SUPPLEMENTAL MATERIAL

Supplemental methods

Discovery

The discovery meta-analysis contained 24 studies from CARDIoGRAM*plus*C4D, ENGAGE and SUMMIT consortia of European descent, except for PROMIS, which included individuals of South Asian descent for which full summary statistics were available (Supplementary Table 1). Cases were selected for inclusion following the standard criteria for CAD and myocardial infarction used in the CARDIoGRAM*plus*C4D consortium.1 There was no sample overlap amongst the studies included from different consortia.

The discovery included both cross-sectional studies and longitudinal studies (analysed as crosssectional studies). We accounted for the contemporaneous diagnoses of T2D and CAD in longitudinal studies by including CAD cases that had a diagnosis of T2D prior and up to 5 years after the CAD event.

To identify loci that were specific to CAD in the context of diabetes, and to identify loci that interacted with T2D to modify the risk of CAD, analyses were stratified by T2D status, which included 24,259 subjects with T2D (10,014 CAD cases) and 42,384 subjects without diabetes (17,694 CAD cases). Studies provided summary statistics for variants typed on the Cardio Metabochip array or provided GWAS data imputed to either HapMap2 or 1000 Genomes phase 1 reference panels.²

Replication

Replication was sought for loci that achieved a discovery p value<1×10⁻⁴ for association with CAD in at least one of the following analyses: all individuals combined regardless of T2D status; subjects with T2D only; subjects without diabetes; or the interaction analysis. Replication was conducted in 11,537 subjects with T2D (3,706 CAD cases) and 106,250 subjects without diabetes (12,988 CAD cases) from four studies of European descent (Supplementary Table 2). The samples used in the replication analyses were independent of those used in the discovery analysis.

1

Joint analysis and combination of evidence

We had access to full summary statistics for the discovery analysis and requested summary statistics for variants selected for replication from replication cohorts. Thus, we performed a joint analysis between the estimates for individual variants from the discovery analyses and summary statistics for a subset of variants selected for replication. Analyses were performed in each study to test the following comparisons: CAD in subjects with T2D and CAD in subjects without diabetes. Association was tested with CAD status in a regression model, adjusted for age, sex and study specific covariates such as principal components to account for population structure, where applicable. Age was defined as age of event for CAD cases and age at sampling for controls.

Genotype characteristics for the discovery cohort are given in Supplementary Table 3. We excluded variants: minor allele frequency (MAF)<1%; 2×N cases ×MAF<10; Hardy-Weinberg equilibrium test *p* value (p_{hwe}) <5×10⁻⁷ and MAF>5% or p_{hwe} <1×10⁻⁴ and MAF<5% for directly typed variants and imputation information score <0.4 (IMPUTE2)/imputation information score <0.3 (MaCH) for imputed variants or a call rate <95% for directly typed variants.

We used the additive model to generate association summary statistics and combined these statistics in a fixed-effect inverse variance-weighted meta-analysis using GWAMA v2.1.³ We used a fixed effects model to estimate the allelic effects in individual strata, under the assumptions that any differences in allelic effect between strata were due to type 2 diabetes background. This method did not account for between study variation in allelic effects. To test for heterogeneous allelic effects by T2D status, we used the method outlined by Magi et al., 2010. 3 We double genomic control (GC) corrected association summary statistics both at the study level and in the overall discovery meta-analysis. Variants were excluded from the discovery meta-analysis if the effective sample size < 4000.

We estimated the interaction effects based on comparing the summary allelic effect on CAD for each variant between subjects with and without T2D. This approach allowed us to include more samples in the meta-analyses as studies that did not contain both subjects with and without T2D could be

2

included in the stratified analyses but would have been excluded from a meta-analysis of the interaction term. By adopting this approach, we were able to increase the sample size but were unable to account for between study variance in allelic effects.

