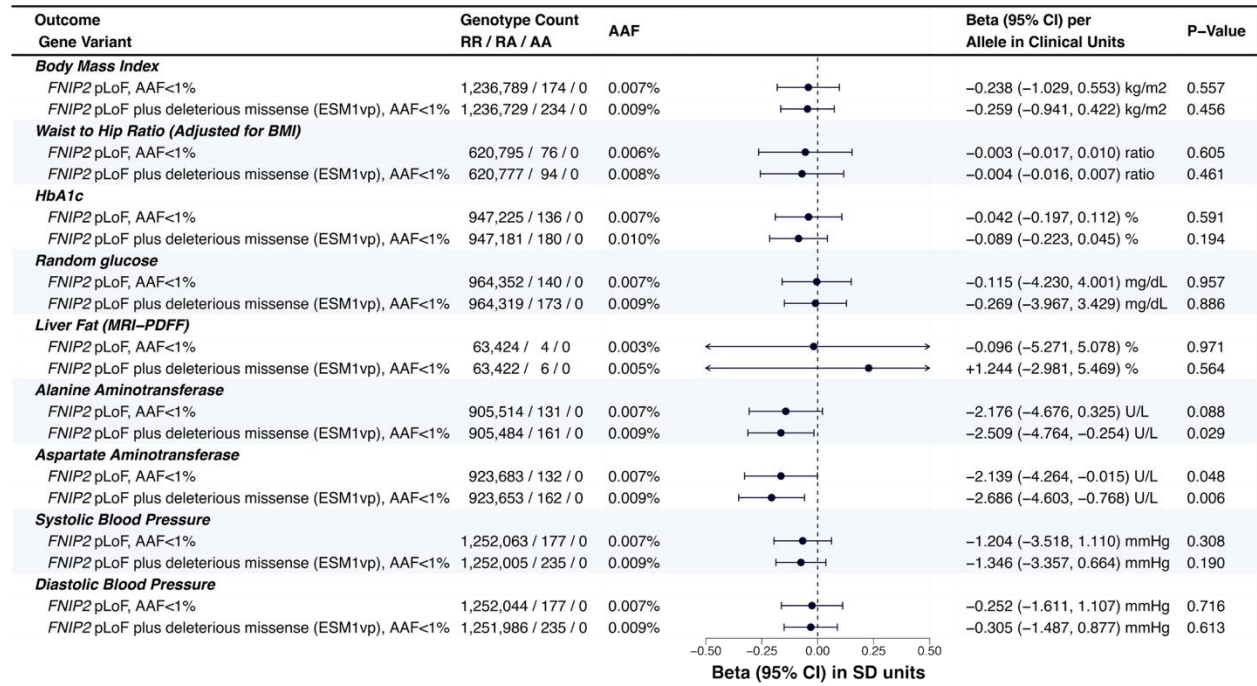
Panel a.



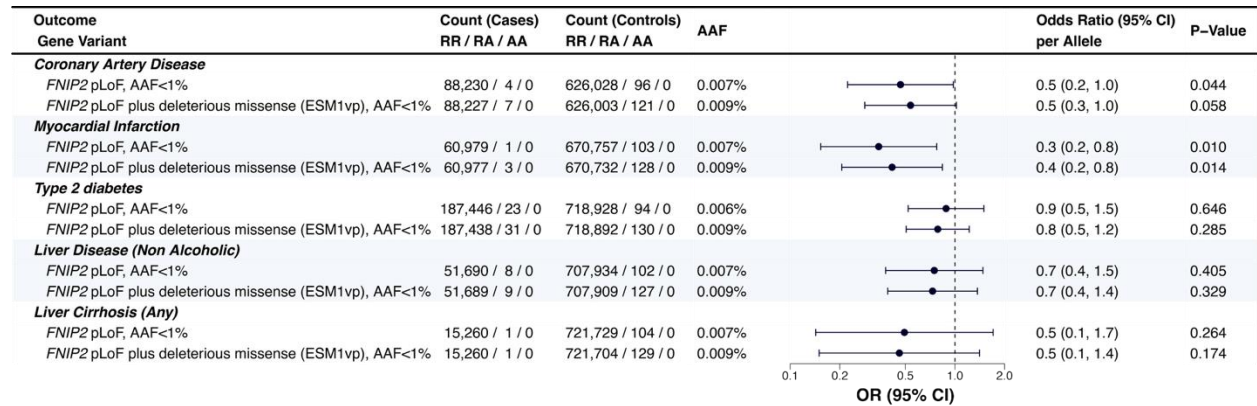
Panel b.



Panel c.



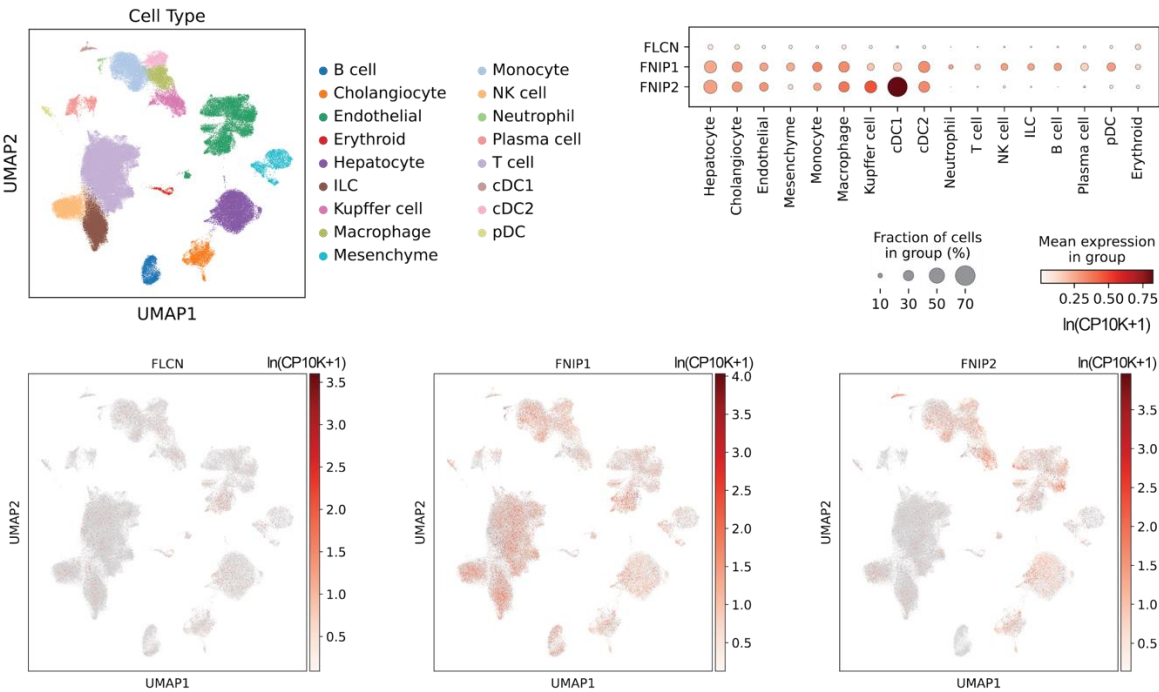
Panel d.



