













Insights into type 2 diabetes from rare coding variants

Jason Flannick

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Statistical Genetics

Data integration and dissemination

> Rare coding variants

Type 2 Diabetes

Computer Science

Computational Biology









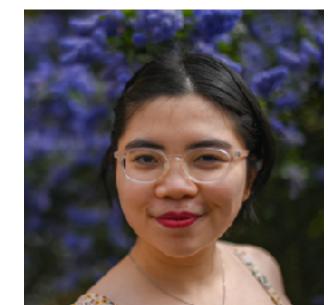
















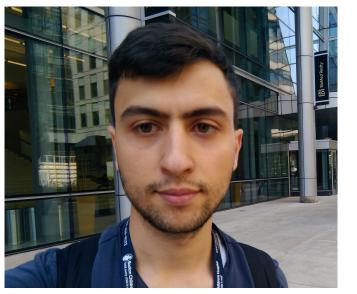


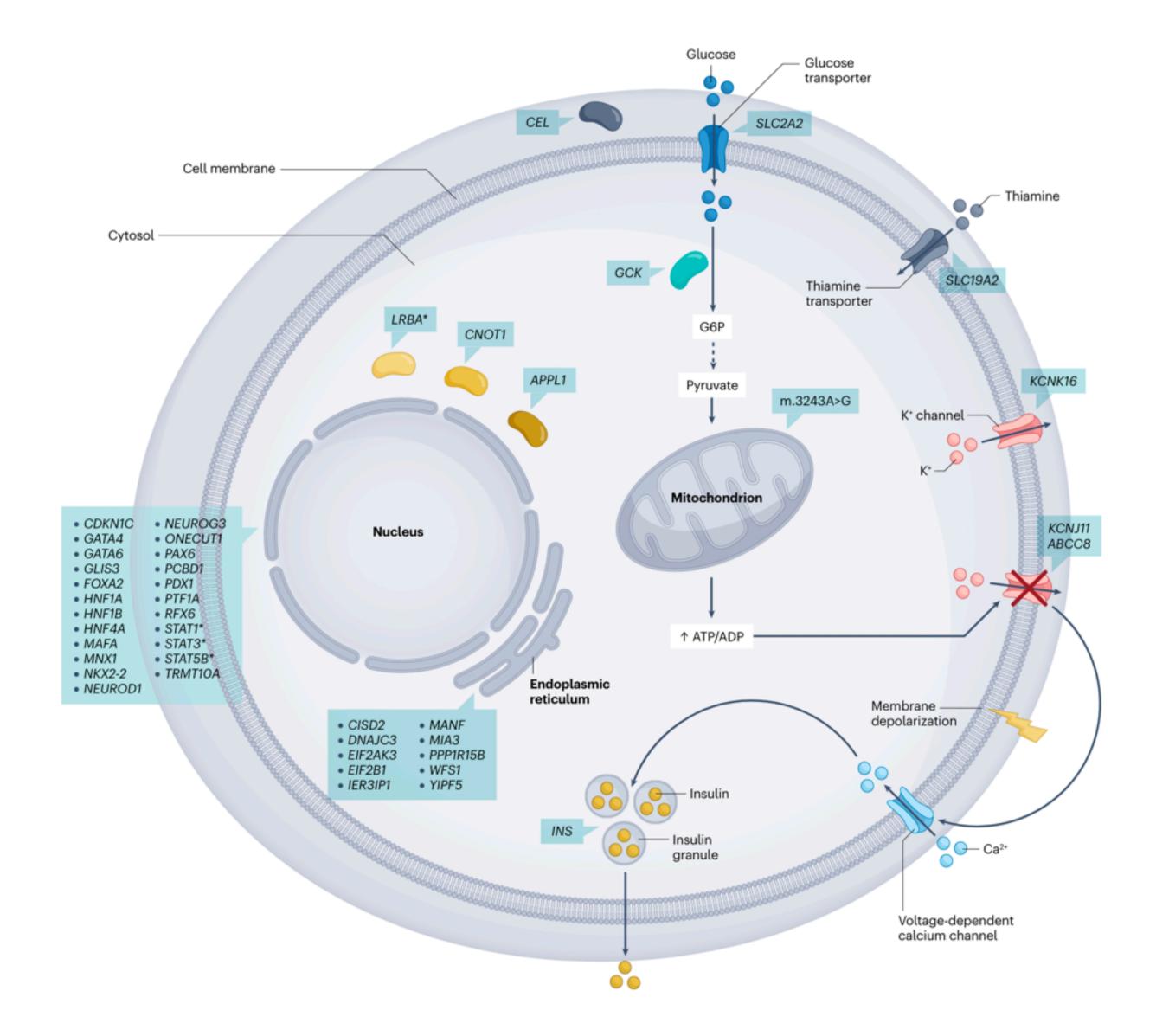


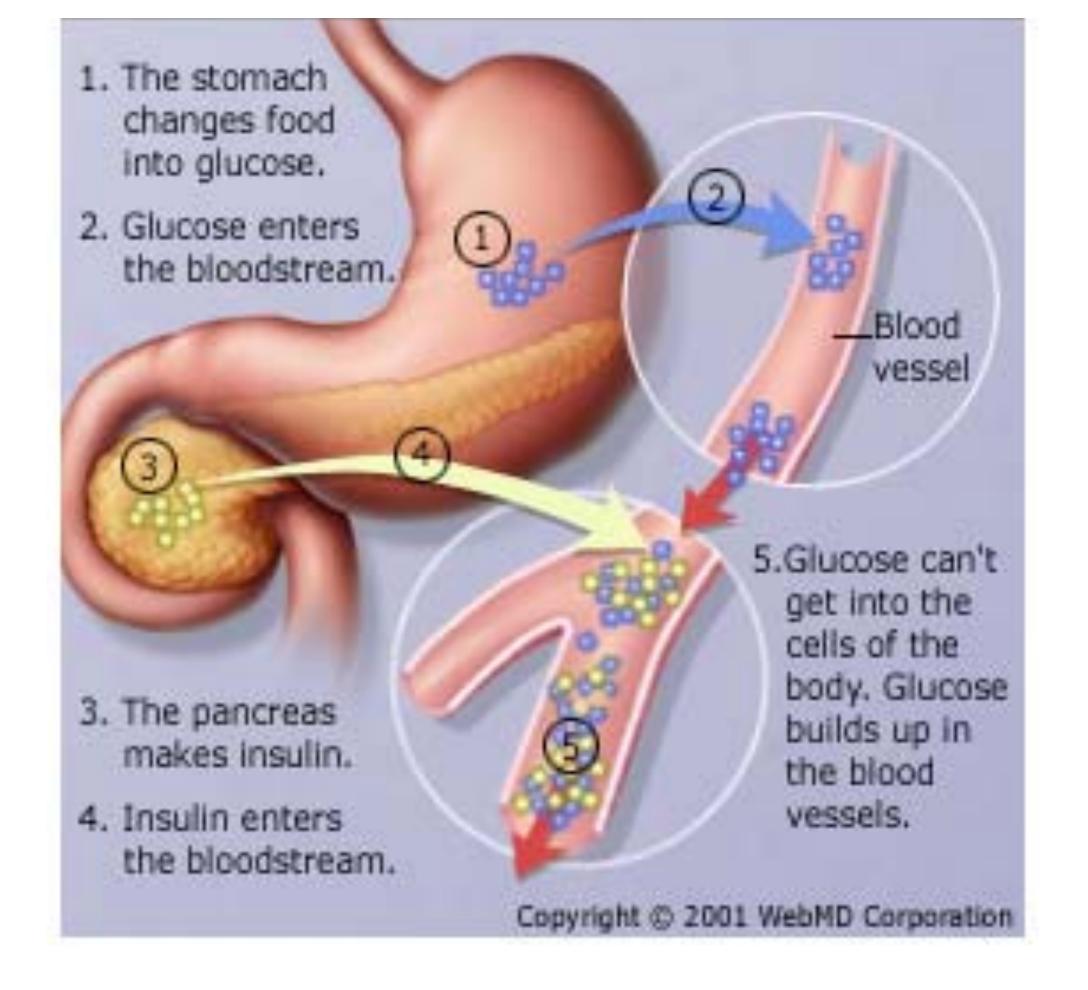


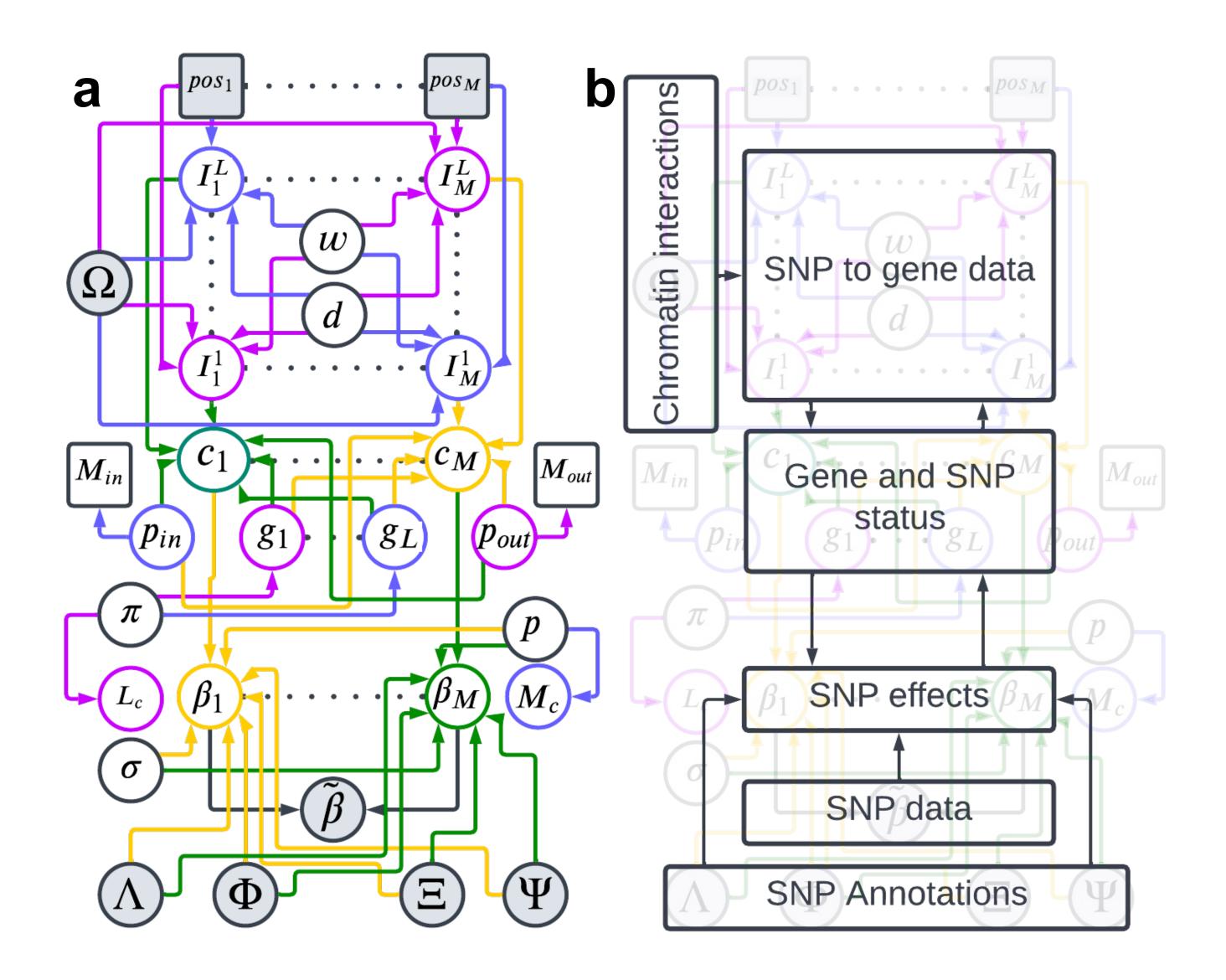












Rare coding variants

Back in 2008...

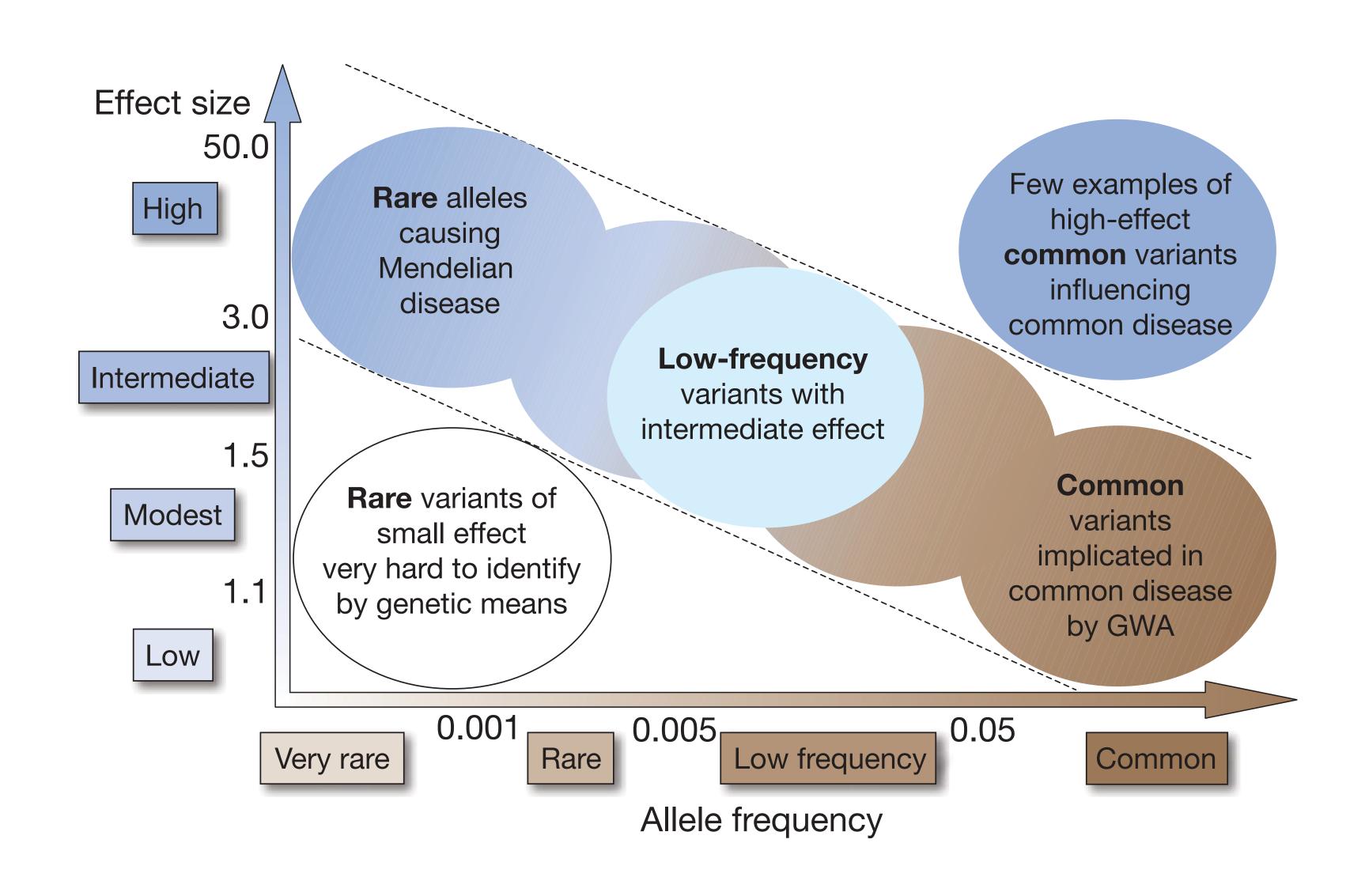


The case of the missing heritability

When scientists opened up the human genome, they expected to find the genetic components of common traits and diseases. But they were nowhere to be seen. **Brendan Maher** shines a light on six places where the missing loot could be stashed away.

Disease	Number of loci	Proportion of heritability explained	Heritability measure	
Age-related macular degeneration ⁷²	5	50%	Sibling recurrence risk	
Crohn's disease ²¹	32	20%	Genetic risk (liability)	
Systemic lupus erythematosus ⁷³	6	15%	Sibling recurrence risk	
Type 2 diabetes ⁷⁴	18	6%	Sibling recurrence risk	
HDL cholesterol ⁷⁵	7	5.2%	Residual* phenotypic variance	
Height ¹⁵	40	5%	Phenotypic variance	
Early onset myocardial infarction ⁷⁶	9	2.8%	Phenotypic variance	
Fasting glucose ⁷⁷	4	1.5%	Phenotypic variance	

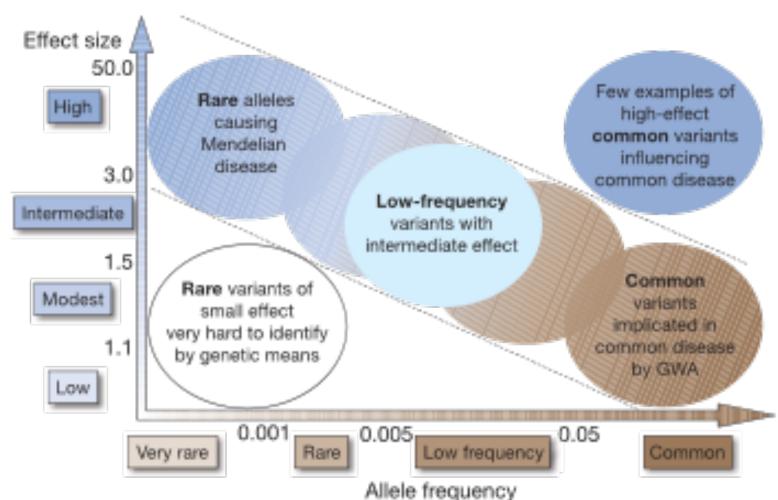
Classes of genetic variation





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Common Genetic Variation and Human Traits

David B. Goldstein, Ph.D.