Signal declaration criteria

We selected loci for replication based on a *p* value of association for the lead variant ≤1×10-4 in the T2D only, non-diabetic only and interaction analyses. The genotype characteristics of the replication cohorts are given in Supplementary Table 4. We estimated the combined effect sizes for variants in a joint analysis based on a fixed-effect inverse variance–weighted meta-analysis using GWAMA v2.1. 3 Novel loci were declared at $p \le 5 \times 10^{-8}$. For declaring interaction signals, we required that the directions of effect for individual strata were consistent across the discovery and replication analyses and achieved a $p_{interaction}$ <0.05/175 (the number of variants selected for replication) in the replication analysis. Suggestive interaction signals were identified as those that showed directional consistency across the discovery and replication analyses, and when combined in joint analysis achieved combined *pinteraction* < discovery *pinteraction*.

Power calculations

Stratified and overall analyses

Power calculations were conducted in R statistics using the gap package.⁴ For the purpose of the power calculations effective population size was used (4/ (1/Ncases+1/Nctrls) and a disease prevalence of 5%. The calculation also considered allele frequency and effect size. We used an α≤5×10-8 for novel loci.

Interaction analysis

Statistical interaction was calculated by testing the difference between two estimates of allelic effect on CAD. The allelic effects were estimated in subjects with diabetes and without diabetes separated and were compared using GWAMA v2.1 to calculate a *pinteraction*. ³ The power to detect an interaction

depends on how accurately the allelic effect can be estimated in each stratum. We assessed the power to detect an interaction effect of a CAD-risk variant with T2D in three allelic effect scenarios: a) an effect on CAD in subjects with T2D only (i.e. OR is 1 in subjects without diabetes, but varies between 1 and 1.2 in subjects with T2D); b) an effect on CAD in subjects with T2D and without diabetes in the same direction but of differing magnitude (i.e. OR is 1.10 in subjects without diabetes, but varies between 1 and 1.2 in subjects with T2D); and c) an effect on CAD in subjects with T2D and without diabetes but in opposite directions (i.e. OR is 0.90 in subjects without diabetes, but varies between 1 and 1.2 in subjects with T2D). For each scenario, we evaluated a range of risk allele frequencies: 10%, 20% and 50%. Power was calculated for $\alpha \le 1 \times 10^{-4}$ in discovery (using discovery sample sizes) based on the threshold for replication.

Genetic correlation with related risk factors

We assessed the genetic correlation of CAD by diabetes subgroup with related risk factors using LDHub.⁵ Genetic correlation was calculated by taking the slope of the regression of the product of trait 1 z scores on trait 2 z scores on the LD score for a SNP. Z scores were derived from the allelic effects and standard error for that trait. We restricted the analysis to 106 traits available in LDHub that are known risk factors for T2D and CAD.

Genetic risk score analysis

SNPs associated with Waist-Hip-ratio (adjusted for body mass index [BMI]), number of SNPs $[N_{SNPs}]$ =53),⁶ BMI (untransformed, N_{SNPs} =95 and z-transformed, N_{SNPs} =23),^{7,8} systolic blood pressure (SBP) (N_{SNPs}=21),^{9,10} LDL-C (N_{SNPs}=143), HDL-C (N_{SNPs}=143), triglycerides (N_{SNPs}=143),¹¹ T1D, T2D $(N_{SNPs}=403)$,¹² 2-hr glucose (adjusted for BMI, $N_{SNPs}=15$),¹³ fasting glucose (FG, adjusted for BMI, $N_{SNPs}=21$),¹⁴ glycated haemoglobin ($N_{SNPs}=15$),¹⁵ fasting insulin (natural log transformed and adjusted for BMI, $N_{SNPs}=13$),¹⁴ fasting pro-insulin (adjusted for BMI and FG, $N_{SNPs}=10$),¹⁶ HOMA-B($N_{SNPs}=15$), HOMA-IR(N_{SNPs}=15)¹⁷ and insulin resistance (N_{SNPs}=10)¹⁸ at genome-wide significance (p≤5×10⁻⁸) were included in a genetic risk score (GRS) for each trait respectively. To account for the pleiotropic effects

amongst the lipid associated loci a multivariable model was employed from in R using the TwoSampleMR package.19 For all other GRS the inverse variance weighted method was used to associate each of the GRS with CAD summary statistics.20

Supplementary Figure 1: Odds ratios (OR) for 160 known coronary artery disease (CAD) loci from this study compared to the published OR in the combined analysis of CAD, CAD in subjects with T2D and for CAD in subjects without diabetes. The blue colour indicates a p<5x10-3 in at least one of the analyses. For these SNPs the odds ratios >/= 1.00 for the published risk allele.