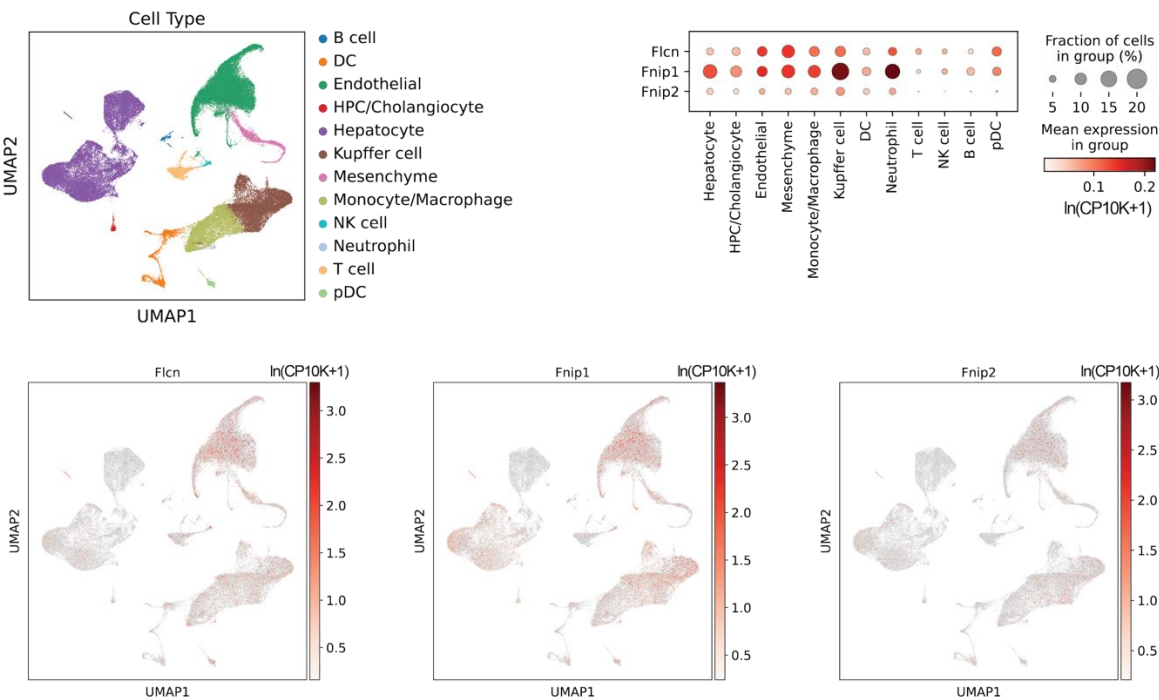
a, Associations of variants in *FNIP2* with lipid traits (Beta $\pm$ 95% CI), **b**, anthropometric traits (Beta $\pm$ 95% CI), **c**, quantitative cardiometabolic traits (Beta $\pm$ 95% CI), and **d**, cardiometabolic outcomes (OR $\pm$ 95% CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; ESM1vp, Evolutionary Scale Modeling; OR, odds ratio; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

Supplementary Figure 28. Single cell RNA expression plots of *FLCN*, *FNIP1* and *FNIP2* in human and mouse liver.

a Gene expression of *Flcn*, *Fnip1* and *Fnip2* in human liver: single cell RNA-sequencing

