# Whole-genome Sequencing-based

### **Association Studies of Cardiovascular Biomarkers**



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#### **PREFACE**

This dissertation is the result of my own work and includes nothing which is the outcome of work done in collaboration except where specifically indicated in the text.

This dissertation is not substantially the same as any that I have submitted, or, is being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other University or similar institution except as declared in the Preface and specified in the text. I further state that no substantial part of my dissertation has already been submitted, or, is being concurrently submitted for any such degree, diploma or other qualification at the University of Cambridge or any other University of similar institution except as declared in the Preface and specified in the text.

The dissertation does not exceed the page limit of 300 specified by the Biology Degree Committee

#### **ABSTRACT**

**Background**: Genome-wide association studies (GWAS) have significantly advanced the genetic study of complex human traits. With the advent of whole-genome sequencing (WGS) technologies and the increased capacity to identify rare variants, GWAS that use WGS data are expected to provide further opportunities for the discovery of variants that have larger and even causal effects. The UK10K project is one of the largest studies that use WGS to investigate the contribution of low frequency and rare genetic variants to medical traits.

Research aims: My research aims to address the utility of WGS-based imputation and associations for identifying the genetic determinants of a select quantitative traits that are associated with cardiovascular risks. Under the UK10K project framework, I study a suite of circulating biomarkers that have been reported for association with CVD. Specifically, I seek to evaluate the following three broad aspects: 1. what are the characteristics of phasing and imputation with WGS data? 2. what novel analytic methods could be applied to a large scale WGS based association study on a rich of phenotypes? 3. can I identify novel and potentially stronger effect genetic variants that are associated with the chosen CVD traits?

**Methods**: My study leverages existing WGS data from the UK10K project (N = ~4,000) and further uses it as a reference to impute more samples (N > 10,000) that have genome-wide SNP array data. In doing so, I first evaluate the quality of the WGS data and its utility for imputation, by comparing it to WGS data from the 1000 Genomes Project. Then, I examine the associations between genotypes and phenotypes for 13 quantitative traits, first in samples having WGS and then in samples having imputed data. The 13 CVD related biomarkers include four lipid traits (high-density lipoprotein cholesterol (HDL), low-density lipoprotein cholesterol (LDL), total cholesterol (TC), triglycerides (TG)), one inflammatory biomarker (C-reactive protein (CRP)), and eight haematological traits (hemoglobin (HGB), mean corpuscular hemoglobin (MCH), mean corpuscular hemoglobin concentration (MCHC), mean corpuscular volume (MCV), packed cell volume (PCV), platelet counts (PLT), red blood cell counts (RBC), white blood cell counts (WBC)).

# To my dear parents: YuanYu Huang & Youquan Deng

To my wife: Weilin Chen

To my daughter Valerie and my son Jimmy

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### **Table of Contents**

1	Intro	oduction	. 21
	1.1	The burden of cardiovascular disease in modern society	21
	1.2	Established and emerging risk factors for CVD	22
	1.3	The allelic architecture of complex traits	26
	1.4	Genome-wide association studies (GWAS)	28
	1.5	GWAS studies of CVD events and cardiovascular biomarkers	30
	1.6	Rare variants and the motivation for whole genome sequencing (WGS)	32
	1.7	The UK10K Project	35
	1.8	This thesis	39
2	Met	hods	. 41
	2.1	Introduction	42
	2.2	Study samples	43
	2.2.1	UK10K WGS cohorts	43
	2.2.2	UK10K GWA cohorts	43
	2.2.3	Expanded discovery cohorts	44
	2.3	Genetic data	49
	2.3.1	UK10K WGS data	49
	2.3.2	Imputation using WGS reference panel	51
	2.4	Phenotype harmonization	51
	2.5	Statistical methods for association studies	55
	2.5.1	Power estimation.	55
	2.5.2	Single-variant based association studies	58
	2.5.3	Loci selection for single marker results	59
	2.5.4	Rare variants aggregation analysis	62
	2.5.5	Loci selection for rare variant aggregation results	63
	2.5.6		
	2.6	Conclusion & Discussion	67
3	lmp	utation	. 71
	3.1	Introduction	72
	3.1.1	How imputation works	72
	3.1.2	Use of imputation in GWAS	72
	3.1.3	Imputation with WGS reference panels	72
	3.1.4	Aims of this study	73
	3.2	Methods	75