Supplementary Figure 2: Interactions can be broadly classified into three classes: A) effect on coronary artery disease (CAD) is specific to subjects with type 2 diabetes (T2D) (i.e. OR is 1.0 in diabetes free subjects, but varies between 1.0 and 1.2 in subjects with T2D); B) effect on CAD is heterogeneous, but is in the same direction irrespective of diabetes status (i.e. OR is 1.10 in diabetes free subjects, but varies between 1.0 and 1.2 in subjects with T2D); and C) effect on CAD is heterogeneous, and is in the opposite direction in subjects with T2D and diabetes free subjects (i.e. OR is 0.9 in diabetes free subjects, but varies between 1.0 and 1.2 in subjects with T2D). The continuous lines represent the power to detect an interaction $p<1\times10^{-4}$ in discovery and the dashed line a $p<0.05$ in the replication.

Supplementary Figure 3: Locuszoom plots of association statistics in the region of *ZNF648* for a published variant rs10911021 with coronary artery disease (A) and the interaction p value with type 2 diabetes (B). This variant has been previously reported to interact with T2D to modify the risk of coronary artery disease.

Supplementary Figure 4: Genetic correlation of coronary artery disease stratified by type 2 diabetes with known risk factors for CAD. Asterisks indicate a p value < $4.1x10^{-4}$ (0.05/121) for accuracy in the estimation of genetic correlation. Where the error bars do not cross zero-line p<0.05. Genetic correlations are calculated from all variants rather than those reaching genome-wide significance and give a broader picture of the overall genetic overlap. A different colour point is assigned to each trait.

Supplementary Figure 5: The heat map of genetic risk scores for known coronary artery disease (CAD) risk factors does not show any significant differences between CAD in subjects with and without diabetes. Genetic risk scores (GRS) were for known CAD risk factors were constructed and associated with CAD in all individuals, CAD in subjects without T2D and with CAD in subjects with T2D. This was to determine if there was a different effect of risk factors on CAD by T2D background. Similar colours indicate a similar strength of association between the GRS for the known CAD risk factor and CAD in the different contexts examined.

Supplementary Table 1: The discovery meta-analysis included 24 studies and the sample characteristics of those studies are provided in the accompanying excel file.

Supplementary Table 3: The phenotypic characteristics of studies included in the discovery meta-analysis can be found in the accompanying excel file.

Supplementary Table 4: Genotypic characteristics of the four studies that were included in the replication analyses.

Supplementary Table 5**:** Results from the T2D stratified analysis for SNPs in known coronary artery disease loci (N=160) in the combined, T2D only and nondiabetic analyses. This table shows the odds ratios from each of the analyses performed and reports the published odds ratio.

The table is available in the supplementary excel file

Supplementary Table 6: Pairwise genetic correlation between 106 traits and coronary artery disease (CAD) stratified by type 2 diabetes (T2D) status using data from LDScore hub. Genetic correlations indicate the overall genetic overlap between traits. Here we wanted to understand the genetic overlap of known CAD risk factors with CAD in the context of T2D.

Supplementary Table 7: Coronary artery disease (CAD) has several risk factors that are in part genetically determined. We constructed genetic risk scores for known CAD risk factors and associated them with CAD by type 2 diabetes status.