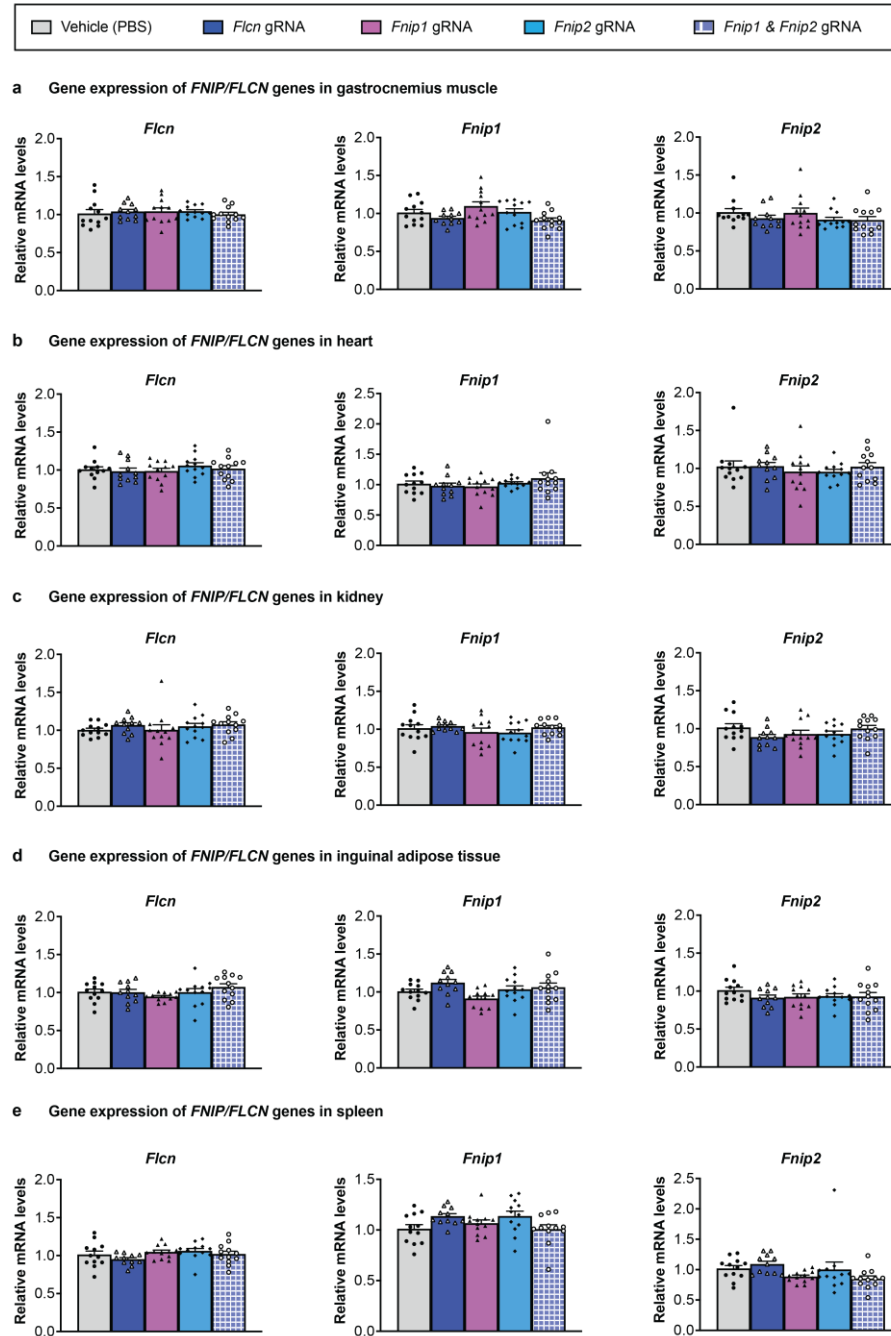


b Gene expression of *Flcn*, *Fnip1* and *Fnip2* in mouse liver: single cell RNA-sequencing



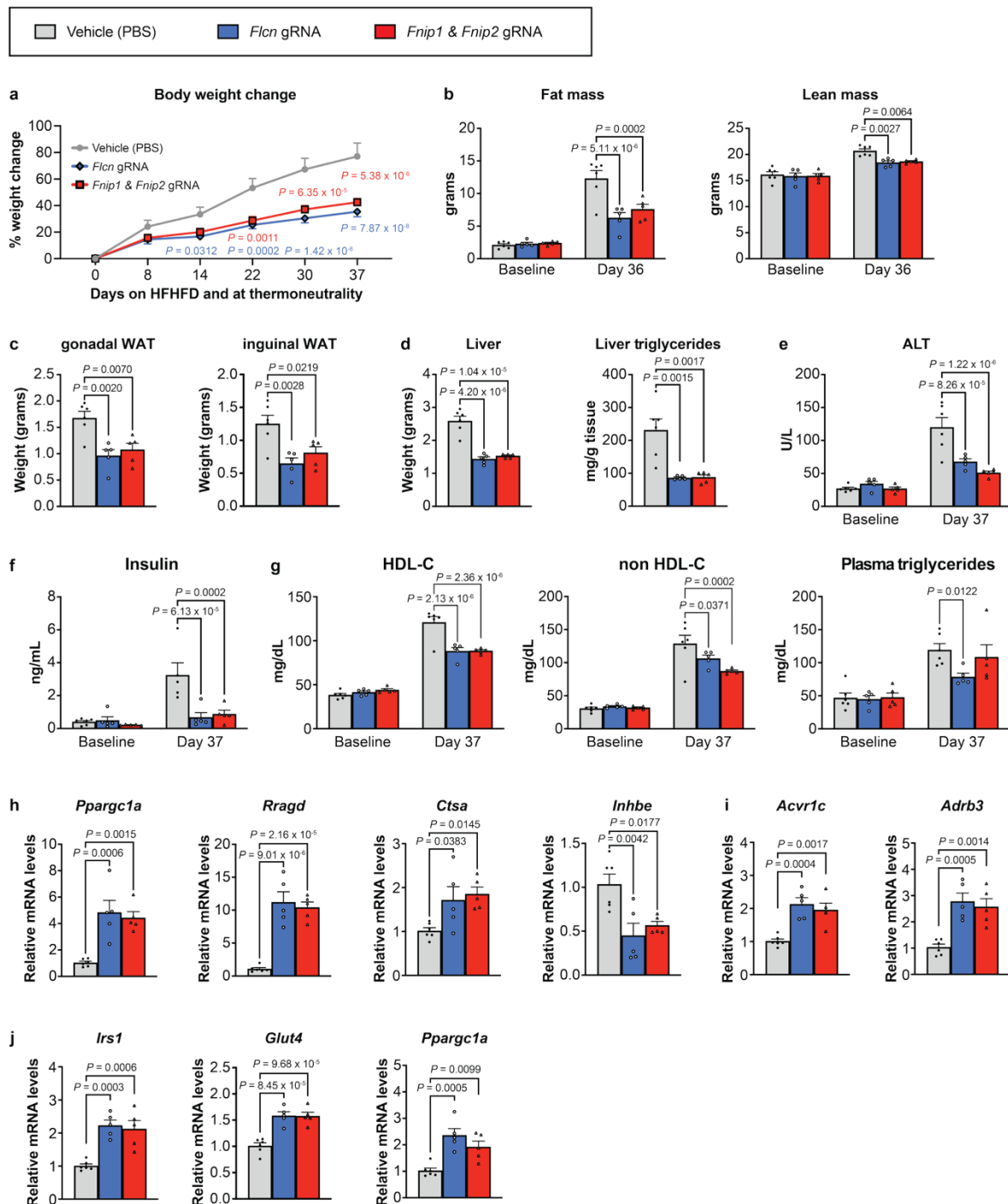
a, Expression of *FLCN*, *FNIP1*, and *FNIP2* in human liver single cell data generated by integrating 5 published datasets (See Methods) with healthy and cirrhosis liver samples. (top left), UMAP of integrated human liver single cell data, colored by unsupervised major cell type clusters. (top right), dot plot of average expression of each gene in each cell type. Color gradient indicates mean expression and spot size indicates percent of cells with non-zero expression. (bottom), expression of each gene projected onto a UMAP, colored by magnitude of expression. Cells with zero expression are shown in grey. **b**, Expression of *Fln*, *Fnip1*, and *Fnip2* in published mouse liver single cell data containing chow-fed and high fat, high fructose diet-fed mice (See Methods). (top left), UMAP of mouse liver single cell data, colored by unsupervised major cell type clusters. (top right), dot plot of average expression of each gene in each cell type. Color gradient indicates mean expression and spot size indicates percent of cells with non-zero expression. (bottom), expression of each gene projected onto a UMAP, colored by magnitude of expression. Cells with zero expression are shown in grey. UMAP, uniform manifold approximation projection; CP10K, counts per 10,000; ILC, innate lymphoid cell; NK, natural killer; cDC1, conventional dendritic cell 1; cDC2, conventional dendritic cell 2; pDC, plasmacytoid dendritic cell; HPC, hepatic progenitor cell.