Genetic Heterogeneity in Human Disease

Jon McClellan^{1,*} and Mary-Claire King^{2,*}

¹Department of Psychiatry

²Departments of Medicine and Genome Sciences

University of Washington, Seattle, WA 98195-7720, USA

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Clan Genomics and the Complex Architecture of Human Disease

James R. Lupski, 1,2,3,* John W. Belmont, 1,2 Eric Boerwinkle, 4,5 and Richard A. Gibbs 1,5,*

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DOI 10.1016/j.cell.2010.03.032

PLOS BIOLOGY

Rare Variants Create Synthetic Genome-Wide Associations

Samuel P. Dickson^{1,2}, Kai Wang³, Ian Krantz^{3,4,5}, Hakon Hakonarson^{3,4,5}, David B. Goldstein¹*

Common and rare variants in multifactorial susceptibility to common diseases

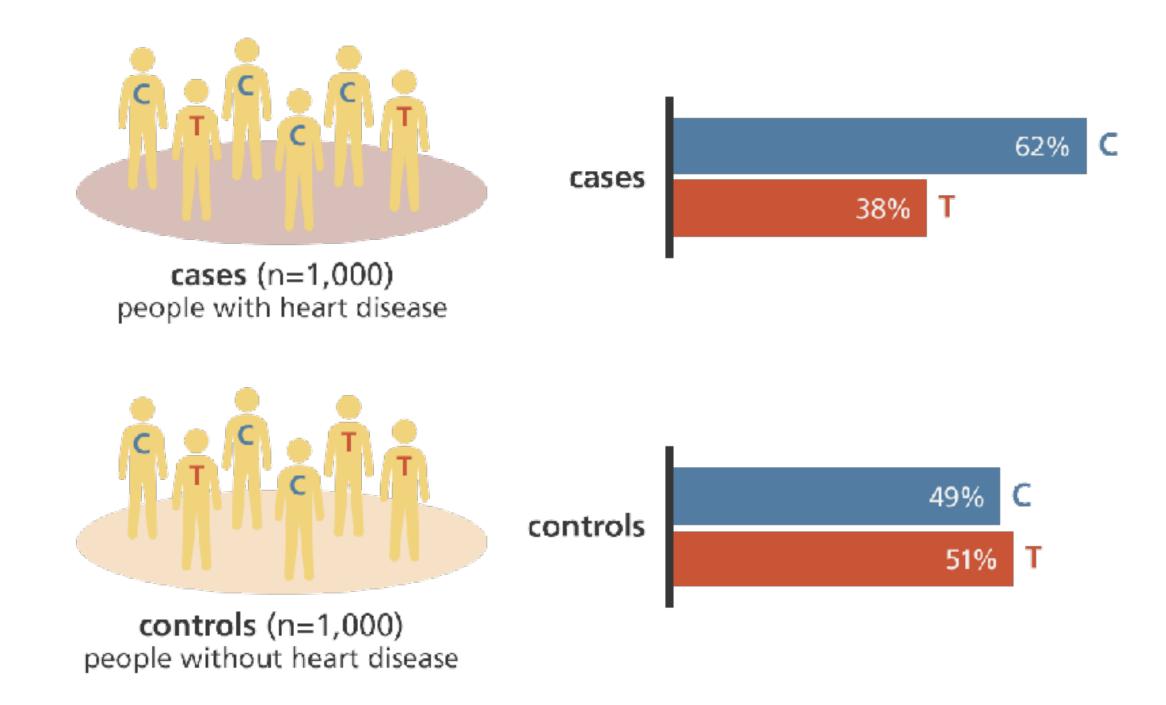
Walter Bodmer & Carolina Bonilla

O APPLICATIONS OF NEXT-GENERATION SEQUENCING

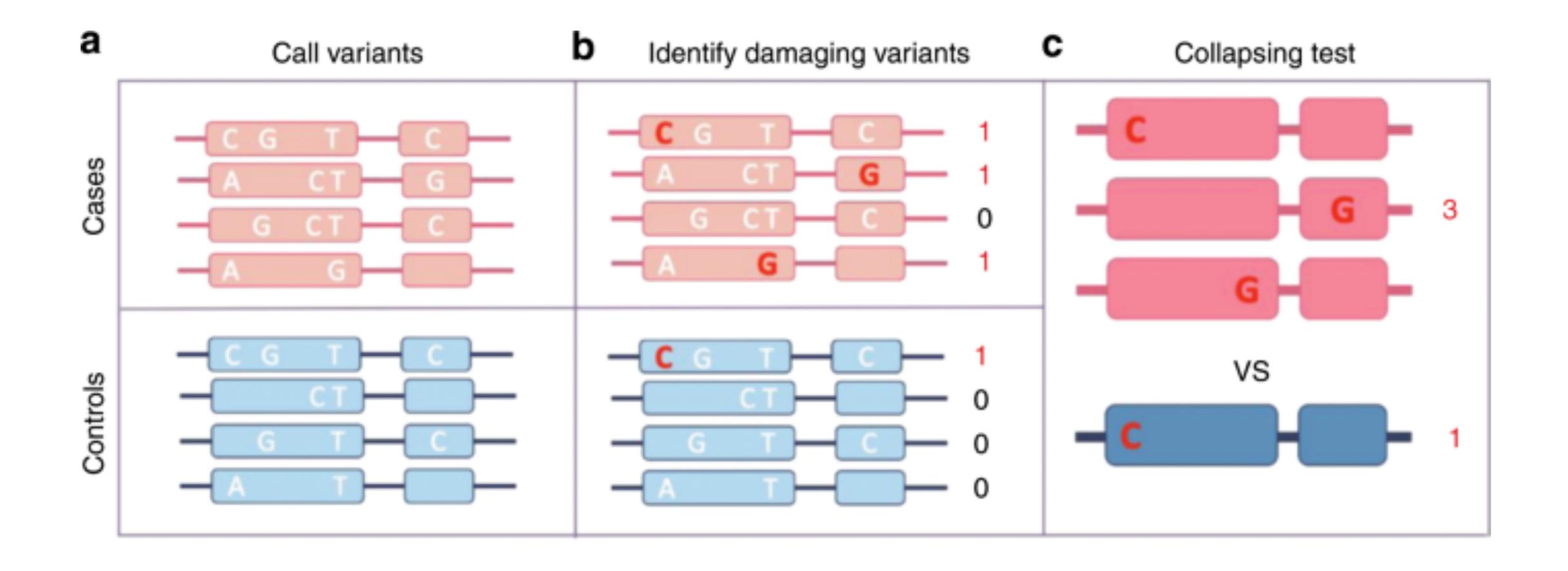
Uncovering the roles of rare variants in common disease through whole-genome sequencing

Elizabeth T. Cirulli and David B. Goldstein

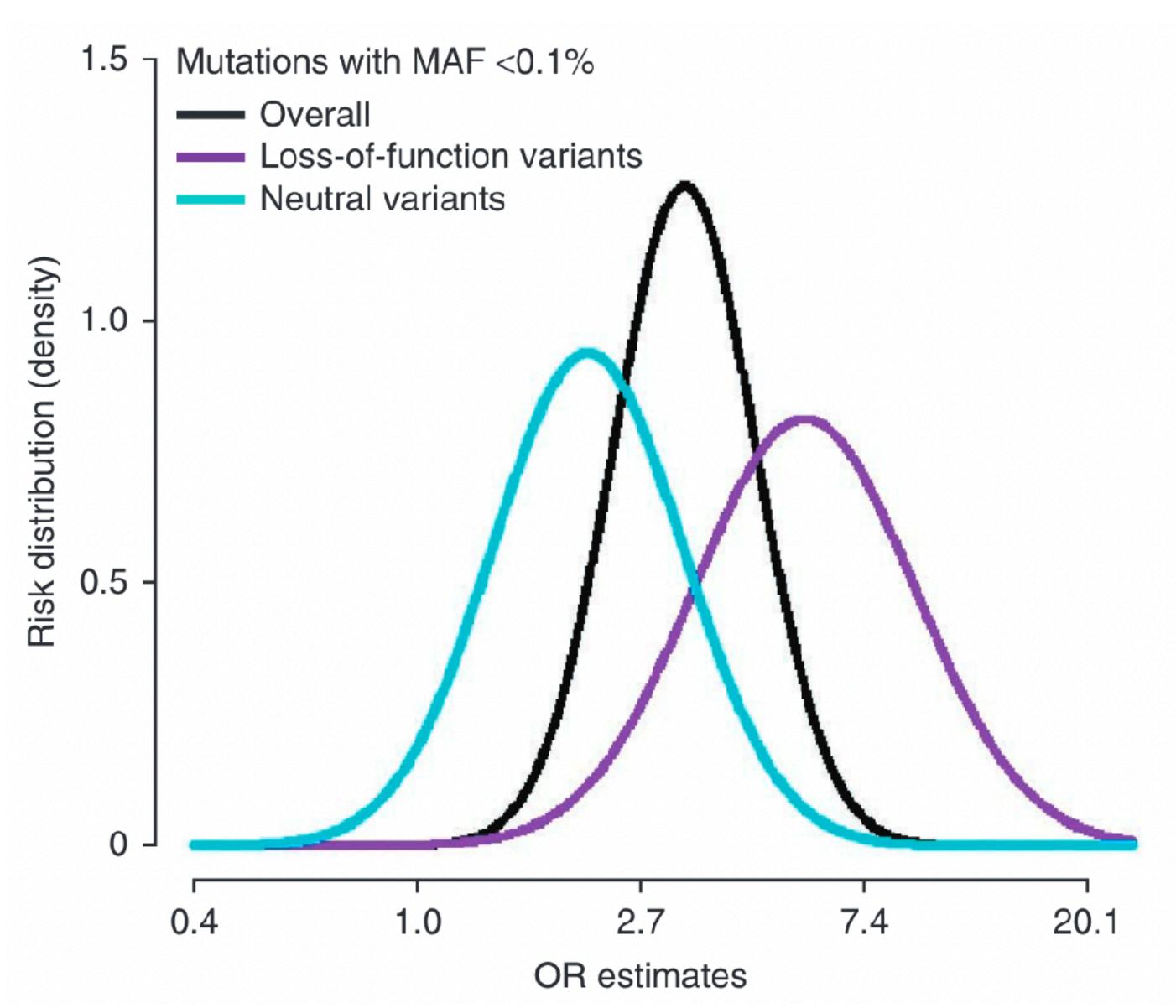
GWAS: individual common variant associations



Rare variants: aggregate gene-level associations



Early successes from targeted sequencing



Early successes from targeted sequencing

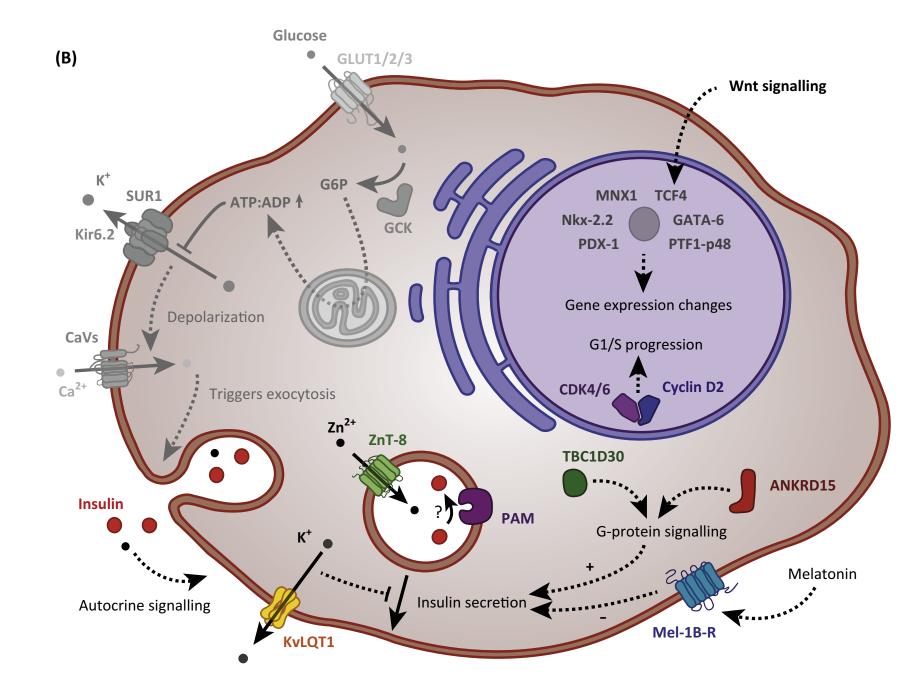
12 loss-of-function SLC30A8 mutations in 149,134 individuals

Aggregate odds ratio: 0.34 $p=1.7 \times 10^{-6}$ a Variants European East Asian South Asian African American Ethnicities Cohorts **b** Frequencies Case Control Flannick et al. Nature Genetics, 2014

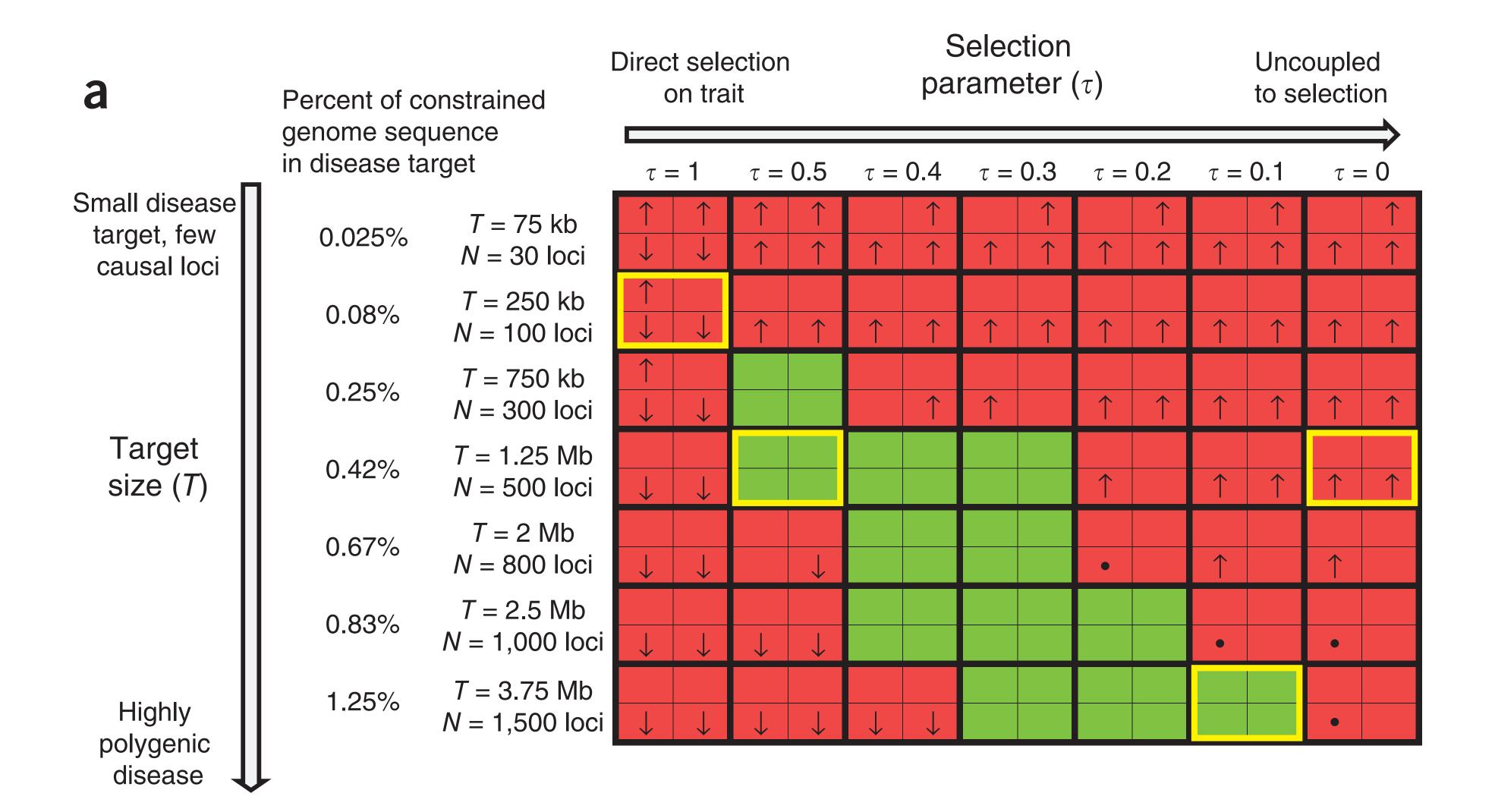
Biological insights

VS.