Supplementary Table 8: CARDIoGRAM*plus*C4D Steering committee members

John Danesh

Department of Public Health and Primary Care, University of Cambridge, UK

Panos Deloukas

William Harvey research Institute, Barts and the London School of medicine & Dentistry, Queen Mary University of London, UK; Wellcome Trust Sanger Institute, Cambridge, UK

Jeanette Erdmann

Institut für Integrative und Experimentelle Genomik, Universität zu Lübeck, Lübeck, Germany

Dongfeng Gu

Department of Population Genetics and Prevention, Fu Wai Hospital & Cardiovascular Institute, Chinese Academy of Medical Sciences & Peking Union Medical College, Beijing, China

Anders Hamsten

Atherosclerosis Research Unit, Department of Medicine Solna, Karolinska Institutet, Stockholm, Sweden Center for Molecular Medicine and Department of Cardiology, Karolinska University Hospital, Stockholm, Sweden

Sekar Kathiresan

Cardiovascular Research Center and Center for Human Genetic Research, Massachusetts General Hospital, Boston, Massachusetts, USA; Broad Institute, Cambridge, Massachusetts, USA; Department of Medicine, Harvard Medical School, Boston, Massachusetts, USA

Jaspal S Kooner

National Heart and Lung Institute (NHLI), Imperial College London, Hammersmith Hospital, London, UK.

Robert Roberts

University of Ottawa Heart Institute, Cardiovascular Research Methods Centre and Ruddy Canadian Cardiovascular Genetics Centre, Ontario, Canada

Nilesh J Samani (Chair)

Department of Cardiovascular Sciences, University of Leicester, Glenfield Hospital, Leicester, UK; National Institute for Health Research (NIHR) Leicester Cardiovascular Biomedical Research Unit, Glenfield Hospital, Leicester, UK.

Heribert Schunkert

Deutsches Herzzentrum München, Technische Universität München, Munich, Germany

Unnur Thorsteinsdottir

deCODE Genetics, Sturlugata 8, Reykjavik, Iceland; University of Iceland, Faculty of Medicine, Reykjavik, Iceland

Hugh Watkins

Wellcome Centre for Human Genetics, University of Oxford, Oxford, UK; Cardiovascular Medicine, Radcliffe Department of Medicine, University of Oxford, Oxford, UK

Themistocles L Assimes

Department of Medicine, Stanford University School of Medicine, Stanford, California, USA

Email: tassimes@stanford.edu

Stefan Blankenberg

University Heart Center Hamburg, Clinic for general and interventional Cardiology, Hamburg, Germany

Bernhard O Boehm

Division of Endocrinology and Diabetes, Department of Internal Medicine, Ulm University Medical Centre, Ulm, Germany

John C Chambers

Epidemiology and Biostatistics, Imperial College London, London, UK

Robert Clarke

Clinical Trial Service Unit and Epidemiological Studies Unit, University of Oxford, Oxford, UK

Rory Collins

Clinical Trial Service Unit and Epidemiological Studies Unit, University of Oxford, Oxford, UK

George Dedoussis

Department of Dietetics-Nutrition, Harokopio University, Athens, Greece

Paul W Franks

Department of Clinical Sciences, Genetic & Molecular Epidemiology Unit, Lund University Diabetes Center, Skåne University Hosptial, Malmö, Sweden Department of Public Health & Clinical Medicine, Genetic Epidemiology & Clinical Research Group, Section for Medicine, Umeå University, Umeå, Sweden; Department of Nutrition, Harvard School of Public Health, Boston, MA USA

G Kees Hovingh

Department of Vascular Medicine, Academic Medical Center, Amsterdam, The Netherlands

Erik Ingelsson

Department of Medical Epidemiology and Biostatistics, Karolinska Institutet, Stockholm, Sweden

Bong-Jo Kim

Division of Structural and Functional Genomics Center for Genome Science, Korea National Institute of Health, Korea

Terho Lehtimäki

Department of Clinical Chemistry, Fimlab Laboratories, Tampere University Hospital, Tampere, Finland; Department of Clinical Chemistry, University of Tampere School of Medicine, Tampere, Finland

Winfried März

Synlab Academy, Mannheim, Germany; Medical Clinic V (Nephrology • Hypertensiology • Endocrinology • Diabetology • Rheumatology), Medical Faculty of Mannheim, University of Heidelberg, Mannheim, Germany

Ruth McPherson

Department of Medicine, Division of Cardiology, University of Ottawa Heart Institute, Ottawa, Canada