Supplementary Figure 29. AAV8 does not perturb FLCN/FNIP in extrahepatic tissues.



Male *Cas9-Ready* mice were challenged with high fat, high fructose diet for 13 weeks. **a-e**, mRNA levels of *Flcn*, *Fnip1* and *Fnip2* in gastrocnemius muscle (**a**), heart (**b**), kidney (**c**), inguinal adipose tissue (**d**) and spleen (**e**). For all mRNA levels, mean $\pm$ s.e.m. are shown. Data are from $n = 12$ (vehicle control), $n = 11$ (*Flcn* gRNA), $n = 12$ (*Fnip1* gRNA), $n = 12$ (*Fnip2* gRNA) and $n = 12$ (*Fnip1* & *Fnip2* gRNAs) biologically independent mice. Statistical analysis was performed using one-way ANOVA with Dunnett's correction posttest relative to vehicle control. See also Source Data.

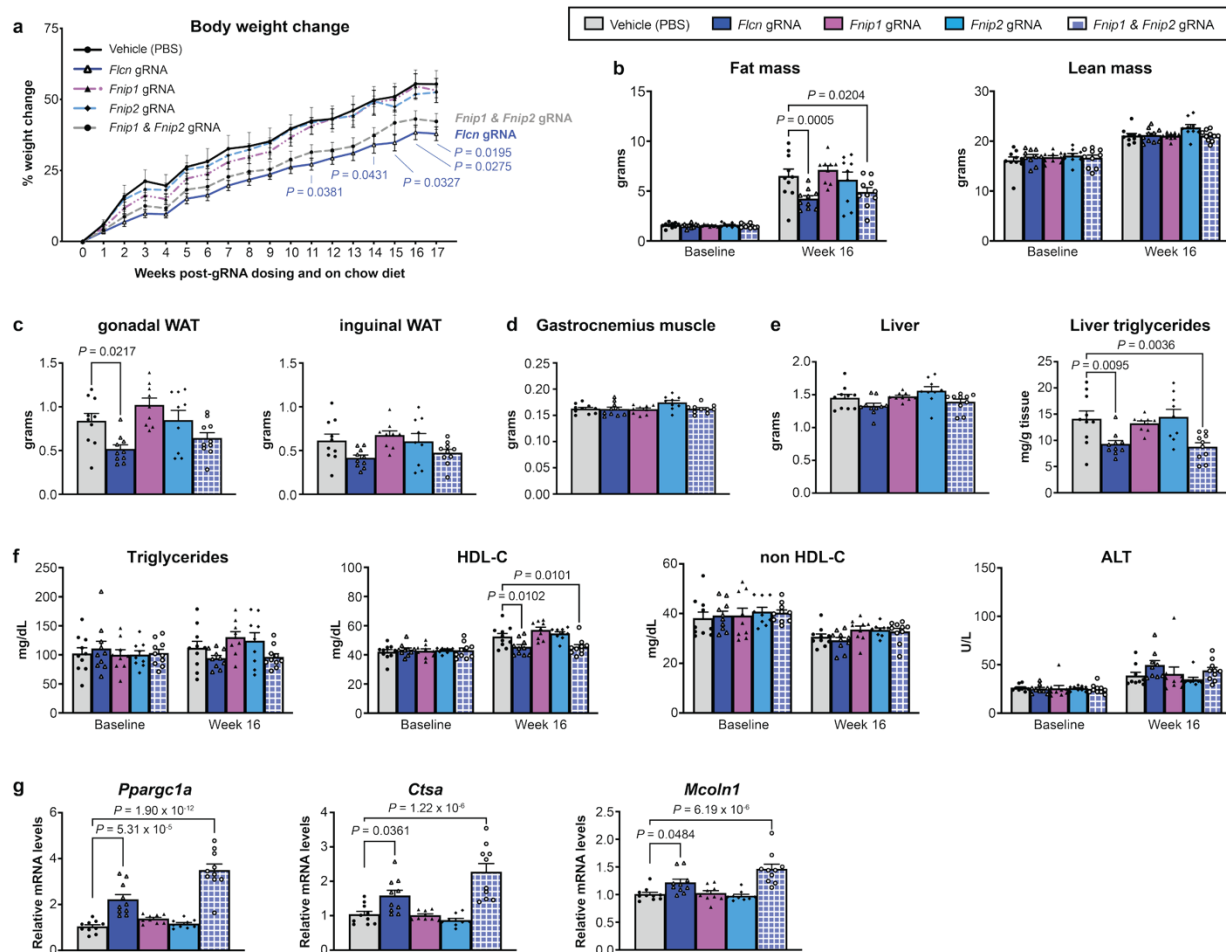
Supplementary Figure 30. *Flcn* or *Fnip1* & *Fnip2* inhibition in liver of *Cas9*-Ready mice protects against diet-induced metabolic disease at thermoneutrality.