Genetic architecture











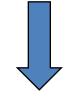
Coding variation

13,000 samples from diverse ancestries



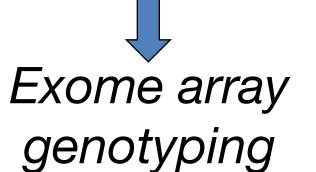
Noncoding variation

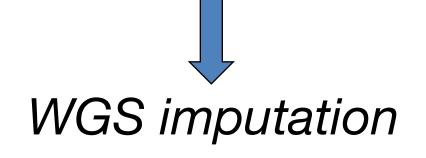
2,700
samples of
European ancestry



Follow-up

82,000 samples





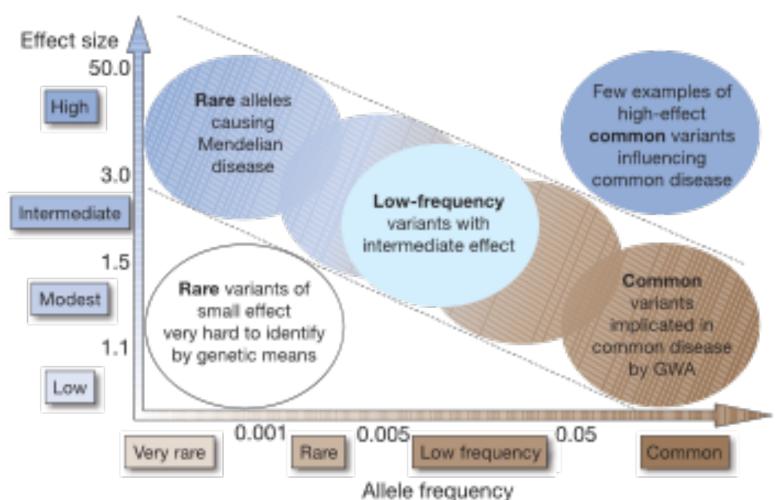
Main finding:

a polygenic, common variant model for T2D



The case of the missing heritability

When scientists opened up the human genome, they expected to find the genetic components of common traits and diseases. But they were nowhere to be seen. **Brendan Maher** shines a light on six places where the missing loot could be stashed away.



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PLOS BIOLOGY

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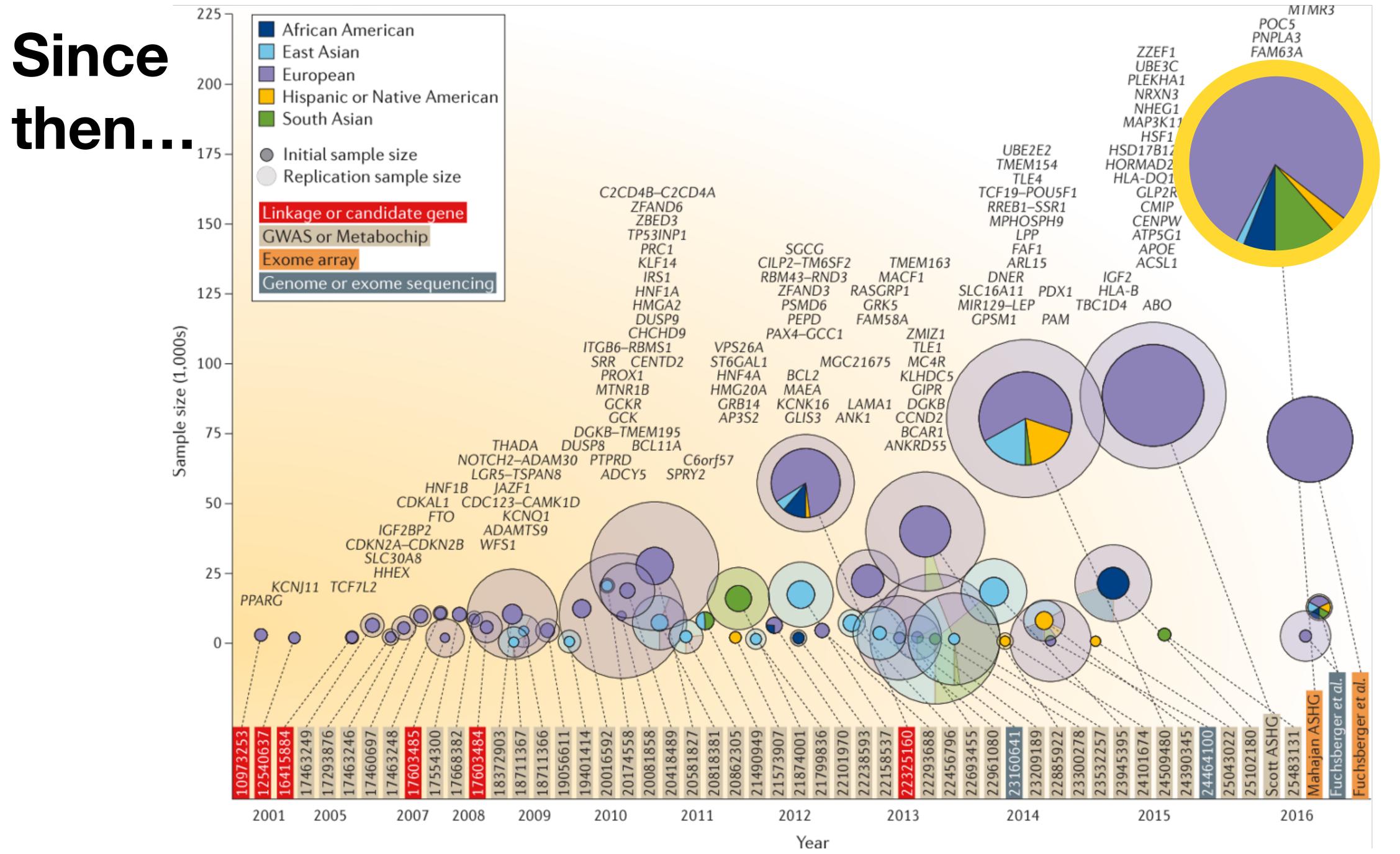
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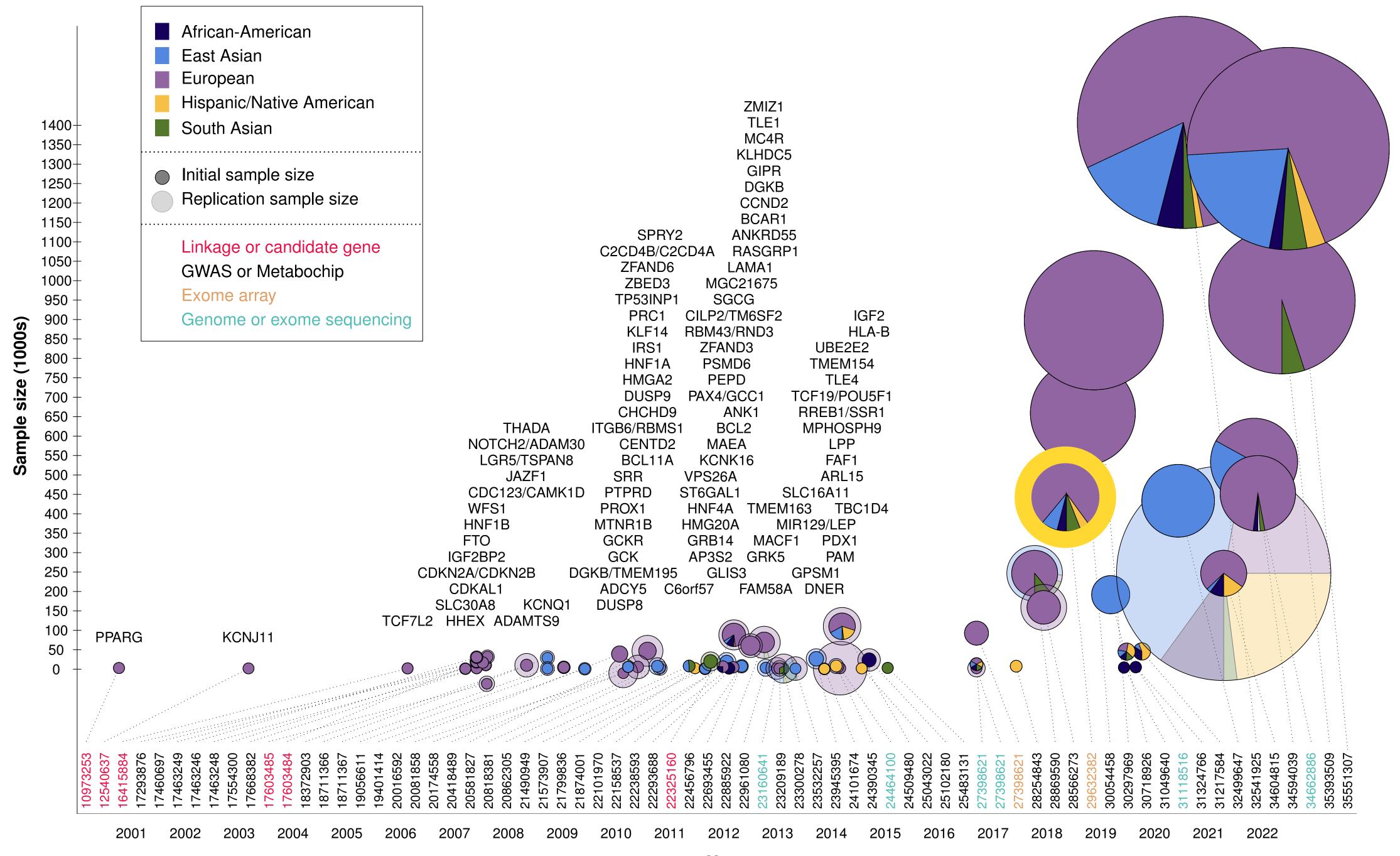
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(10) APPLICATIONS OF NEXT-GENERATION SEQUENCIN

Uncovering the roles of rare variants in common disease through whole-genome sequencing

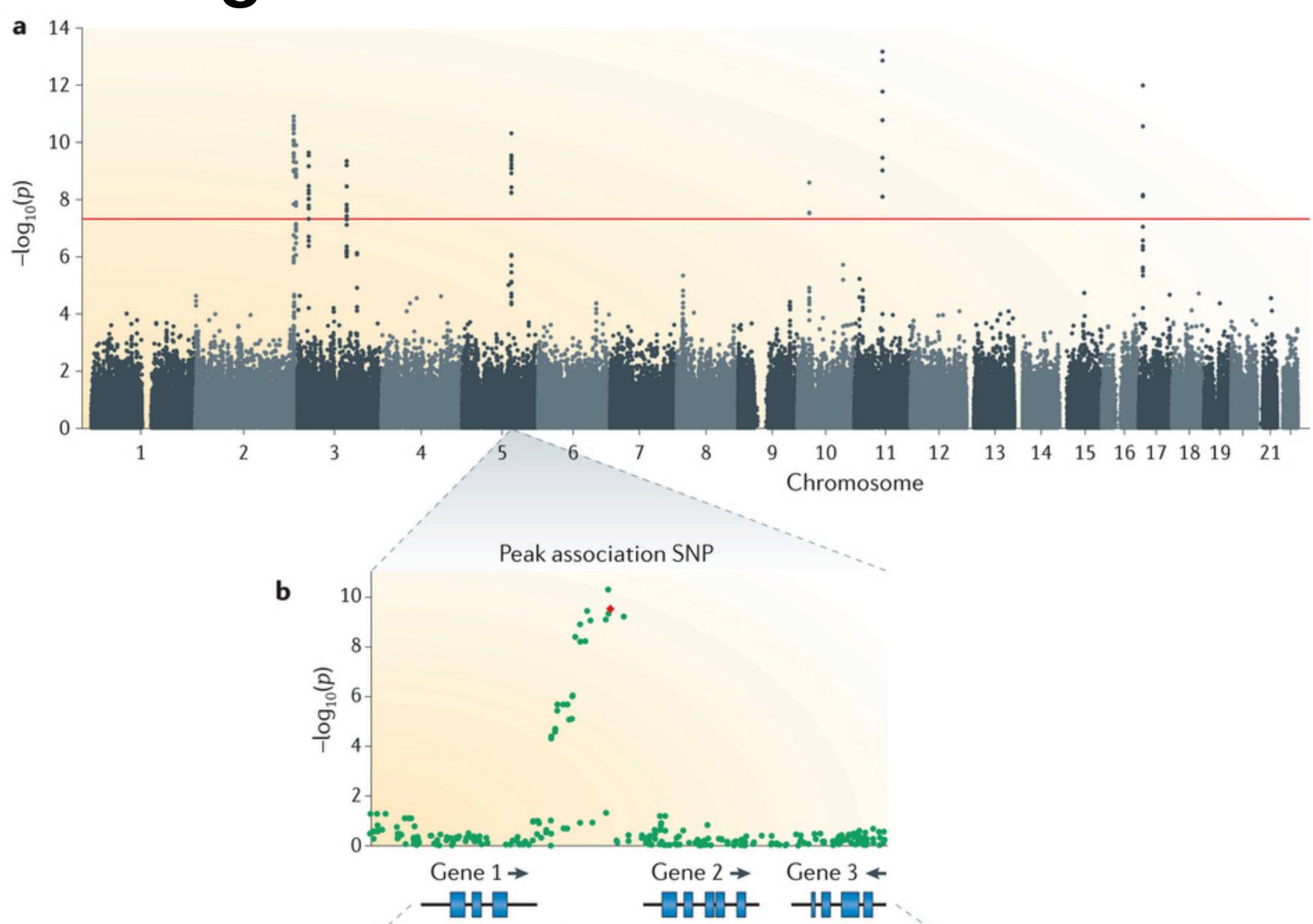
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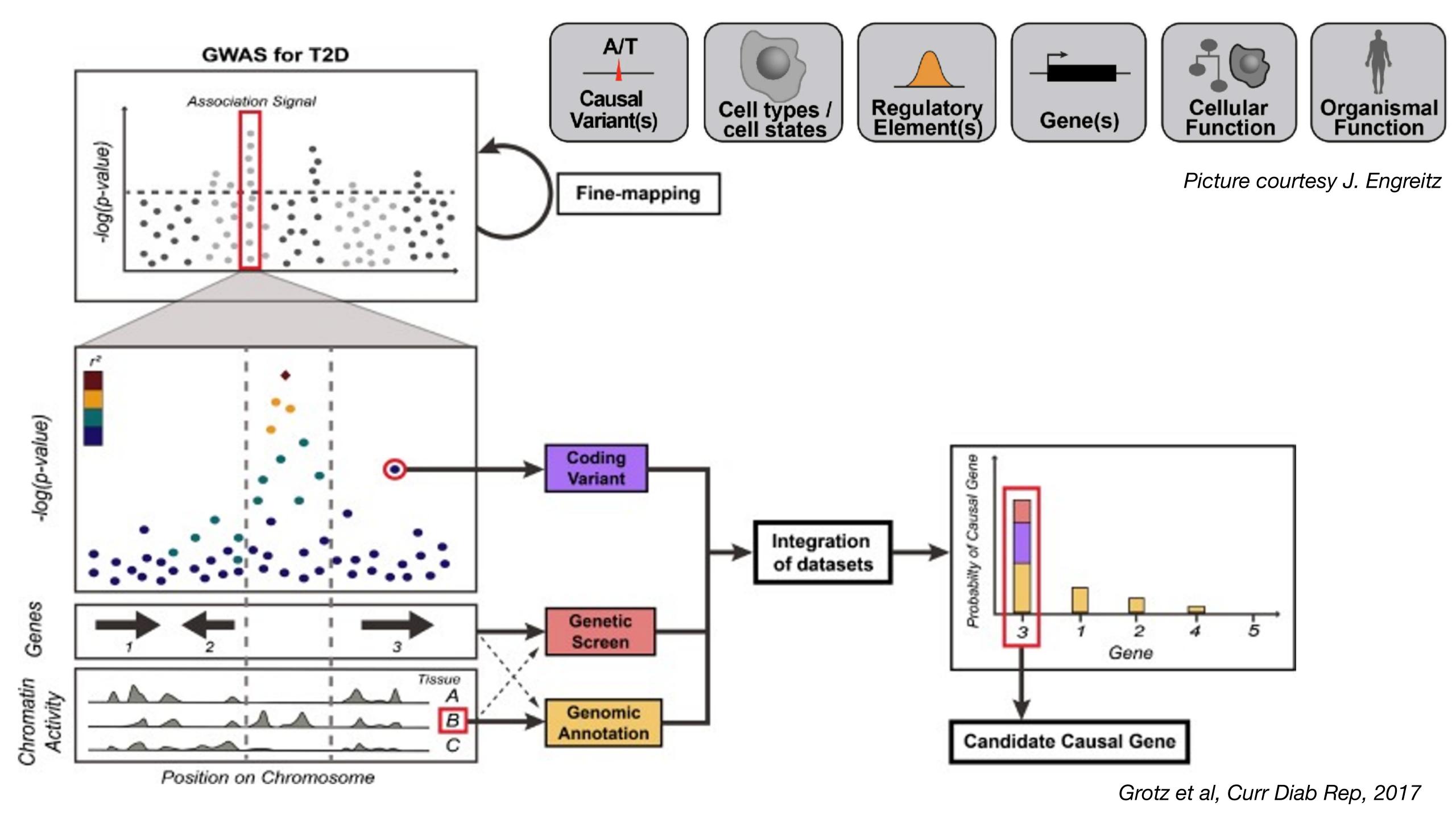




Problem: what are the genes?