	3.2.1	WGS Reference Haplotypes	75
	3.2.2	2 Test GWAS datasets	77
	3.2.3	Running imputation	78
;	3.3	Results	80
	3.3.1	Characteristics of UK10K WGS panel	80
	3.3.2	Imputation evaluation on UK10K vs. 1000GP reference panels	83
	3.3.3	8 Evaluation of metrics for choosing reference haplotypes	84
	3.3.4	Evaluation of combining two reference panels	88
;	3.4	Conclusion & Discussion	90
4	Lipi	ds	93
	4.1	An introduction to lipids.	93
	4.1.1	Biology and physiology circulating lipids	93
	4.1.2	2 Lipids as risk factors for CVD	94
	4.1.3	Genetic determinants of lipids levels	97
	4.1.4	Aims of this study	103
	4.2	Methods	104
	4.2.1	Cohorts & phenotype measurements	104
	4.2.2	2 Single marker based discovery and follow-up	108
	4.2.3	Rare variant aggregation based discovery and follow-up	109
	4.2.4	Fine-mapping of known loci	110
	4.4	Results	111
	4.4.1	Novel loci and novel variants from single marker analysis	111
	4.3.2	2 Fine mapping of known and novel loci	123
	4.3.3	Novel loci based on rare variants aggregation test	126
	4.4	Conclusion & Discussion	130
	4.4.1	Summary of main findings	130
	4.4.2	2 Interpretation of results	130
	4.4.3	Future direction	133
5	Full	Blood Counts	135
;	5.1	An introduction to full blood counts	135
	5.1.1	Biology and physiology of FBC	135
	5.1.2	PBC traits as risk factors for CVD	136
	5.1.3	Genetic determinants of FBC	137
	5.1.4	Aims of this study	140
;	5.2	Methods	141
	5.2.1	Cohorts & phenotype measurements	141

	5.2.2	Single marker based discovery and follow-up	143
	5.2.3	Rare variant aggregation based discovery and follow-up	143
	5.2.4	Fine-mapping of known loci	144
	5.3	Results	146
	5.3.1	Novel loci and novel variants from single marker analysis	146
	5.3.2	Fine mapping of known and novel loci	160
	5.3.3	Novel loci based on rare variants aggregation test	162
	5.3.4	Host-response eQTL	166
	5.4	Conclusion & Discussion	168
	5.4.1	Summary of main findings	168
	5.4.2	Interpretation of results	168
	5.4.3	Future direction	169
6	CRF	o	173
	6.1	An introduction on CRP	173
	6.1.1	Biology and physiology of circulating CRP	173
	6.1.2	CRP as risk factors for CVD	174
	6.1.3	Genetic determinants of CRP	175
	6.1.4	Aims of this study	178
	6.2	Methods	178
	6.2.1	Cohorts & phenotype measurements	178
	6.2.2	Single marker based discovery and follow-up	179
	6.2.3	Rare variant aggregation based discovery and follow-up	180
	6.2.4	Fine-mapping of known loci	180
	6.3	Results	182
	6.3.1	Novel loci and novel variants from single marker analysis	182
	6.3.2	Fine mapping of known and novel loci	192
	6.3.3		
	6.4	Conclusion & Discussion	
	6.4.1	Summary of main findings	
	6.4.2	•	
	6.4.3	Future direction.	196
CI	hapter	7. Summary & Discussion	199
	7.1	This thesis	199
	7.2	Implication of findings for genetics of complex traits	199
	7.3	Strength and limitations of the current study	203
	7.4	Recommendations for future research in the field	205

	Append	ix 1 Manhattan plots of individual GWA	238
Αp	pendix	<u> </u>	238
References			211
	7.4.6	Thinking genetics in the context of the trend of metabolic syndrome	
	7.4.5	Pleiotropy analysis	
	7.4.4	System biology approach that integrates various functional data	
	7.4.3		
	7.4.2	High genotyping accuracy through high-depth WGS	206
	7.4.1	Larger sample size with increased power	205