Male *Cas9*-Ready mice were challenged with high fat, high fructose diet and housed at thermoneutral conditions (30°C) for 37 days. **a**, Body weight % change of 6–11 week old male AAV8-gRNA or vehicle (PBS)-treated *Cas9*-Ready mice. Mean $\pm$ s.e.m. are shown. *P* values are from two-way ANOVA with Dunnett's correction posttest relative

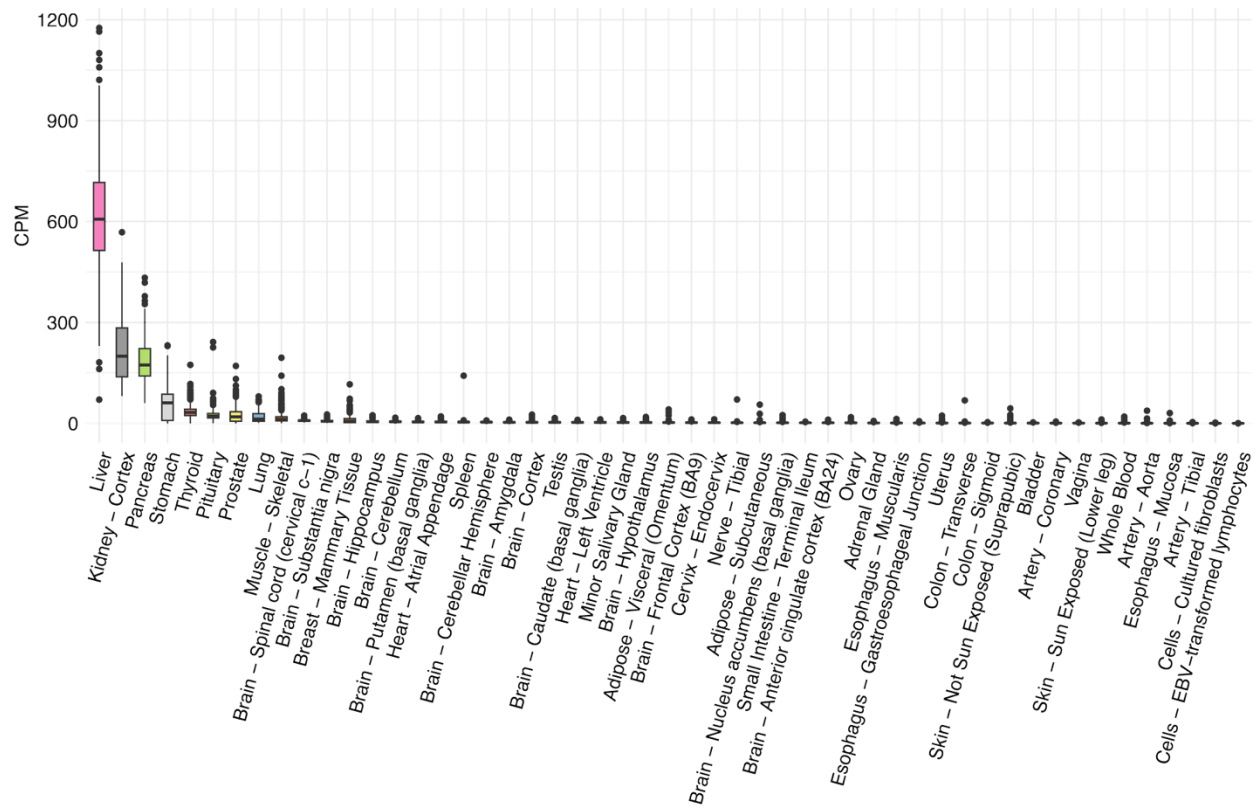
to vehicle control. **b**, Fat and lean mass was determined by echoMRI at baseline and 36 days post-AAV-gRNA administration. Mean $\pm$ s.e.m. are shown. *P* values are from two-way ANOVA with Dunnett's correction posttest relative to vehicle control. **c**, Adipose tissue weights at day 37. Mean $\pm$ s.e.m. are shown. *P* values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. **d**, Liver weights and liver triglyceride content at Day 37. Mean $\pm$ s.e.m. are shown. *P* values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. **e-g**, Plasma ALT (**e**), insulin (**f**) and lipid levels (**g**) were determined at baseline and 37 days after housing at thermoneutral conditions while challenged with high fat, high fructose diet. Mean $\pm$ s.e.m. are shown. *P* values are from two-way ANOVA with Dunnett's correction posttest relative to vehicle control. **h**, mRNA levels measured at day 37 in liver. **i-j**, mRNA levels measured at day 37 in gonadal adipose tissue showing genes related to lipolysis (**i**) and energy metabolism (**j**). For all mRNA levels, mean $\pm$ s.e.m. are shown. *P* values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. For all measurements, data are from *n* = 6 (vehicle control), *n* = 5 (*Fln* gRNA), and *n* = 5 (*Fnip1* & *Fnip2* gRNAs) biologically independent mice, and exact *P* values are shown in the corresponding panels. See also Source Data.

Supplementary Figure 31. *Flcn* or *Fnip1* & *Fnip2* inhibition in liver of *Cas9-Ready* mice lowers weight gain and liver fat accumulation on chow diet.



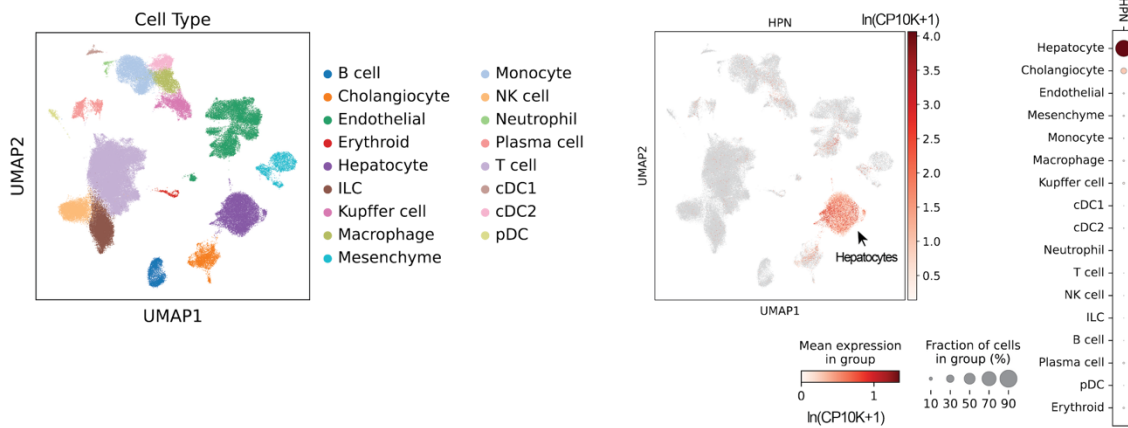
Male *Cas9-Ready* mice were monitored on chow diet for 17 weeks. **a**, Body weight % change of 7–24 week old male AAV8-gRNA or vehicle (PBS)-treated *Cas9-Ready* mice. Mean $\pm$ s.e.m. are shown. P values are from two-way ANOVA with Dunnett's correction posttest relative to vehicle control. **b**, Fat and lean mass were determined by echoMRI at baseline and 16 weeks post-AAV-gRNA administration. Mean $\pm$ s.e.m. are shown. P values are from two-way ANOVA with Dunnett's correction posttest relative to vehicle control. **c**, Adipose tissue weights at week 17. Mean $\pm$ s.e.m. are shown. P values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. **d**, Gastrocnemius muscle weights at week 17. Mean $\pm$ s.e.m. are shown. P values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. **e**, Liver weights and liver triglyceride content at week 17. Mean $\pm$ s.e.m. are shown. P values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. **f**, Plasma triglycerides, HDL-C, non HDL-C and ALT levels were determined at baseline and 16 weeks post-AAV-gRNA administration on chow diet. Mean $\pm$ s.e.m. are shown. P values are from two-way ANOVA with Dunnett's correction posttest relative to vehicle control. **g**, Hepatic mRNA levels measured at week 17 showing genes related to mitochondrial and lysosomal function. Mean $\pm$ s.e.m. are shown. P values are from one-way ANOVA with Dunnett's correction posttest relative to vehicle control. For all measurements, data are from $n = 10$ (vehicle control), $n = 10$ (*Flcn* gRNA), $n = 9$ (*Fnip1* gRNA), $n = 9$ (*Fnip2* gRNA) and $n = 10$ (*Fnip1* & *Fnip2* gRNAs) biologically independent mice, and exact P values are shown in the corresponding panels. See also Source Data.