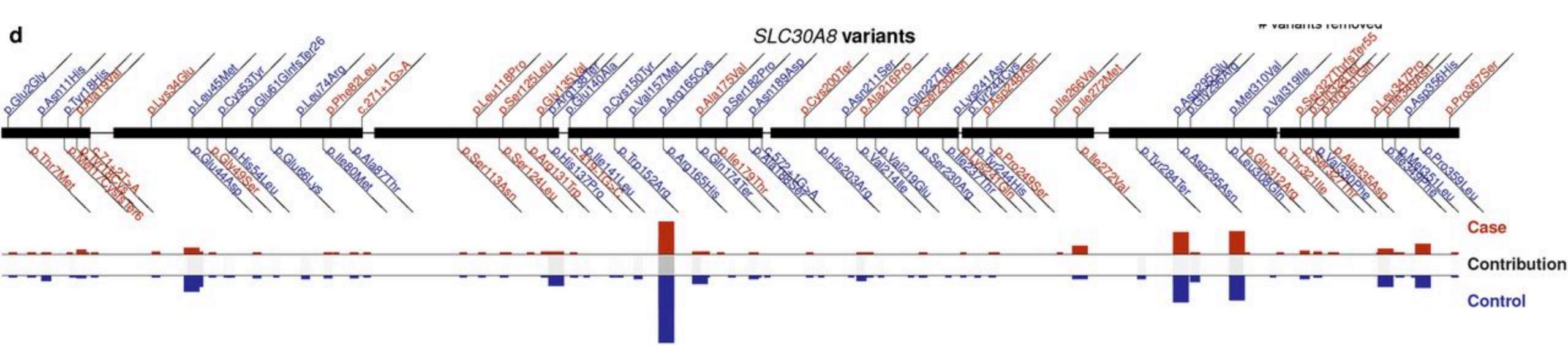
 Usually only one (or a few) variants are causal





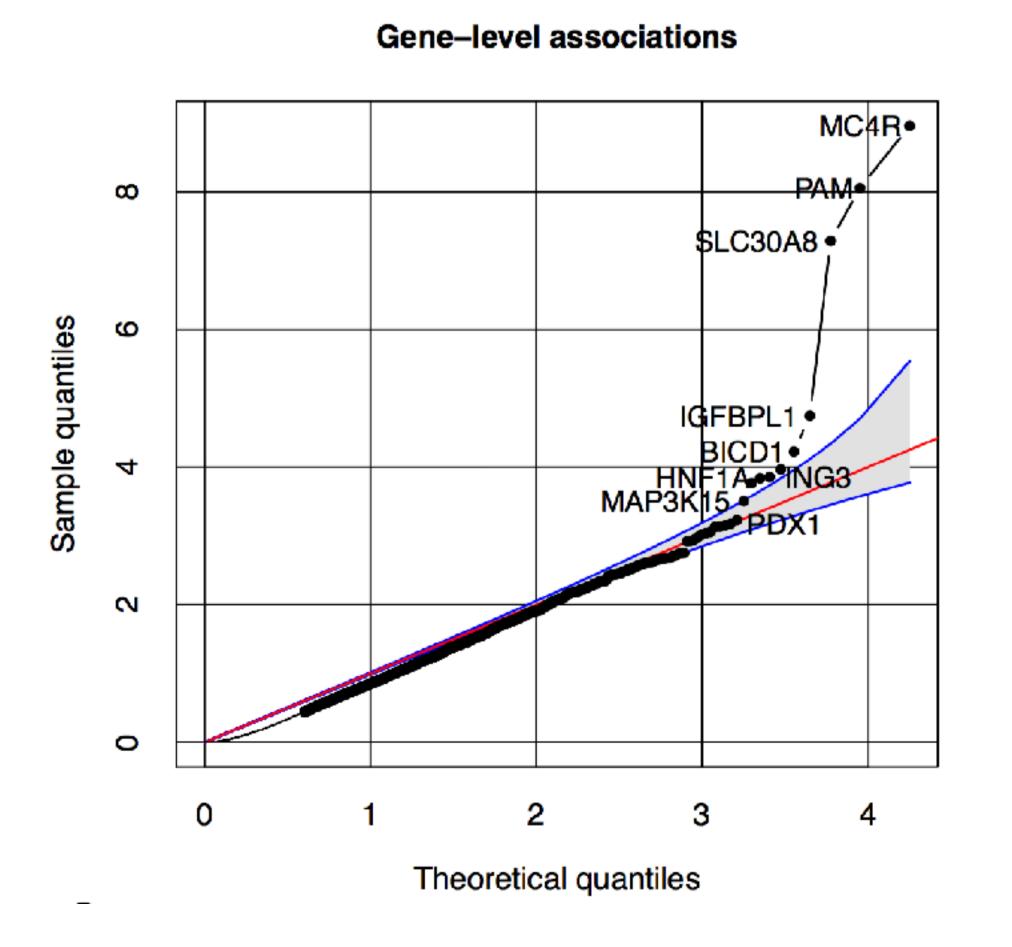
Meanwhile, rare variants...

- When significant: direct links from disease to genes
- When variants inactivate protein: directional link with disease risk



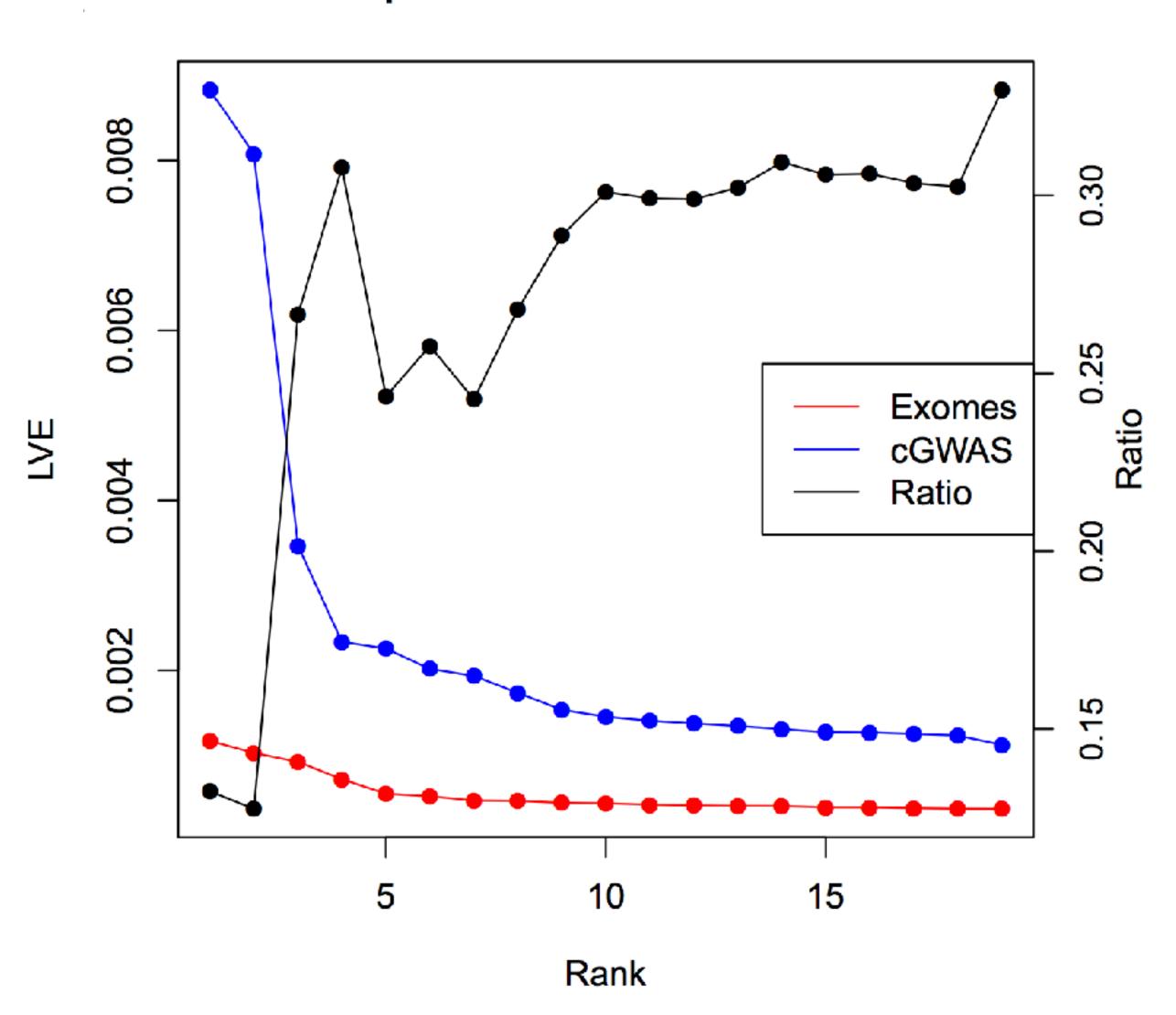
More recent (45,000 sample) exome sequencing