### LIST OF TABLES

Table 1.1 List of traits in UK10K-Cohorts	37
Table 3.1 Sequence quality and variation metrics for UK10K Cohorts	81
Table 3.2 Descriptive for imputation reference panels	
Table 3.2 Descriptive for imputation reference panels	02
Table 4.1 Gene discovery in monogenic dyslipidemias	100
Table 4.2 GWAS studies of lipids	102
Table 4.3 NGS studies on lipids	103
Table 4.4 Characteristics of participating cohorts	106
Table 4.5 Phenotype harmonization protocol for lipids traits	107
Table 4.6 Putative novel variants of low or rare frequency from UK10K WGS	114
Table 4.7 Replication results of WGS top hits	115
Table 4.8 SKAT results for single point test top hits	116
Table 4.9 Expanded discovery(14-way meta-analysis) top hits	120
Table 4.10 Cohort specific results for four top variants based on 14-way meta-analysis	121
Table 4.11 Predictive causal variants based on fine mapping	125
Table 5.1 CWAS and in an EDC and	1.40
Table 5.1 GWAS studies on FBC traits	
Table 5.2 Phenotype harmonization protocol for FBC traits	
Table 5.3 Characteristics of participating cohorts	
Table 5.4 Putative novel variants of low or rare frequency from UK10K WGS	
Table 5.5 Novel FBC variants based on expanded discovery (12-way meta-analysis)	
Table 5.6 Cohort specific results of top hits from expanded discovery analysis	
Table 5.7 Top hits from a further expanded discovery (18-way meta-analysis)	
Table 5.8 LD of three putative novel variants in known locus	157
Table 5.9 Putative causal variants based on fine mapping	161
Table 5.10 Rare variants aggregation tests based top hits for FBC traits	164
Table 6.1 GWAS studies of CRP	177
Table 6.2 Characteristics of participating cohorts	
Table 6.3 Novel associations of CRP from expanded discovery meta-analysis	187

Table 6.4 Cohort specific results of novel associations from expanded discovery	188
Table 6.5 LD between novel and known variants in HIST1H3G	191
Table 6.6 Putative causal variants based on fine mapping	193

### LIST OF FIGURES

Figure 1.1 Established and new/emerging risk factors for CVD	24
Figure 1.2 The cardiovascular disease continuum	25
Figure 1.3 The allelic spectrum of human disease predisposition	34
Figure 2.1 UK10K WGS samples data production	50
Figure 2.2 Evaluation of batch effects and trait distribution	53
Figure 2.3 Phenotype harmonization protocol	54
Figure 2.4 Power calculation in the UK10K cohorts	57
Figure 2.5 Flow of step-wise conditional analysis	61
Figure 3.1 imputation evaluation workflow	79
Figure 3.2 Imputation performance for different reference panels and strategies	86
Figure 3.3 Illustration of reference states (haplotypes) copied by IMPUTE2	87
Figure 3.4 Performance of combining UK10K and 1000GP panels	89
Figure 4.1 Lipids loci overlap between candidate gene studies and GWAS	101
Figure 4.2. Single point association results of lipids on WGS samples	113
Figure 4.3 Association results of 14-way meta-analysis of the four main lipid traits	119
Figure 4.4 Regional plots of two loci with replicated novel associations	122
Figure 4.5 Number of putative causal variants within fine-mapped loci	123
Figure 4.6 QQ plots of SKAT tests for lipids	127
Figure 4.7 Rare variants aggregation test results for lipids	128
Figure 4.8 Regional plot of SKAT-O locus EGF-ELOVL6	129
Figure 4.9 Statistical power and novel variants from single marker analysis	132
Figure 5.1 Association results for WGS based samples for FBC traits	148
Figure 5.2 Results for 12-way meta-analysis.	152
Figure 5.3 Regional plots of two known loci with putative novel variants	158
Figure 5.4 Regional plots of top hits from 18-way meta-analysis	159
Figure 5.5 Rare variants aggregation test results for FBC traits	163
Figure 5.6 Regional plots of <i>RHBDL2</i>	165
Figure 5.7 eSNPs associated with host response to TB and Malaria	167

Figure 5.8 Statistical power and novel variants from single marker analysis	171
Figure 6.1 Association Results of CRP based on WGS samples	183
Figure 6.2 Single marker association results of CRP from expanded meta-analysis	186
Figure 6.3 Regional plots of two novel associations of CRP	190
Figure 6.4 Rare variants aggregation test results for CRP	194
Figure 6.5 Statistical power and novel variants from single marker analysis	197
Figure 7.1 Allelic spectrum for single marker association results in UK10K	201
Figure 7.2 QQ plot of association tests for 31 UK10K core traits	202