Supplementary Figure 32. *HPN* gene expression across tissues. Data are from the GTEx resource.

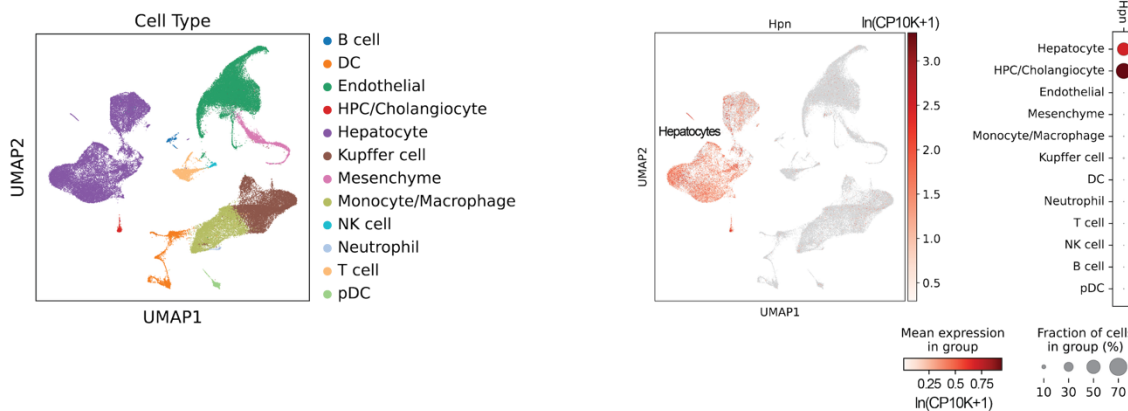


Supplementary Figure 33. Hepatic *Hpn* inhibition lowers plasma cholesterol and protein levels.

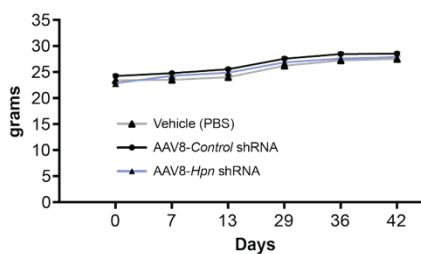
a Gene expression of *HPN* in human liver: single cell RNA-sequencing



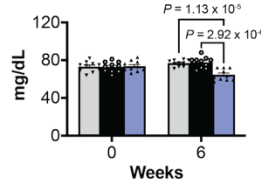
b Gene expression of *Hpn* in mouse liver: single cell RNA-sequencing