Three exome-wide significant gene-level associations

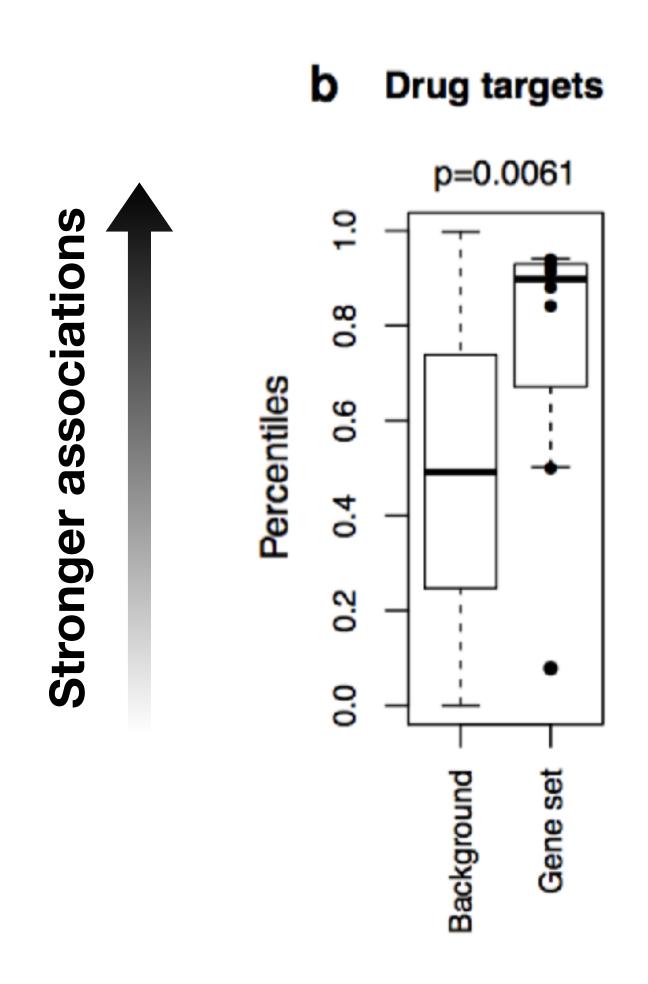


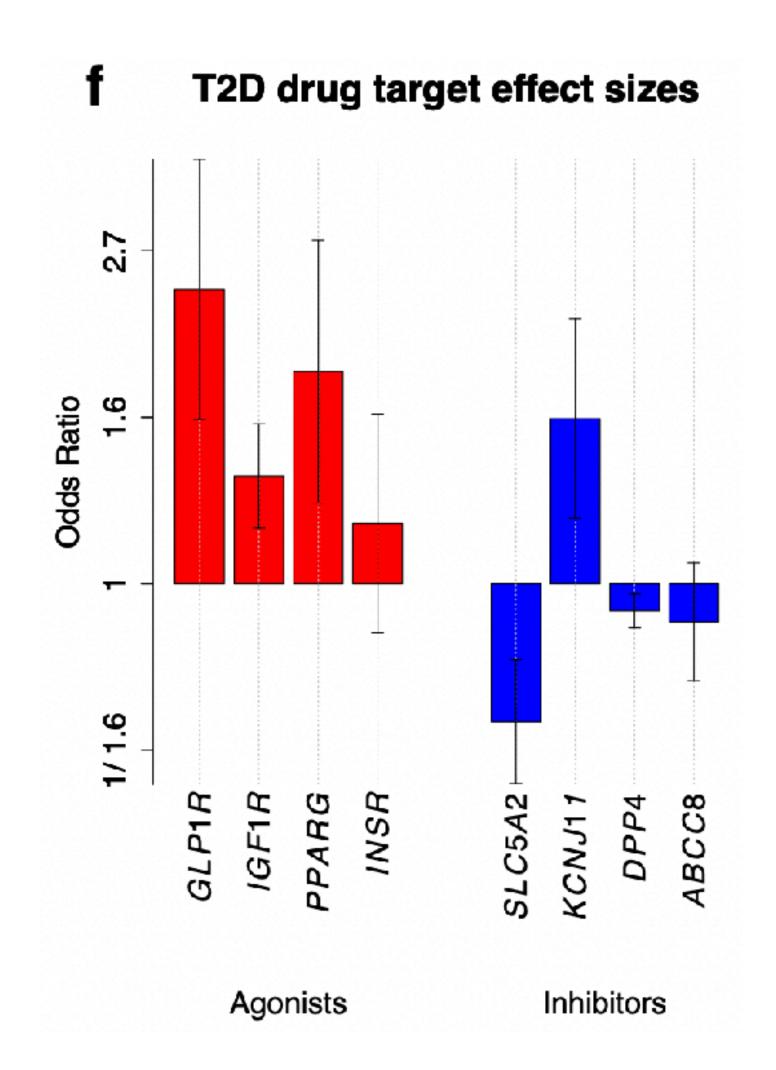
Explaining minimal heritability

LVE of top cGWAS and exomes associations

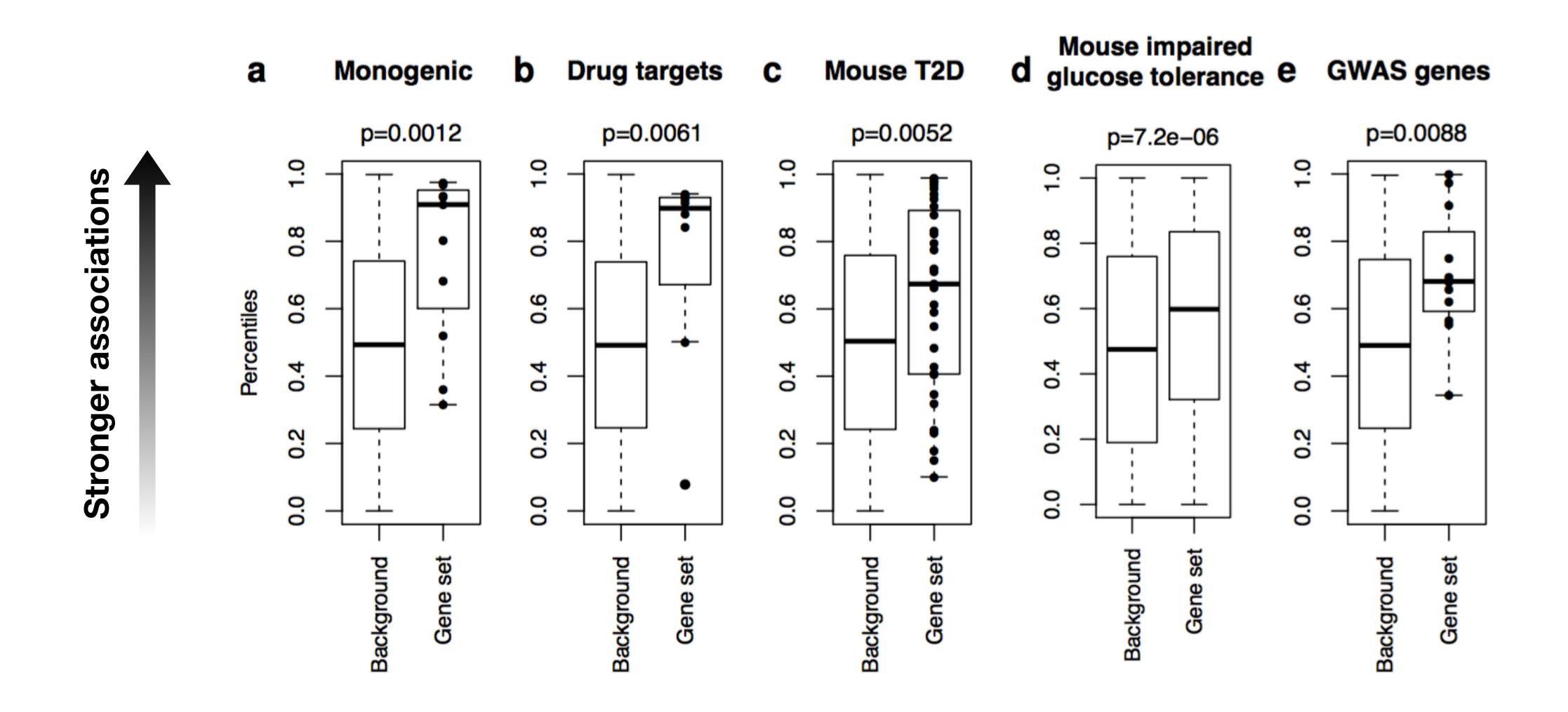


But: many signals beyond





But: many signals beyond



Further support for this model

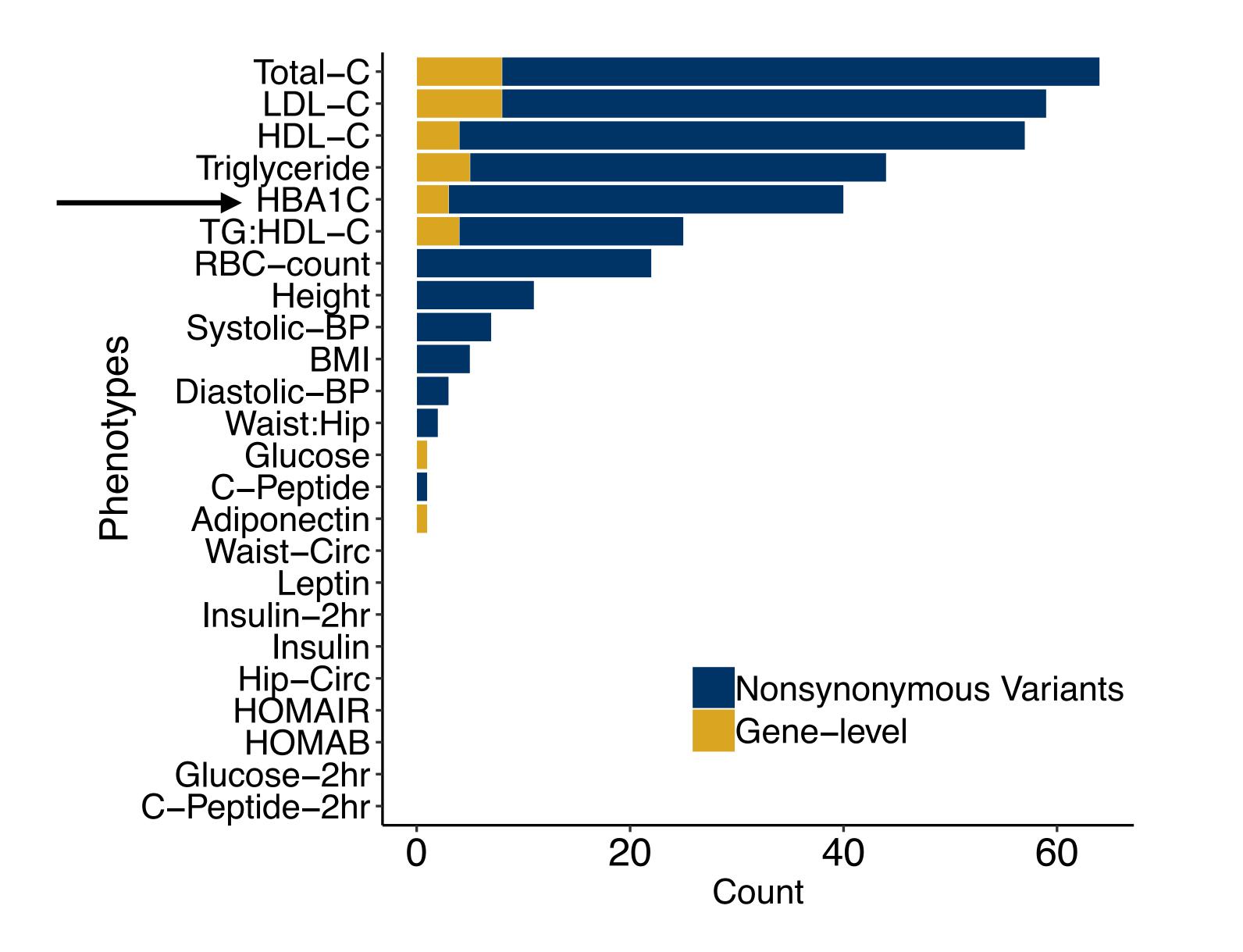
Beyond type 2 diabetes

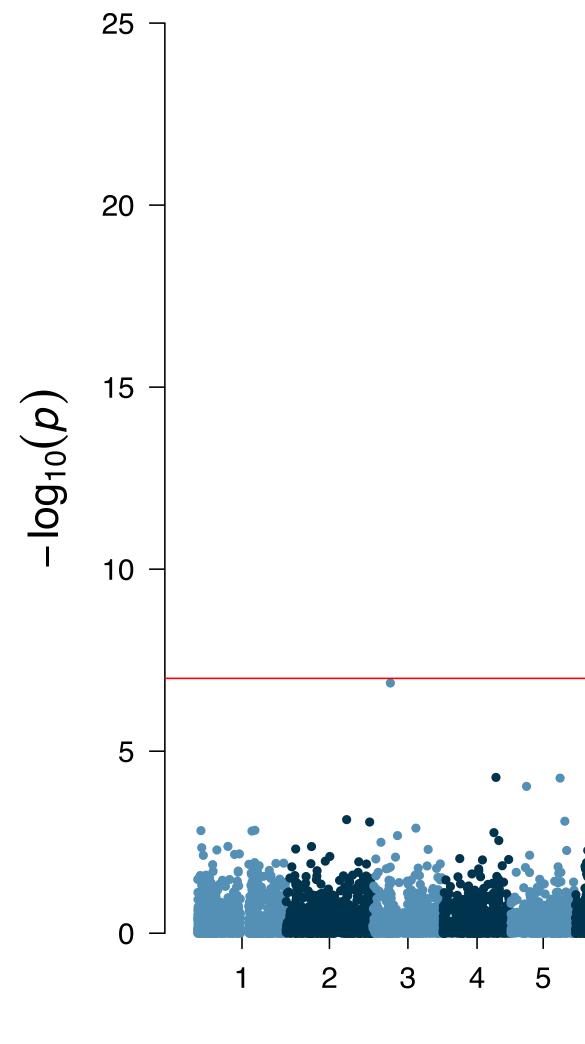
Study design:

- Exome sequencing of 85,474 non-diabetic individuals
- UKBB exomes (n=40,151; 100% European)
- AMP-T2D exomes (n=45,323; 15.8% African American; 25.6% East Asian; 18.7% European; 18.0% Hispanic; and 22.2% South Asian)
- 24 quantitative traits
- Single variant analysis (mostly for common variants)
- Gene-level analysis (for rare variants)



HbA1C G

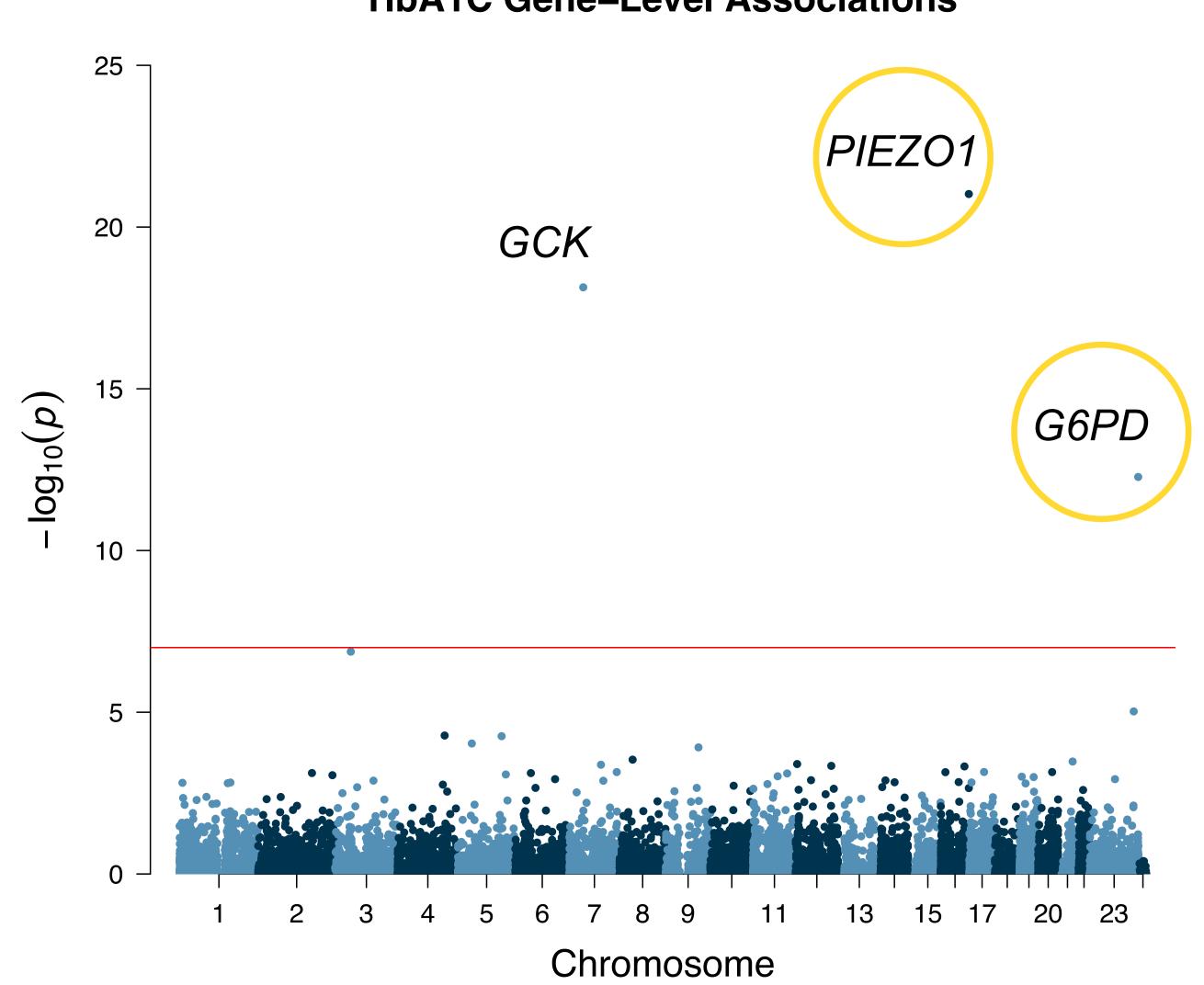




HbA1C is commonly used in T2D diagnosis

	HbA1c (percent)	Fasting Plasma Glucose (mg/dL)	Oral Glucose Tolerance Test (mg/dL)		
Diabetes	≥ 6.5	≥ 126	≥ 200		
Prediabetes	5.7 — 6 .4	100 - 125	140 — 199		
Normal	~ 5.7	≤ 99	≤ 139		