Andres Metspalu

Estonian Genome Center, University of Tartu, Tartu, Estonia; Institute of Molecular and Cell Biology, University of Tartu, Tartu, Estonia

Markku S Nieminen

Division of Cardiology, Department of Medicine, Helsinki University Central Hospital (HUCH), Helsinki, Finland

Christopher O'Donnell

Framingham Heart Study, National Heart, Lung and Blood Institute, Framingham, MA 01702, USA

Colin N A Palmer

Medical Research Institute, University of Dundee, Ninewells Hospital and Medical School, Dundee, UK

Markus Perola

Department of Chronic Disease Prevention, National Institute for Health and Welfare, Helsinki, Finland

Muredach P Reilly

Cardiovascular Institute, Perelman School of Medicine at the University of Pennsylvania, Philadelphia, USA

Samuli Ripatti

Department of Chronic Disease Prevention, National Institute for Health and Welfare, Helsinki FIN-00271, Finland; Wellcome Trust Sanger Institute, Hinxton, UK

Danish Saleheen

Center for Non-Communicable Diseases, Karachi, Pakistan; Department of Public Health and Primary Care, University of Cambridge, Cambridge, UK; Department of Medicine, University of Pennsylvania, Philadelphia, Pennsylvania, USA

Manjinder S Sandhu

MRC Epidemiology Unit, Institute of Metabolic Science, Addenbrooke's Hospital, Cambridge, UK; Wellcome Trust Sanger Institute, Hinxton, UK

Stefan Schreiber

Institut für Klinische Molekularbiologie, Christian-Albrechts Universität, Kiel, Germany

Agneta Siegbahn

Uppsala Clinical Research Center, Uppsala University, Uppsala, Sweden

Cristen J Willer

Department of Internal Medicine , Division of Cardiovascular Medicine, and Department of Human Genetics, University of Michigan, Ann Arbor, Michigan, USA