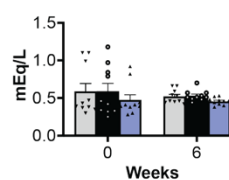
c Body weight



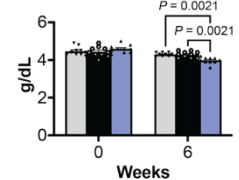
d Total cholesterol



e NEFAs



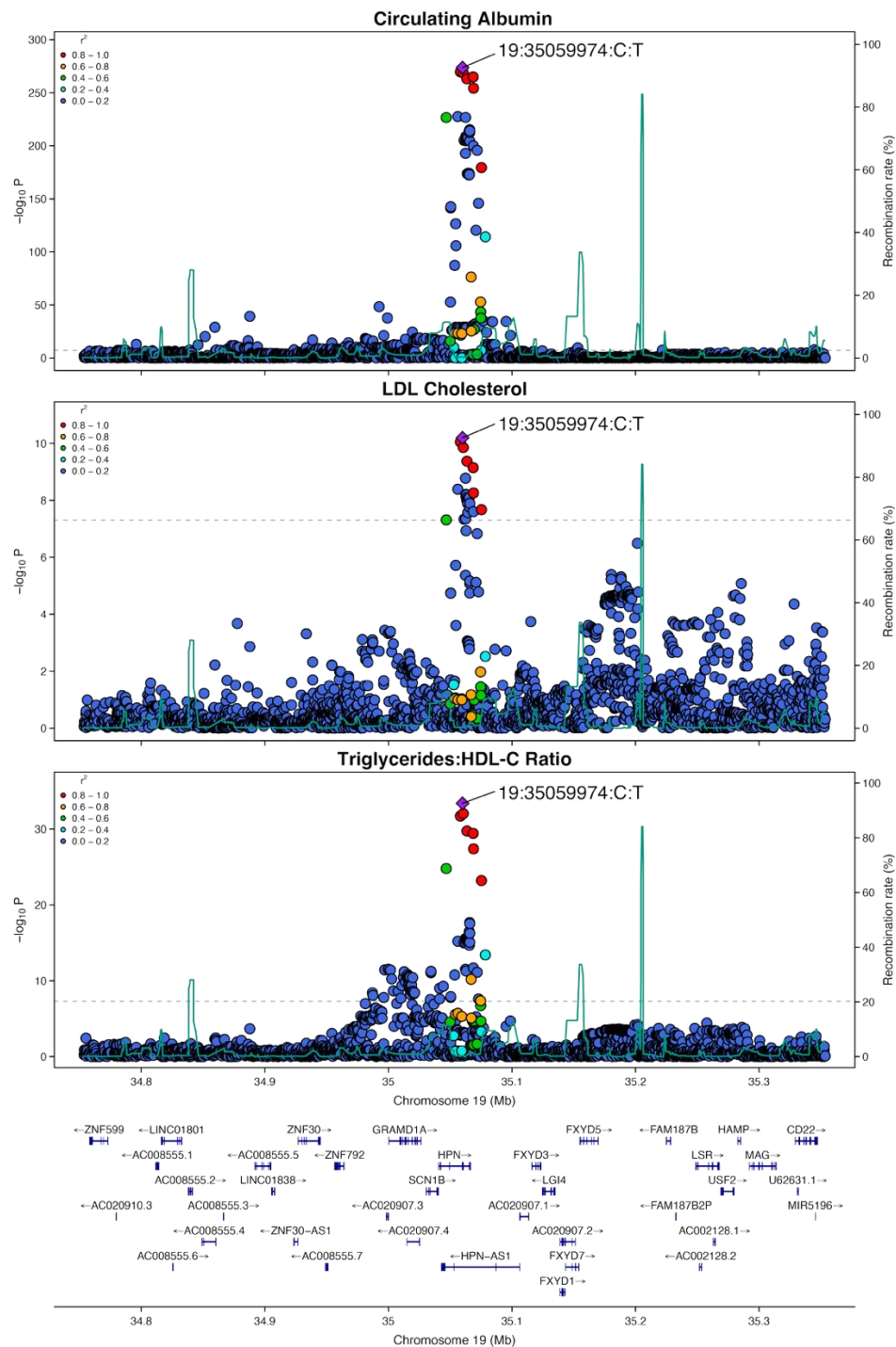
f Total protein



a, Expression of *HPN* in human liver single cell data generated by integrating 5 published datasets (See Methods) with healthy and cirrhosis liver samples. (left), UMAP of integrated human liver single cell data, colored by unsupervised major cell type clusters. (middle), expression of *HPN* projected onto a UMAP, colored by magnitude of expression. Cells with zero expression are shown in grey. (right), dot plot of average *HPN* expression in each cell type. Color gradient indicates mean expression and spot size indicates percent of cells with non-zero expression. **b**, Expression of *Hpn* in published mouse liver single cell data containing chow-fed and high fat, high fructose diet (HFHFD)-fed mice (See Methods). (left), UMAP of integrated mouse liver single cell data, colored by unsupervised major cell type clusters. (middle), expression of *Hpn* projected onto a UMAP, colored by magnitude of expression. Cells with zero expression are shown in grey. (right), dot plot of average *Hpn* expression in each cell type. Color

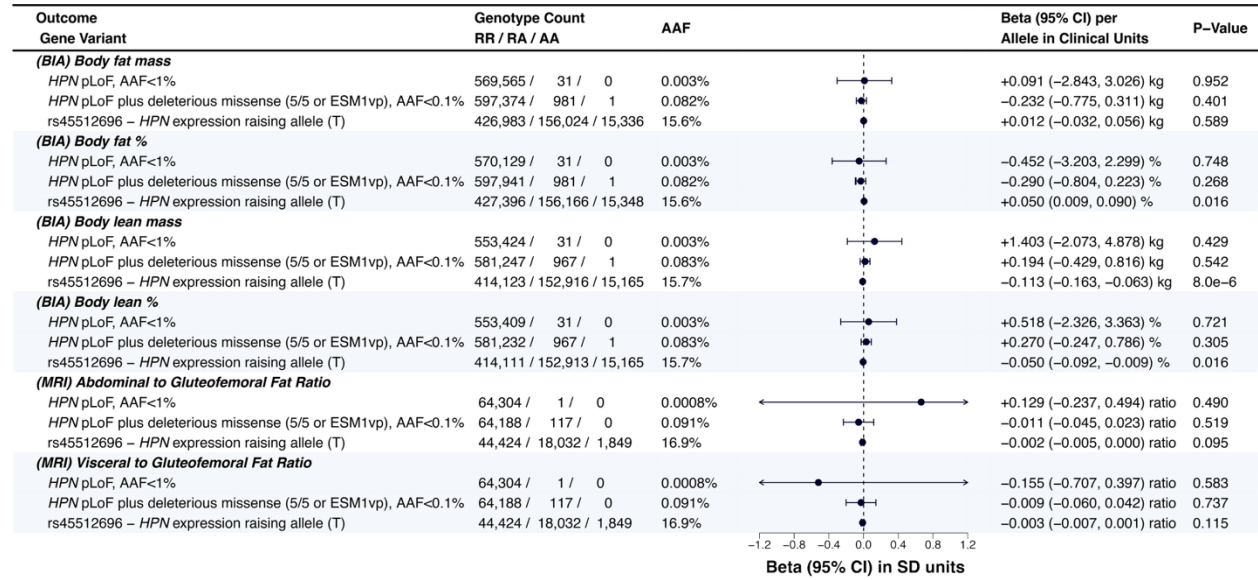
gradient indicates mean expression and spot size indicates percent of cells with non-zero expression. UMAP, uniform manifold approximation projection; CP10K, counts per 10,000; ILC, innate lymphoid cell; NK, natural killer; cDC1, conventional dendritic cell 1; cDC2, conventional dendritic cell 2; pDC, plasmacytoid dendritic cell; HPC, hepatic progenitor cell. **c**, Body weights of 7–12 week old male AAV8-*Control* shRNA, AAV8-*Hpn* shRNA or vehicle (PBS)-treated WT mice on standard diet (n = 10). **d**, Non-fasted plasma cholesterol and non-esterified fatty acids (NEFAs) of WT mice before (week 0) and 6 weeks after AAV-shRNA or vehicle administration. **e**, Non-fasted plasma total protein levels of WT mice before (week 0) and 6 weeks after AAV-shRNA or vehicle administration. For all measurements, mean $\pm$ s.e.m. are shown (n = 10 mice per group). *P* values are from two-way ANOVA with Tukey correction posttest relative to vehicle or control shRNA. In **d-e**, exact *P* values are shown in the corresponding panels. See also Source Data.