onsynonymous Variants ene-level

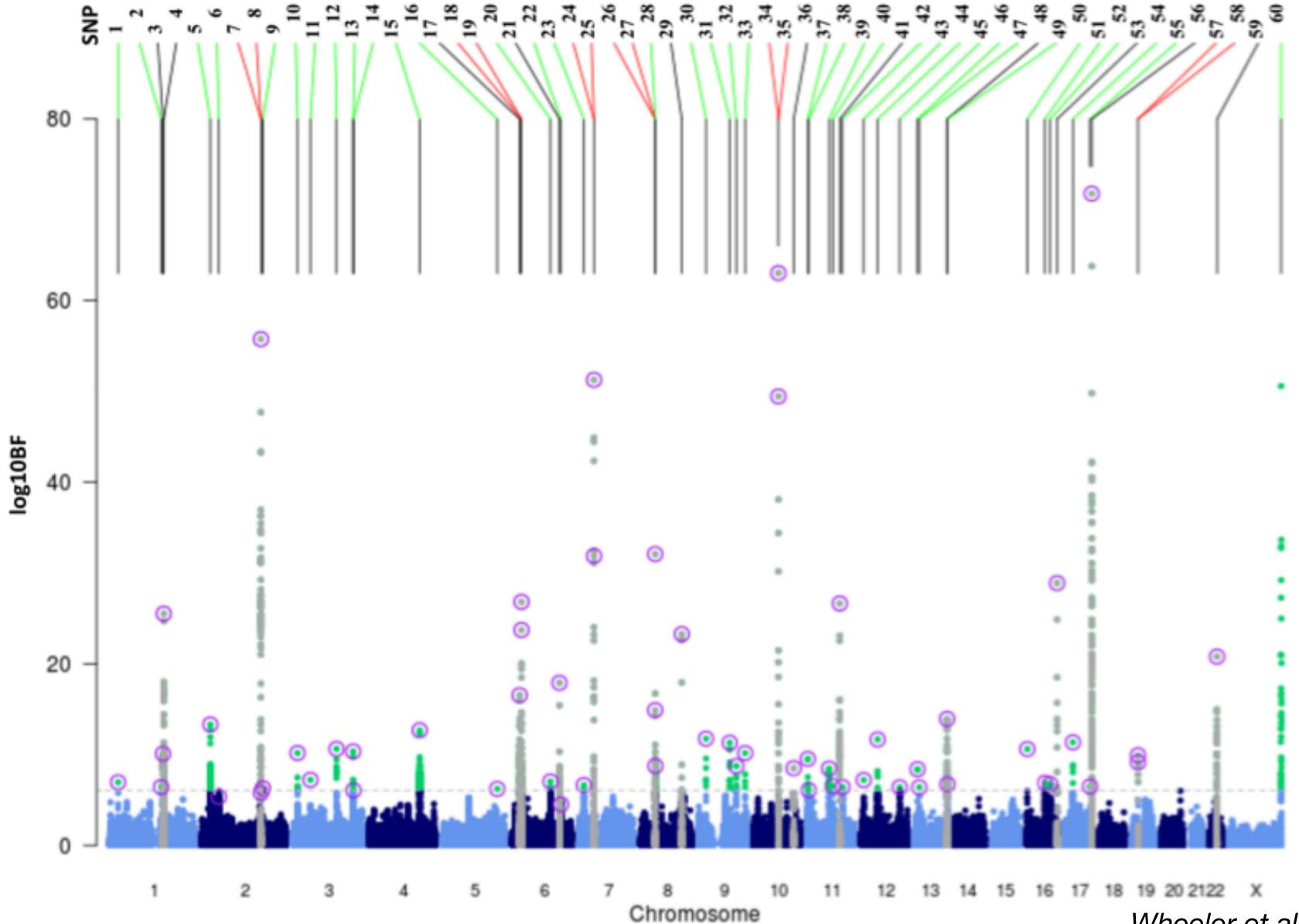
40 60 unt

Dornbos et al, Nature Genetics 2022

Common variants and HbA1C



60 common variant associations



G6PD variant
11% of
AfricanAmericans

0.81%
reduction in
HbA1c

Common variants and HbA1c

Associations can be grouped into two classes

Associated with red blood cell traits

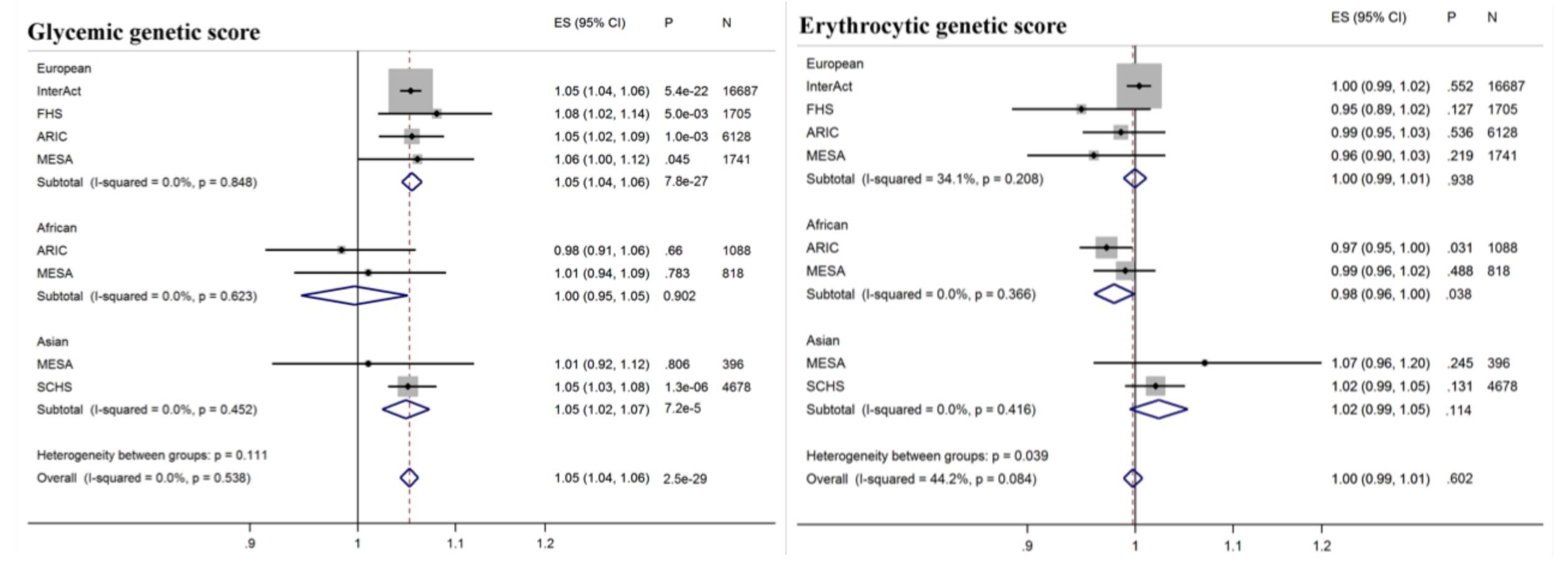
Associated with other glycemic traits

Table 1.	(Continued)
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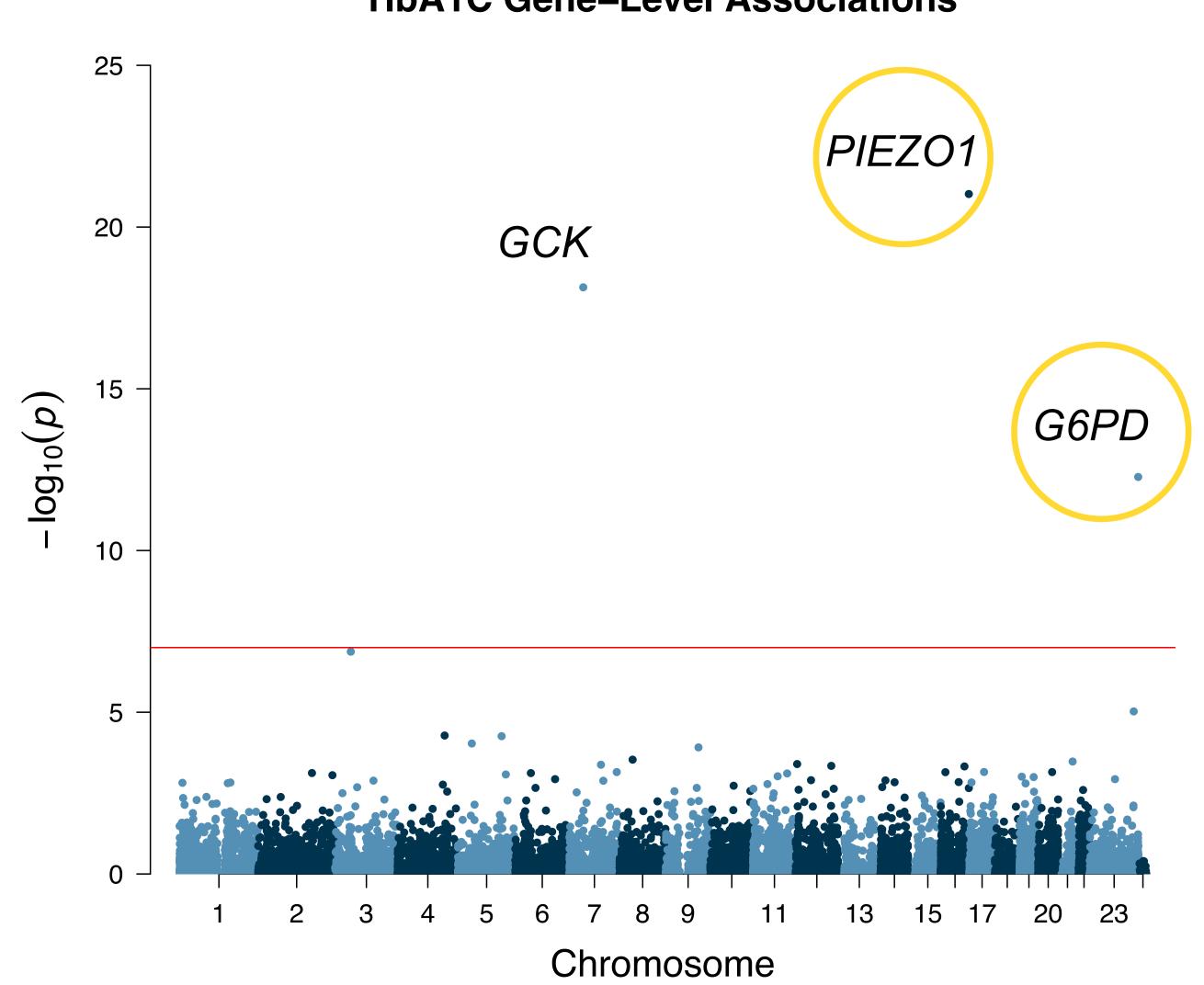
SNP	Markername	Chr.	Position (bp)	Effect Allele	Other Allele	Gene	Status	Signals	Classification	European ancestry METAL <i>p</i> -value	Trans-ethnic MANTRA log10BF
45	rs10774625	12	110394602	G	Α	ATXN2	Novel	Single	Erythrocytic	1.46 × 10 ⁻⁸	6.38
46	rs11619319	13	27385599	G	Α	PDX1	Novel	Single	Glycemic	4.58×10^{-7}	8.38
47	rs576674	13	32452302	G	Α	KL	Novel	Single	Glycemic	1.39×10^{-5}	6.38
48	rs282587	13	112399663	G	Α	ATP11A	Known	Single	Unclassified	1.70 × 10 ⁻¹²	13.92
49	rs9604573	13	113571085	Т	С	GAS6	Novel	Single	Unclassified	9.50 × 10 ⁻⁹	6.72
50	rs11248914	16	233563	Т	С	ITFG3	Novel	Single	Erythrocytic	2.56×10^{-14}	10.60
51	rs1558902	16	52361075	Α	Т	FTO	Novel	Single	Unclassified	3 27 × 10 ⁻⁸	6.88
52	rs4783565	16	67307691	Α	G	CDH3	Novel	Single	Erythrocytic	1.73×10^{-7}	6.73
53	rs837763	16	87381230	Т	С	CDT1	Known	Single	Erythrocytic	1.68 × 10 ⁻²⁸	28.89
54	rs9914988	17	24207230	Α	G	ERAL1	Novel	Single	Erythrocytic	2.77×10^{-11}	11.34
55	rs2073285	17	73628956	С	Т	TMC6	Novel	Single	Unclassified	1.27 × 10 ⁻⁴	6.47
56	rs1046896	17	78278822	Т	С	FN3KRP	Known	Single	Unclassified	4.46 × 10 ⁻⁶⁴	71.79
57	rs11086054	19	17107737	Α	Т	MYO9B	Novel	Multiple	Unclassified	8.16 × 10 ⁻⁶	9.12
58	rs17533903	19	17117523	Α	G	MYO9B	Known	Multiple	Erythrocytic	5.27 × 10 ⁻¹²	9.912
59	rs4820268	22	35799537	G	Α	TMPRSS6	Known	Single	Erythrocytic	1.40 × 10 ⁻²²	20.79
60	rs1050828	Х	153417411	Т	С	G6PD	Novel	Single	Erythrocytic	NA*	NA

Different biological effects

- Glycemic associations, but not erythrocytic associations, predict future development of T2D
 - ~2% of African-Americans could be misclassified due to G6PD variant





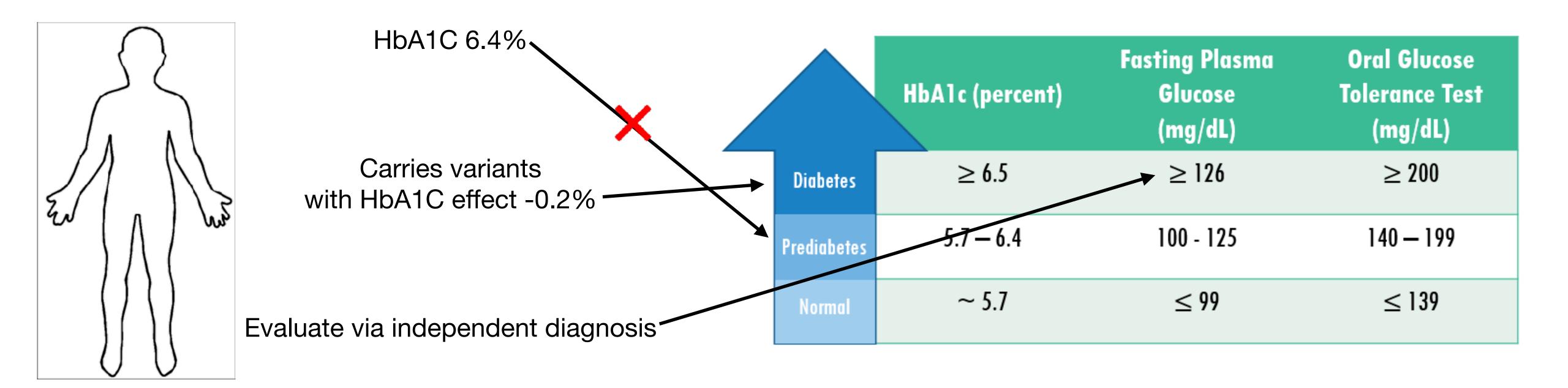


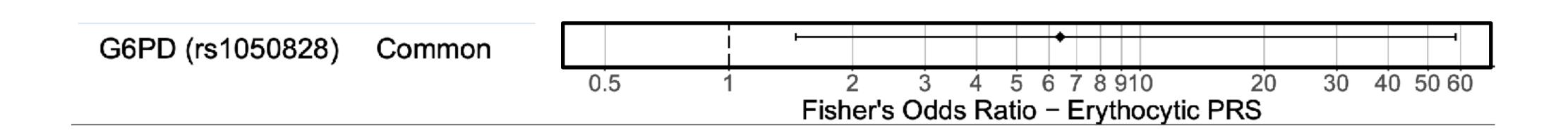
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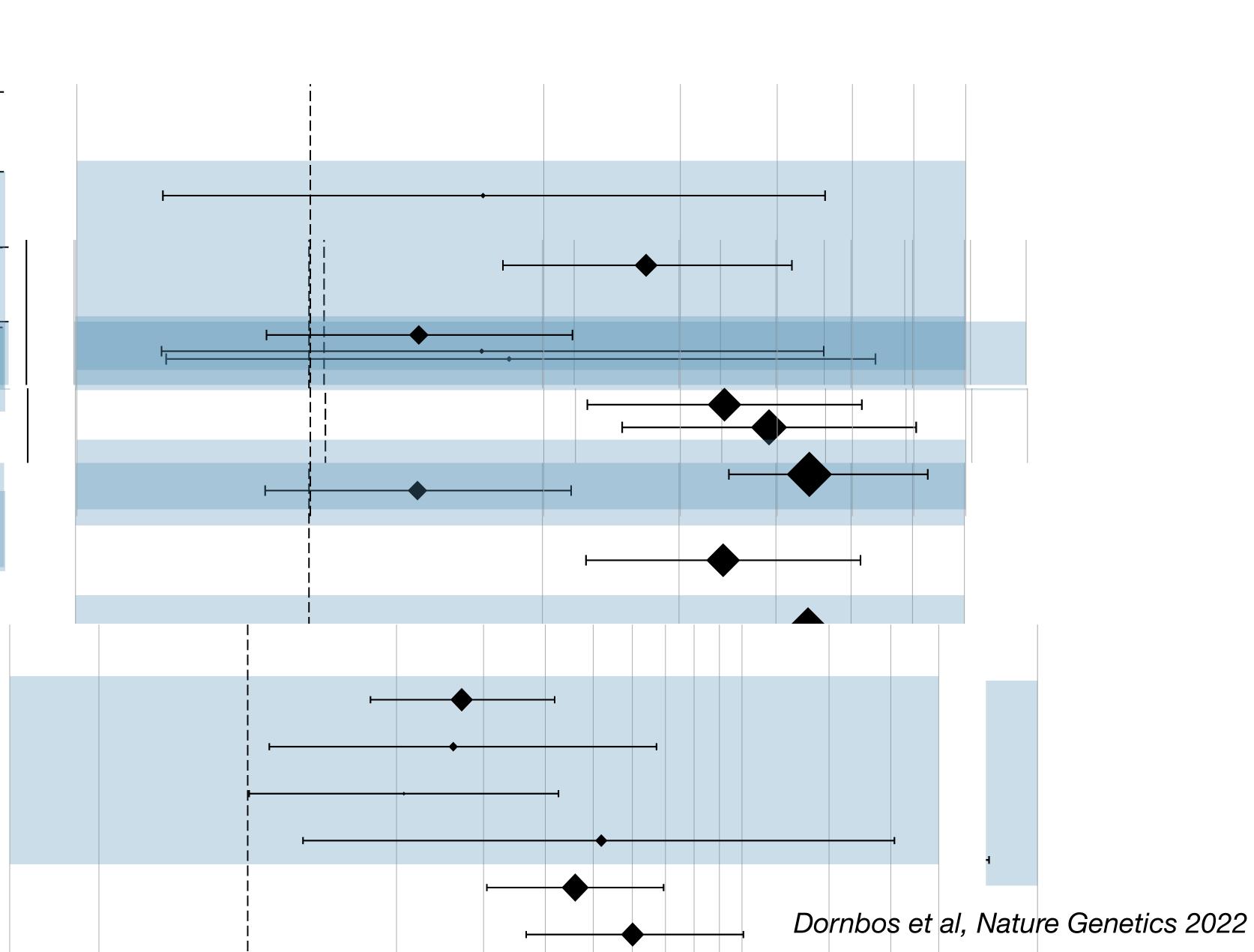
How do these variants affect HbA1c diagnosis?





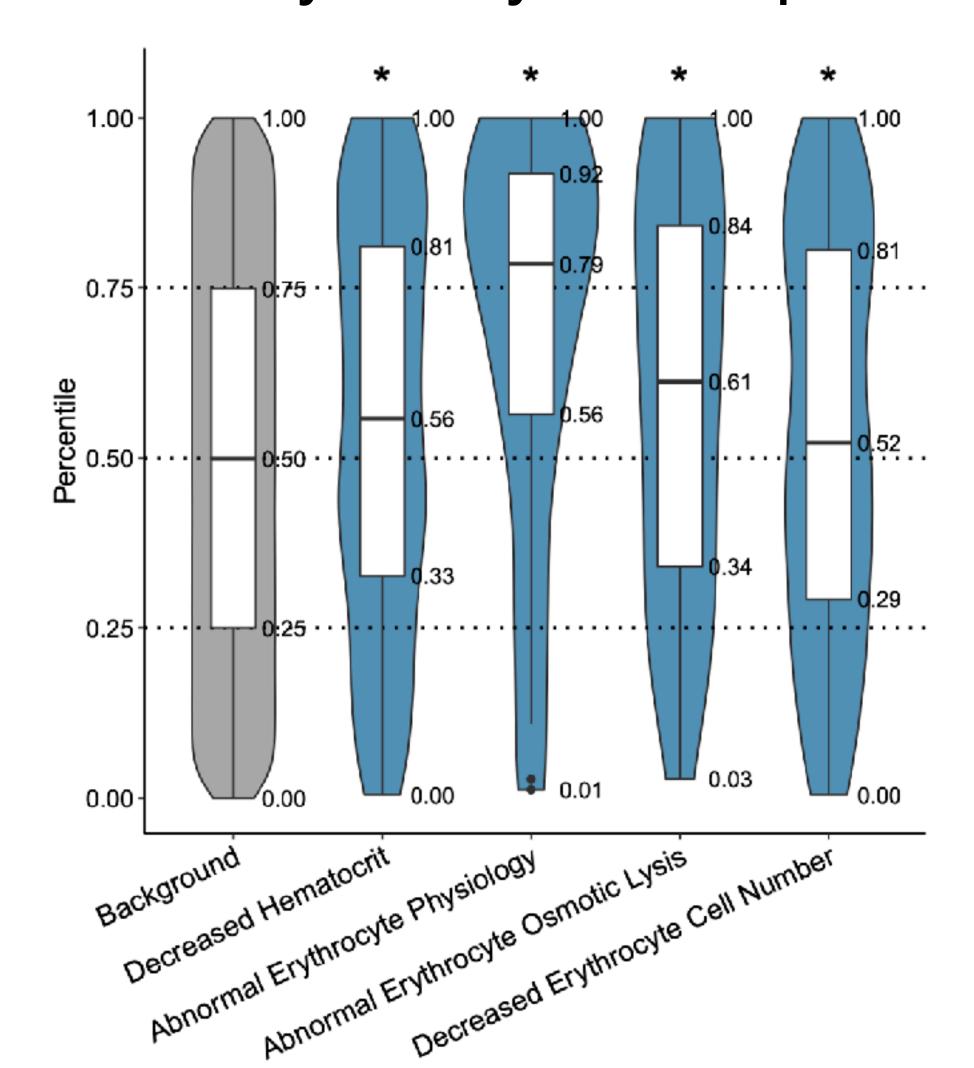
How do these variants affect HbA1c diagnosis?