### LIST OF ABBREVIATIONS

1000GP 1000 Genomes Project

ADH Autosomal dominant hypercholesterolemia

ALSPAC Avon Longitudinal Study of Parents and Children

Apo-A1 apolipoprotein A-I
Apo-B apolipoprotein B
Apo-E apolipoprotein E

AMD age-related macular degeneration

BF Bayes' factor

BGI Beijing Genomics Institute

BP blood pressure

CAD coronary artery disease
CBR Cambridge BioResource

CHD coronary heart disease
CNV copy number variation
CKD chronic kidney disease

CRP C-reactive protein

CVD cardiovascular disease

DALYs disability-adjusted life years
DHS DNaseI hypersensitive sites

EAF effect allele frequency

EMR electronic medical records

ERFC Emerging Risk Factors Collaboration

FHS Framingham Heart Study

FVG Friuli Venezia Giulia

GWAS genome-wide association studies

HDL high-density lipoprotein

HGB hemoglobin

HELIC HELlenic Isolated Cohorts study

HMM hidden markov model

HWE hardy-weinberg equilibrium

IBD identify by descent

IBS identify by state

InDel insertion/deletion polymorphism

INGI Italian Network of Genetic Isolates

LD linkage disequilibrium LDL low-density lipoprotein

22 2 10 W demondy inpoprovem

LMT lipid modification therapies

LoF loss of function

LOLIPOP London Life Sciences Population study

LURIC Ludwigshafen Risk and Cardiovascular Health

MAF minor allele frequency

HGB haemoglobin

MCH mean corpuscular hemoglobin

MCHC mean corpuscular hemoglobin concentration

MCV mean cell volume

MDS multidimensional scaling

MI myocardial infarction

MR mendelian randomisation

OR odds ratio

PCA principle component analysis

PCV packed cell volume

PLT platelet count

PROCARDIS Precocious Coronary Artery Disease Study

QC quality control
RBC red blood cell

RCT reverse cholesterol transport

SKAT sequence kernel association test

SKAT-O sequence kernel association test - optimized

SNP single nucleotide polymorphism

SNV single nucleotide variation

TC total cholesterol

TFBS transcription factor binding sites

TG triglycerides

TSS transcription start site

TwinsUK UK Adult Twin Registry

UK10K 10,000 UK genome sequencing project

UTR untranslated regions

VB Val Borbera

WBC white blood cell

WGS Whole Genome Sequencing

WTCCC Wellcome Trust Case Control Consortium

WTSI Wellcome Trust Sanger Institute

#### PUBLICATIONS ARISING FROM THIS DISSERTATION

- o \* Co-first author
- For papers with more than 10 authors, my name is listed together with the first 3 and the last 3 authors. When there are more than 3 co-starred first-authors, all of them are listed.
  - Gormley P\*, Downes K\*, Huang J\*, Kettunen J, Aki S, ..., Palotie A, Ripatti S, Soranzo N. A polygenic panel of platelet-associated SNPs is associated with risk of incident ischaemic stroke. (*submitted*)
  - 2. Walter K\*, Min M\*, **Huang J\***, Lucy Crooks\*, ..., Timpson NJ, Durbin R , Soranzo N. The UK10K project: rare variants in health and disease. (*under revision*)
  - 3. **Huang J**, Howie B, Memari M, ..., Timpson NJ, Marchini J, Soranzo N, UK10K Project. A reference panel of 3,781 genomes from the UK10K Project increases imputation performance over the 1000 Genomes Project. *Nature Communications*. (accepted)
  - 4. Taylor P, Porcu E, Chew S, ... **Huang J**, ..., Soranzo N, Timpson NJ, Wilson S, the UK10K Consortium. Whole genome sequence based analysis of thyroid function. *Nature Communications*. 2015 Mar 6;6:5681
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  - O'Connell J, Gurdasani D, Delaneau O, ..., Huang J, ..., Soranzo N, Sandhu MS, Marchini J. A general approach for haplotype phasing across the full spectrum of relatedness. <u>PLOS Genetics</u> 2014 Apr 17;10(4):e1004234

### **PUBLICATIONS ARISING ELSEWHERE (from 2012-01 to 2015-01)**

- o \* Co-first author
- o For papers with more than 10 authors, my name is listed together with the first 3 and the last 3 authors. When there are more than 3 co-starred first-authors, all of them are listed.
- 1. Baumert J\*, **Huang J**\*, McKnight B\*, Sabater-Lleal M\*, Steri M\*, ..., Strachan DP, Peters A, Smith NL. No evidence for genome-wide interactions on plasma fibrinogen by smoking, alcohol consumption and body mass index: results from meta-analyses of 80,607 subjects. *PLoS One*. December 31, 2014 DOI: 10.1371
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