Pierre A Zalloua

Lebanese American University, Chouran, Beirut, Lebanon

Supplementary Table 9: Members of the SUMMIT consortium

References

- 1. Webb TR, Erdmann J, Stirrups KE, Stitziel NO, Masca NGD, Jansen H, Kanoni S, Nelson CP, Ferrario PG, König IR, et al. Systematic Evaluation of Pleiotropy Identifies 6 Further Loci Associated With Coronary Artery Disease. J *Am Coll Cardiol.* 2017;69:823–836.
- 2. Voight BF, Kang HM, Ding J, Palmer CD, Sidore C, Chines PS, Burtt NP, Fuchsberger C, Li Y, Erdmann J, et al. The Metabochip, a Custom Genotyping Array for Genetic Studies of Metabolic, Cardiovascular, and Anthropometric Traits. *PLoS Genet.* 2012;8:e1002793.
- 3. Mägi R, Morris AP. GWAMA: software for genome-wide association meta-analysis. *BMC Bioinformatics.* 2010;11:288.
- 4. R Core Team. R: A Language and Environment for Statistical Computing 2013. R Foundation for Statistical Computing. 2019. Vienna, Austria.
- 5. Zheng J, Erzurumluoglu AM, Elsworth BL, Kemp JP, Howe L, Haycock PC, Hemani G, Tansey K, Laurin C, Pourcain BS, et al. LD Hub: A centralized database and web interface to perform LD score regression that maximizes the potential of summary level GWAS data for SNP heritability and genetic correlation analysis. *Bioinformatics.* 2017;33:272–279.
- 6. Shungin D, Winkler TW, Croteau-Chonka DC, Ferreira T, Locke AE, Mägi R, Strawbridge RJ, Pers TH, Fischer K, Justice AE, et al. New genetic loci link adipose and insulin biology to body fat distribution. *Nature* 2015;518:187–196.
- 7. Locke AE, Kahali B, Berndt SI, Justice AE, Pers TH, Day FR, Powell C, Vedantam S, Buchkovich ML, Yang J, et al. Genetic studies of body mass index yield new insights for obesity biology. *Nature.* 2015;518:197–206.
- 8. Thorleifsson G, Walters GB, Gudbjartsson DF, Steinthorsdottir V, Sulem P, Helgadottir A, Styrkarsdottir U, Gretarsdottir S, Thorlacius S, Jonsdottir I, et al. Genome-wide association yields new sequence variants at seven loci that associate with measures of obesity. *Nat Genet*. 2009;41:18–24.
- 9. Newton-Cheh C, Johnson T, Gateva V, Tobin MD, Bochud M, Coin L, Najjar SS, Zhao JH, Heath SC, Eyheramendy S, et al. Genome-wide association study identifies eight loci associated with blood pressure. *Nat Genet*. 2009;41:666–676.
- 10. Ehret GB, Munroe PB, Rice KM, Bochud M, Johnson AD, Chasman DI, Smith AV, Tobin MD, Verwoert GC, Hwang SJ, et al. Genetic variants in novel pathways influence blood pressure and cardiovascular disease risk. *Nature.* 2011;478:103–109.
- 11. Willer CJ, Sanna S, Jackson AU, Scuteri A, Bonnycastle LL, Clarke R, Heath SC, Timpson NJ, Najjar SS, Stringham HM, et al. Newly identified loci that influence lipid concentrations and risk of coronary artery disease. *Nat Genet*. 2008;40:161–169.
- 12. Mahajan A, Taliun D, Thurner M, Robertson NR, Torres JM, Rayner NW, Payne AJ, Steinthorsdottir V, Scott RA, Grarup N, et al. Fine-mapping type 2 diabetes loci to singlevariant resolution using high-density imputation and islet-specific epigenome maps. *Nat Genet.* 2018;50:1505–1513.
- 13. Saxena R, Hivert M-F, Langenberg C, Tanaka T, Pankow JS, Vollenweider P, Lyssenko V, Bouatia-Naji N, Dupuis J, Jackson AU, et al. Genetic variation in *GIPR* influences the glucose and insulin responses to an oral glucose challenge. *Nat Genet.* 2010;42:142–148.
- 14. Manning AK, Hivert M-F, Scott RA, Grimsby JL, Bouatia-Naji N, Chen H, Rybin D, Liu CT, Bielak LF, Prokopenko I, et al. A genome-wide approach accounting for body mass index identifies genetic variants influencing fasting glycemic traits and insulin resistance. *Nat Genet.* 2012;44:659–669.
- 15. Soranzo N, Sanna S, Wheeler E, Gieger C, Radke D, Dupuis J, Bouatia-Naji N, Langenberg C, Prokopenko I, Stolerman E, et al. Common variants at 10 genomic loci influence hemoglobin A1C levels via glycemic and nonglycemic pathways. *Diabetes.* 2010;59:3229–3239.
- 16. Strawbridge RJ, Dupuis J, Prokopenko I, Barker A, Ahlqvist E, Rybin D, Petrie JR, Travers ME, Bouatia-Naji N, Dimas A S, et al. Genome-Wide Association Identifies Nine Common Variants Associated With Fasting Proinsulin Levels and Provides New Insights Into the Pathophysiology of Type 2 Diabetes. *Diabetes.* 2011;60:2624–2634.
- 17. Dupuis J, Langenberg C, Prokopenko I, Saxena R, Soranzo N, Jackson AU, Wheeler E, Glazer NL, Bouatia-Naji N, Gloyn AL, et al. New genetic loci implicated in fasting glucose homeostasis and their impact on type 2 diabetes risk. *Nat Genet.* 2010;42:105–116.
- 18. Lotta LA, Gulati P, Day FR, Payne F, Ongen H, van de Bunt M, Gaulton KJ, Eicher JD, Sharp SJ, Luan J, et al. Integrative genomic analysis implicates limited peripheral adipose storage capacity in the pathogenesis of human insulin resistance. *Nat Genet.* 2017;49:17–26.
- 19. Burgess S. R: A Language and Environment for Statistical Computing Package "MendelianRandomization" 2018.
- 20. Burgess S, Butterworth A, Thompson SG. Mendelian Randomization analysis with multiple genetic variants using summarized data. *Genet Epidemiol.* 2013;37:658–665.