Variation	Model
Rare	PIEZO1/G6PD
Variention	Mythologytic Genes
Rareare	GIPCEMIC GERES
Common Common	Erythrocytic Variant Erythrocytic Variants
Combined	Etytholighess
Common	Erythrocytic Variants
Valvatietion	Andest try
Combined Rafeare	Erythrocytic PS Meta-analysis
	African American African American
Valvatietion	A A Biastry Asian
RaRare	Hispanicalysis Hispanic
Common Common	Meta-analysisan Meta-analysis



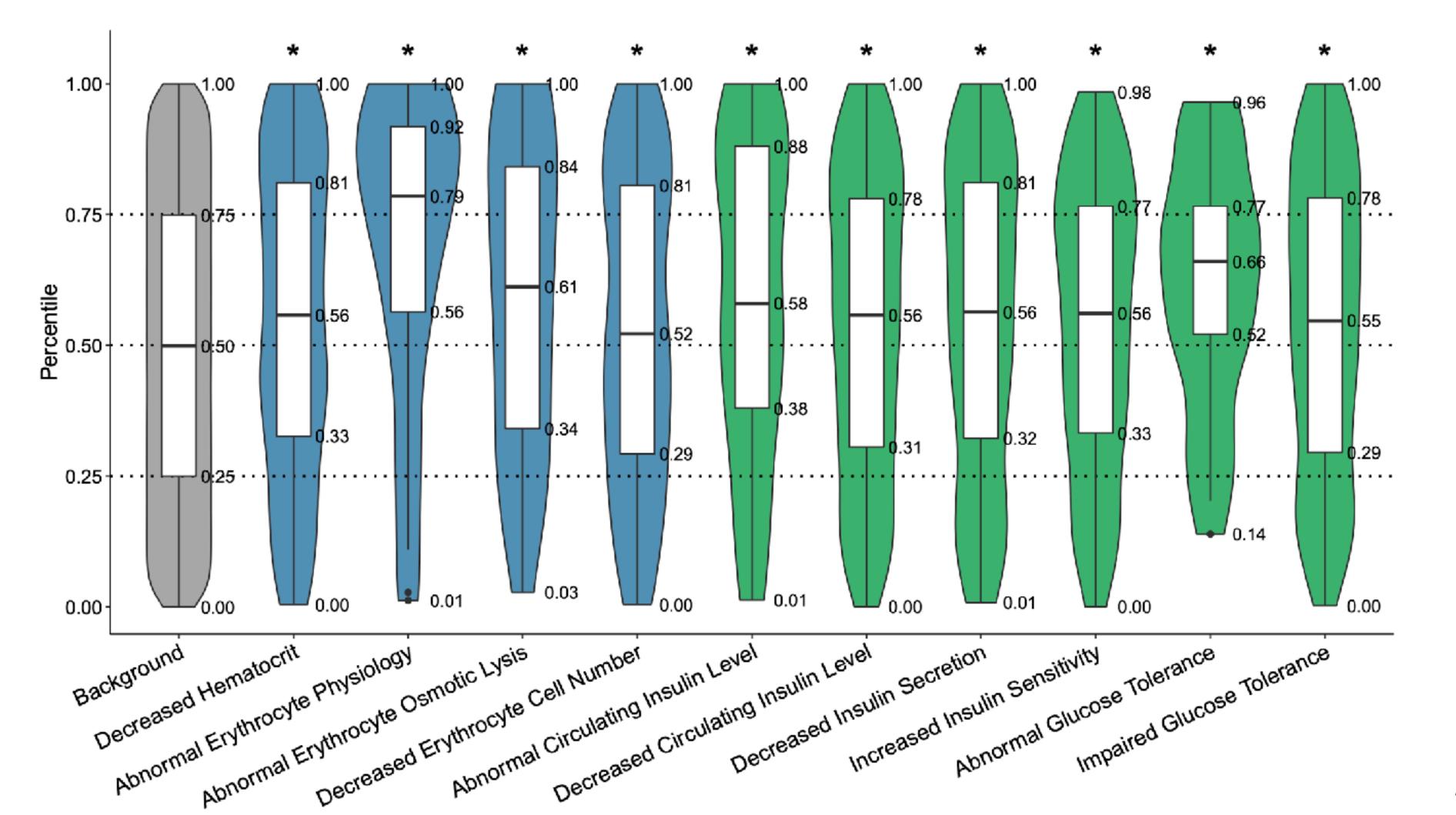
Expanding the model

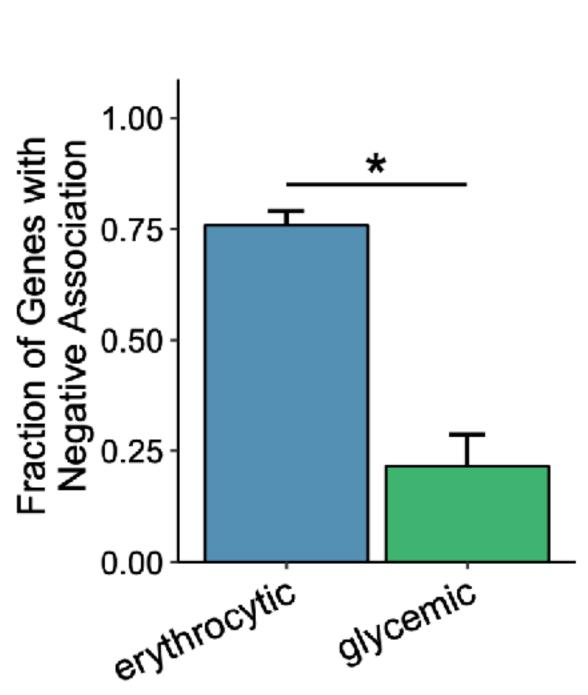
 Significant associations in many sets of genes with known function on erythrocytic lifespan in mice



Evidence for associations across many genes

 Compared to rare variants in genes involved in glycemia in mice, rare variants in erythrocytic genes are more likely to decrease HbA1c



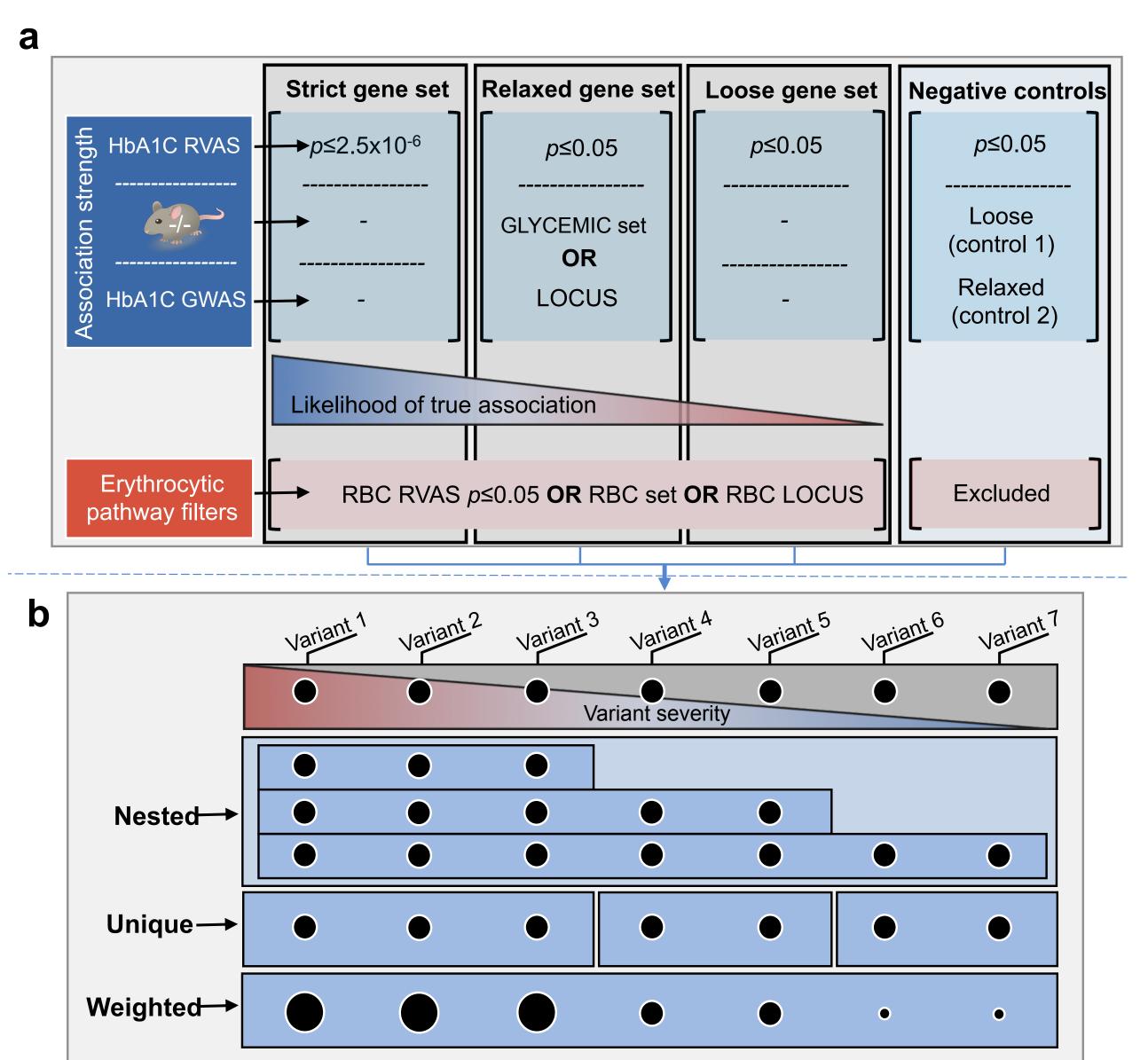


Putting this together in a polygenic score

Filtering to true associations

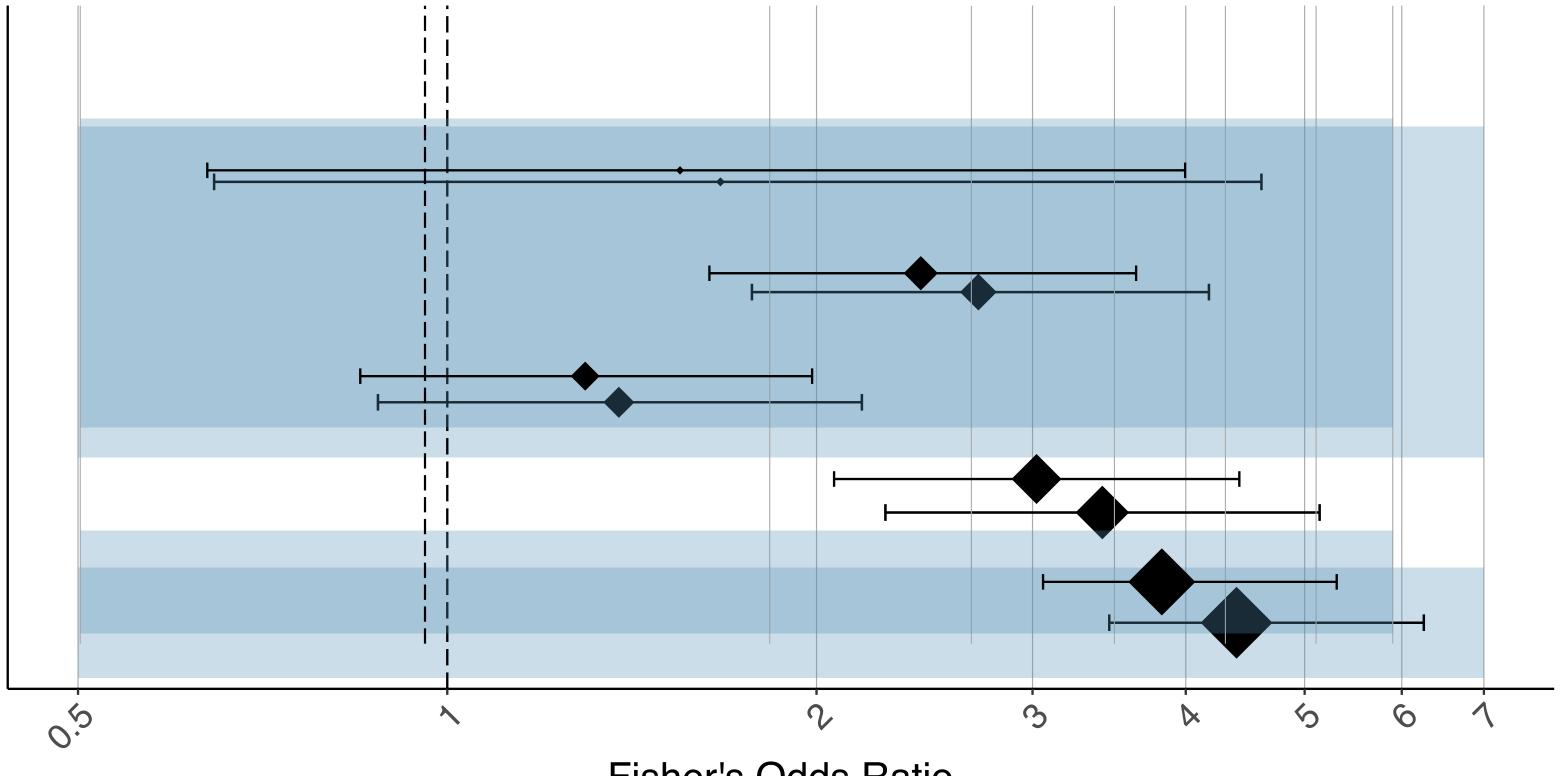
Filtering to erythrocytic variants

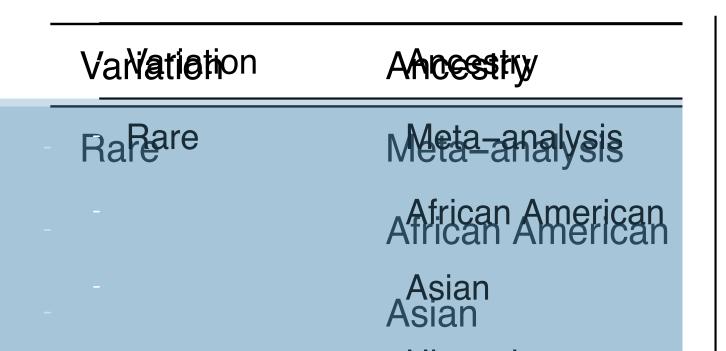
Estimate variant effect size

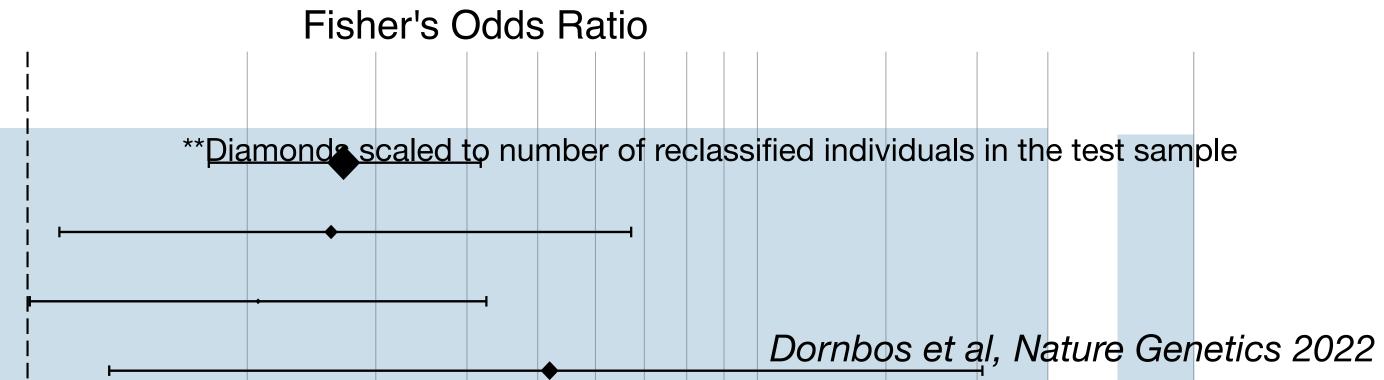


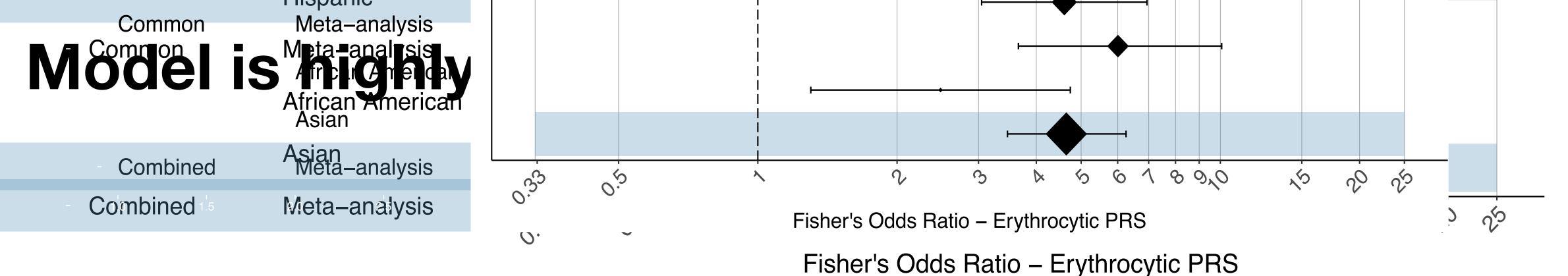
Final model: 21,293 variants

Var Mar ion	MMedel
Rareare	PIELEGO/1666BP
	Erythrocytic Genes Erythrocytic Genes
	Glycemic Genes Glycemic Genes
Common Common	Erythrocytic Variants Erythrocytic Variants
Combined Combined	Erythrocytic PGS Erythrocytic PS 2.0 2.5