Supplementary Figure 34. Regional plot for the associations of common variants at the *HPN* locus.

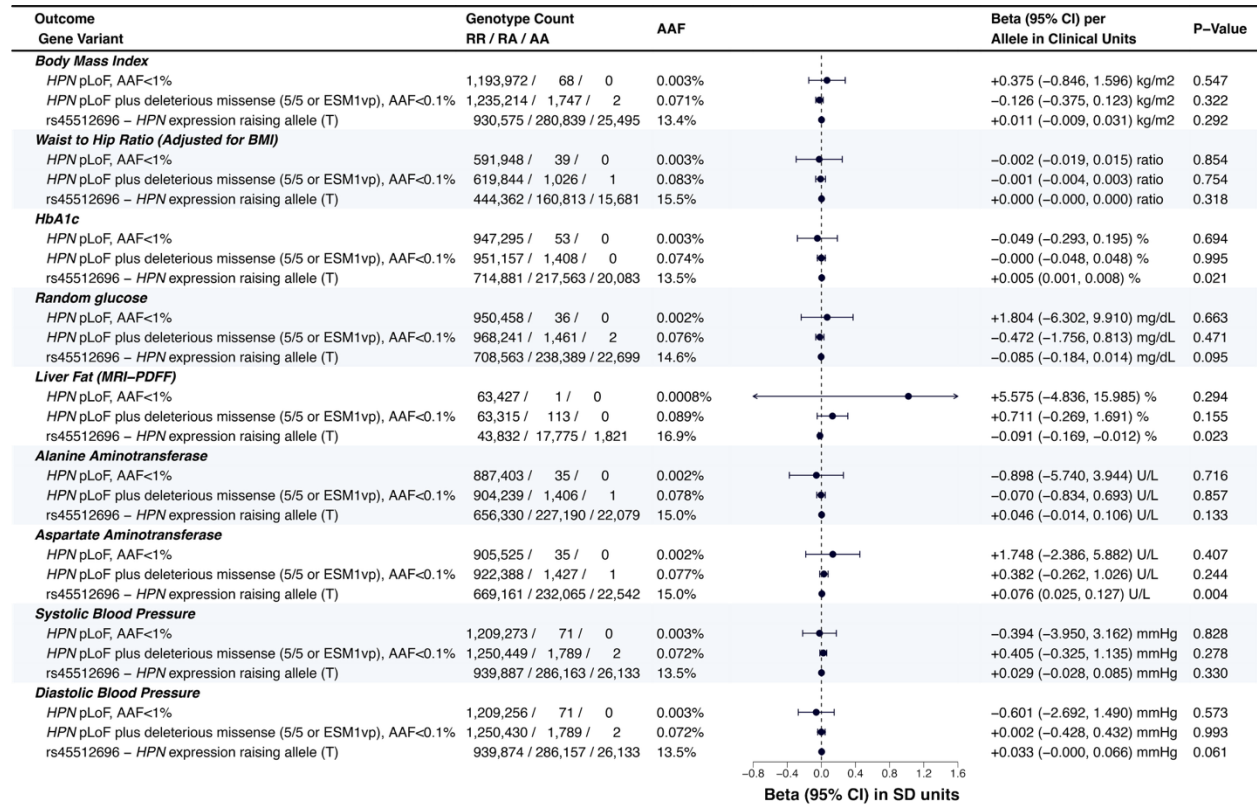


Supplementary Figure 35. Genetic associations for *HPN* common and rare variants.

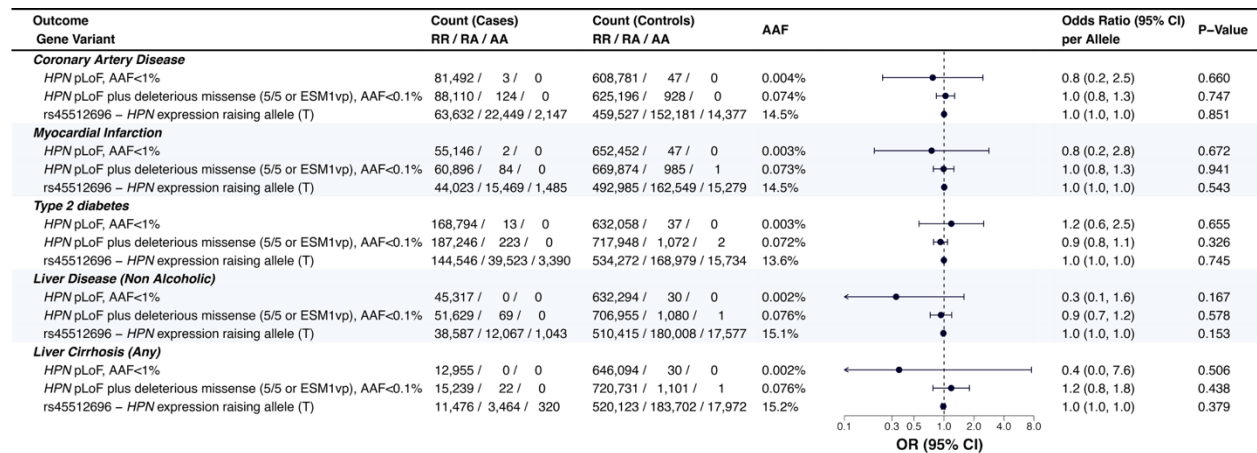
Panel a.



Panel b.



Panel c.



a, Associations of variants in *HPN* with anthropometric traits (Beta $\pm$ 95% CI), **b**, quantitative cardiometabolic traits (Beta $\pm$ 95% CI), and **c**, cardiometabolic outcomes (OR $\pm$ 95% CI). Association estimates are from inverse-variance weighted fixed-effect meta-analysis and *P* values are from two-sided Wald tests. AAF, alternative allele frequency; CI, confidence interval; ESM1vp, Evolutionary Scale Modeling; OR, odds ratio; pLoF, predicted loss-of-function; RR, homozygous for the reference allele; RA, heterozygous; AA, homozygous for the alternative allele.

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