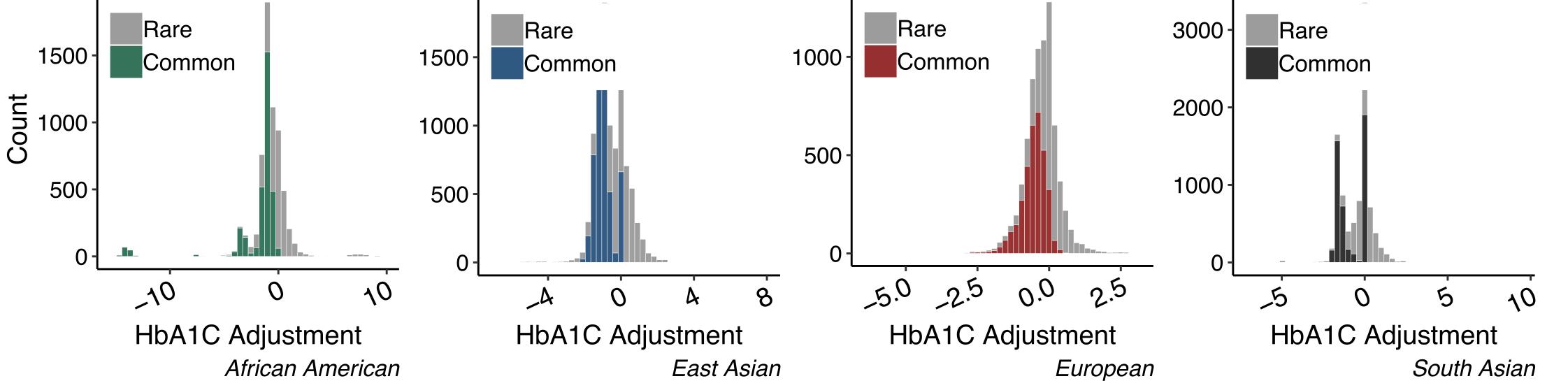




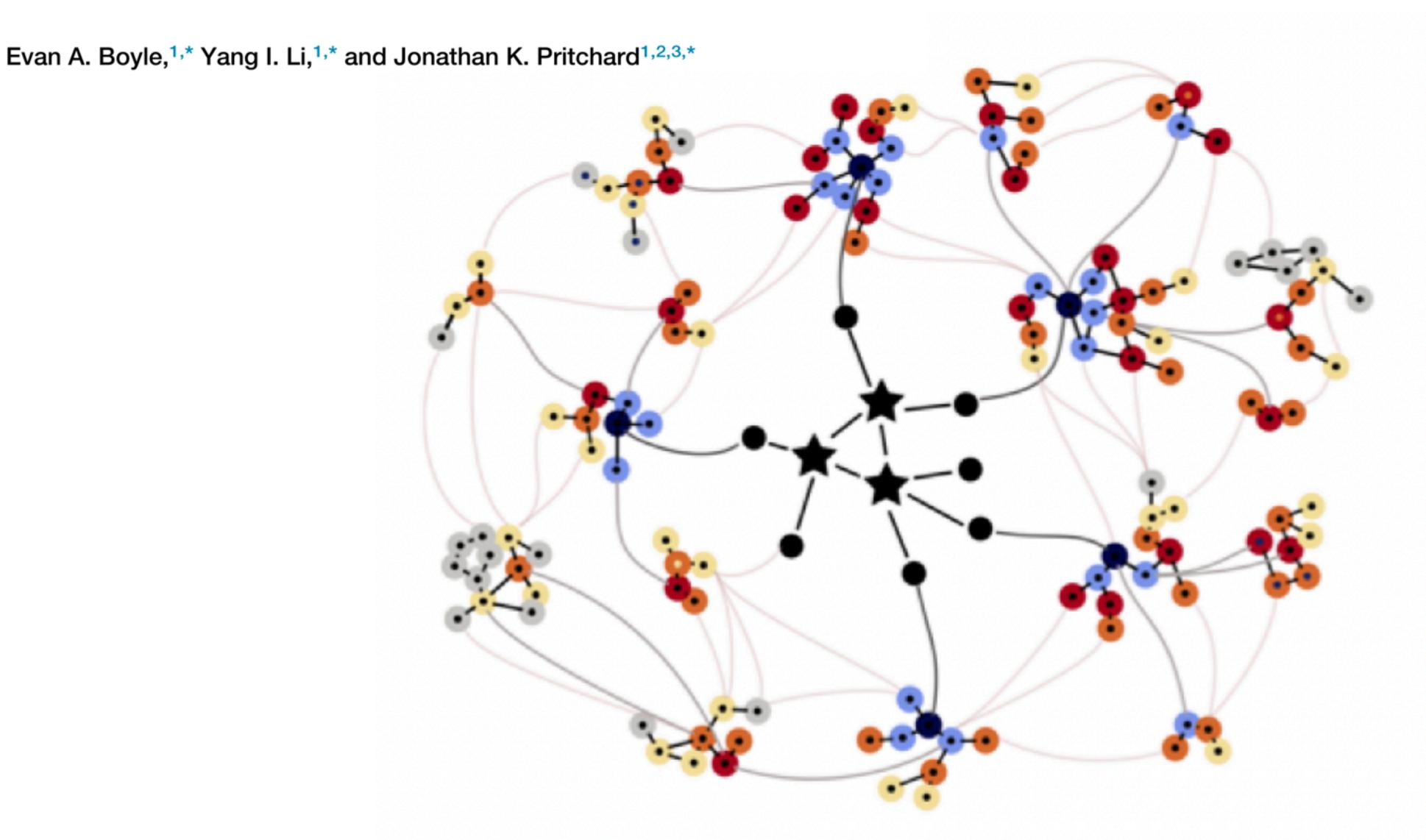


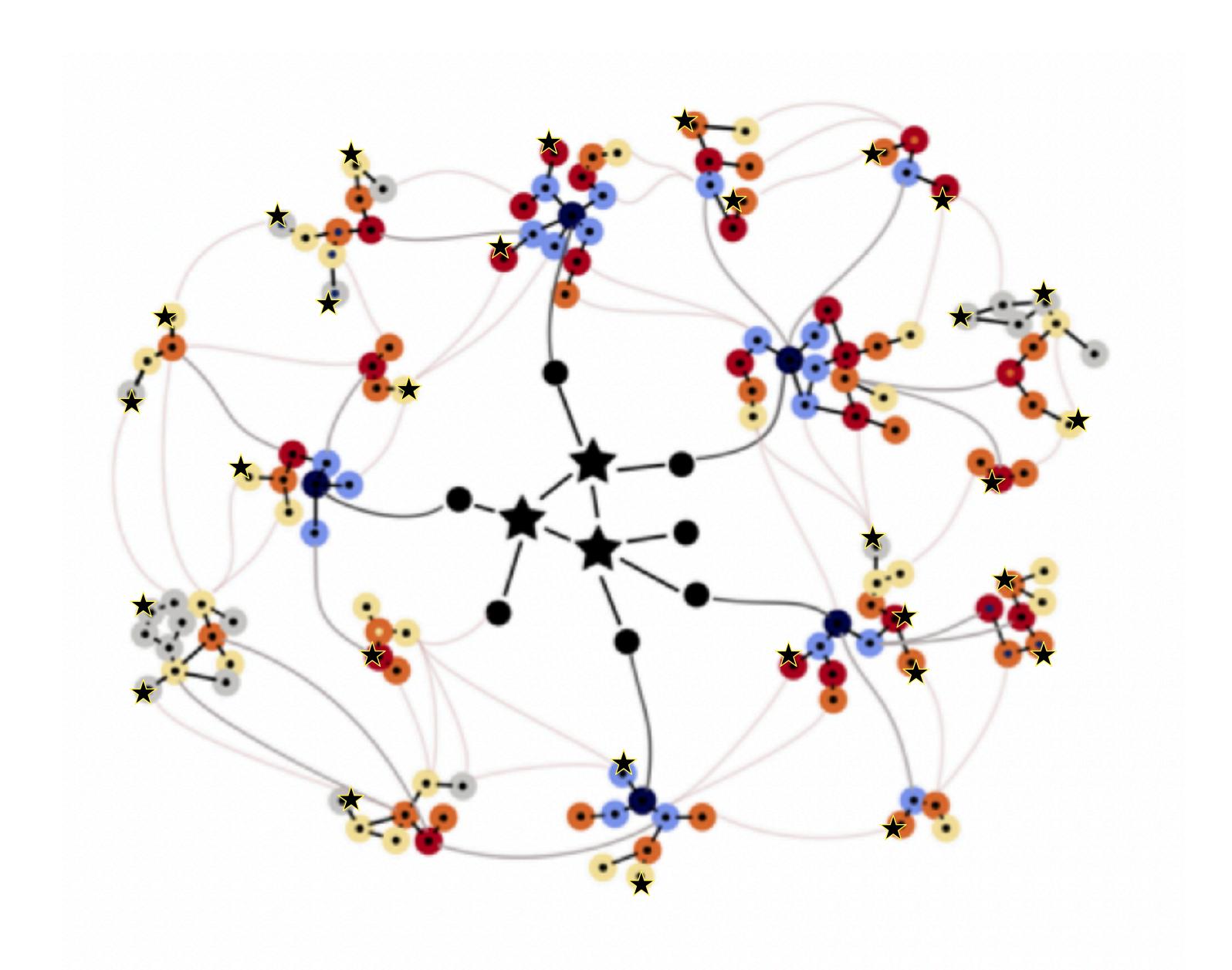


Rare Rare 3000-



An Expanded View of Complex Traits: From Polygenic to Omnigenic



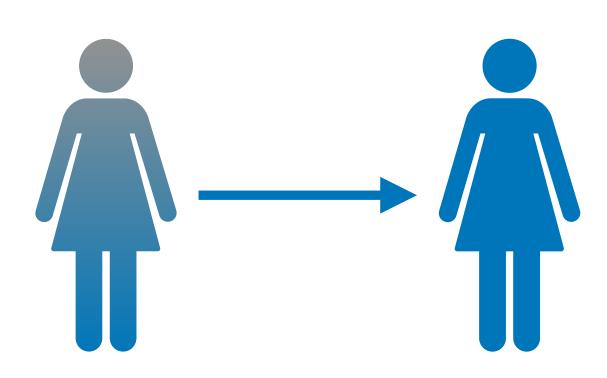


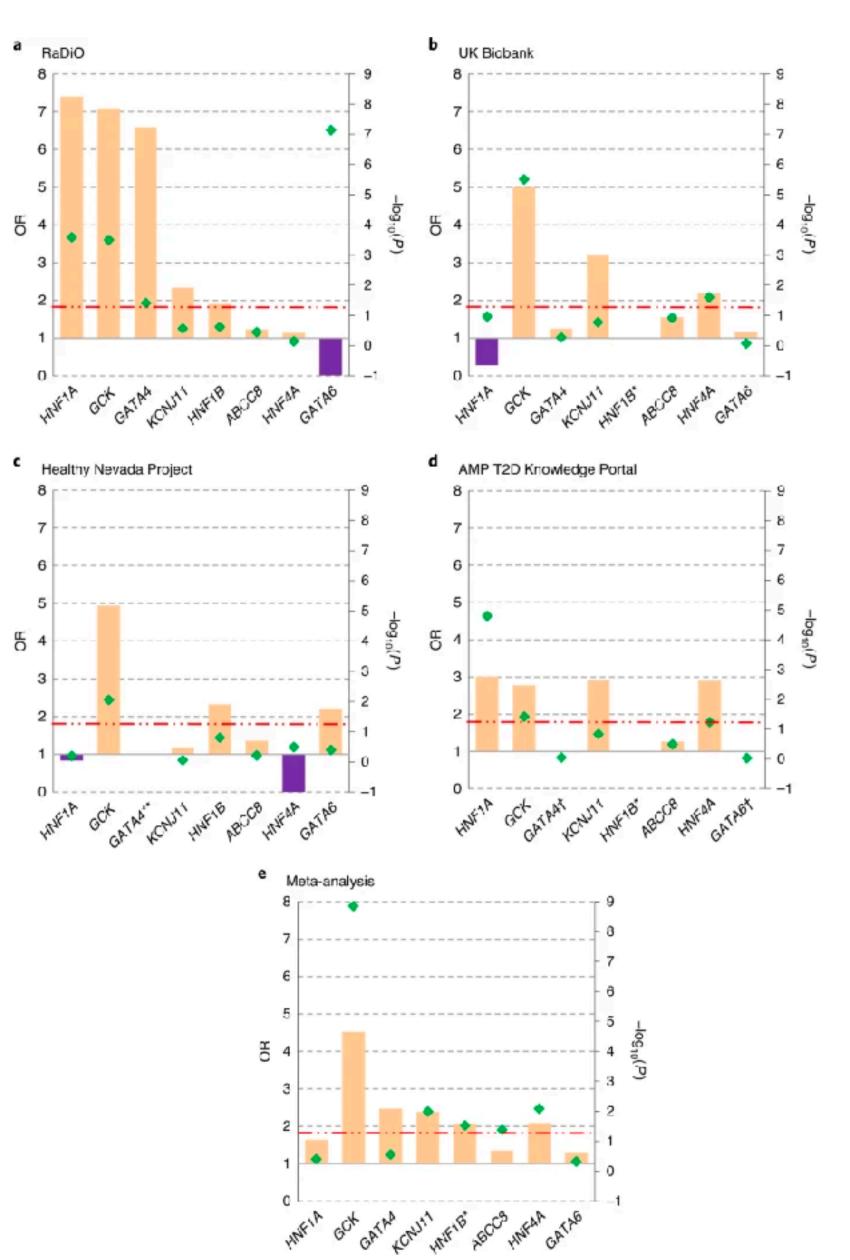




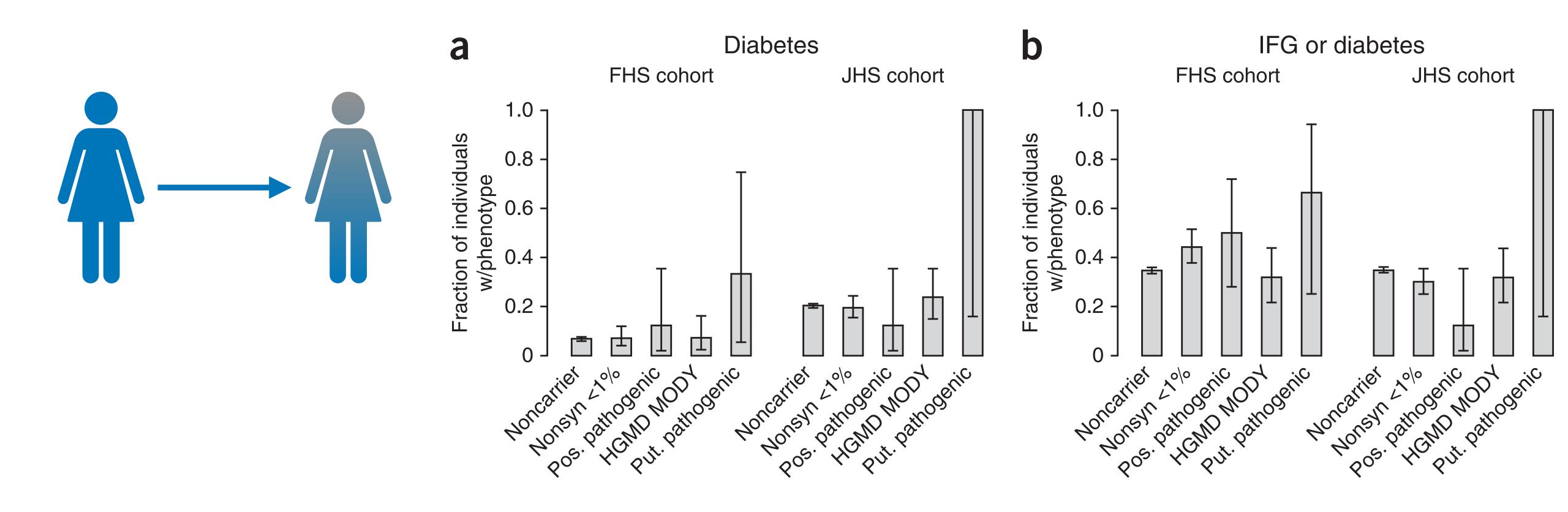


Many T2D patients carry pathogenic variants in MODY genes

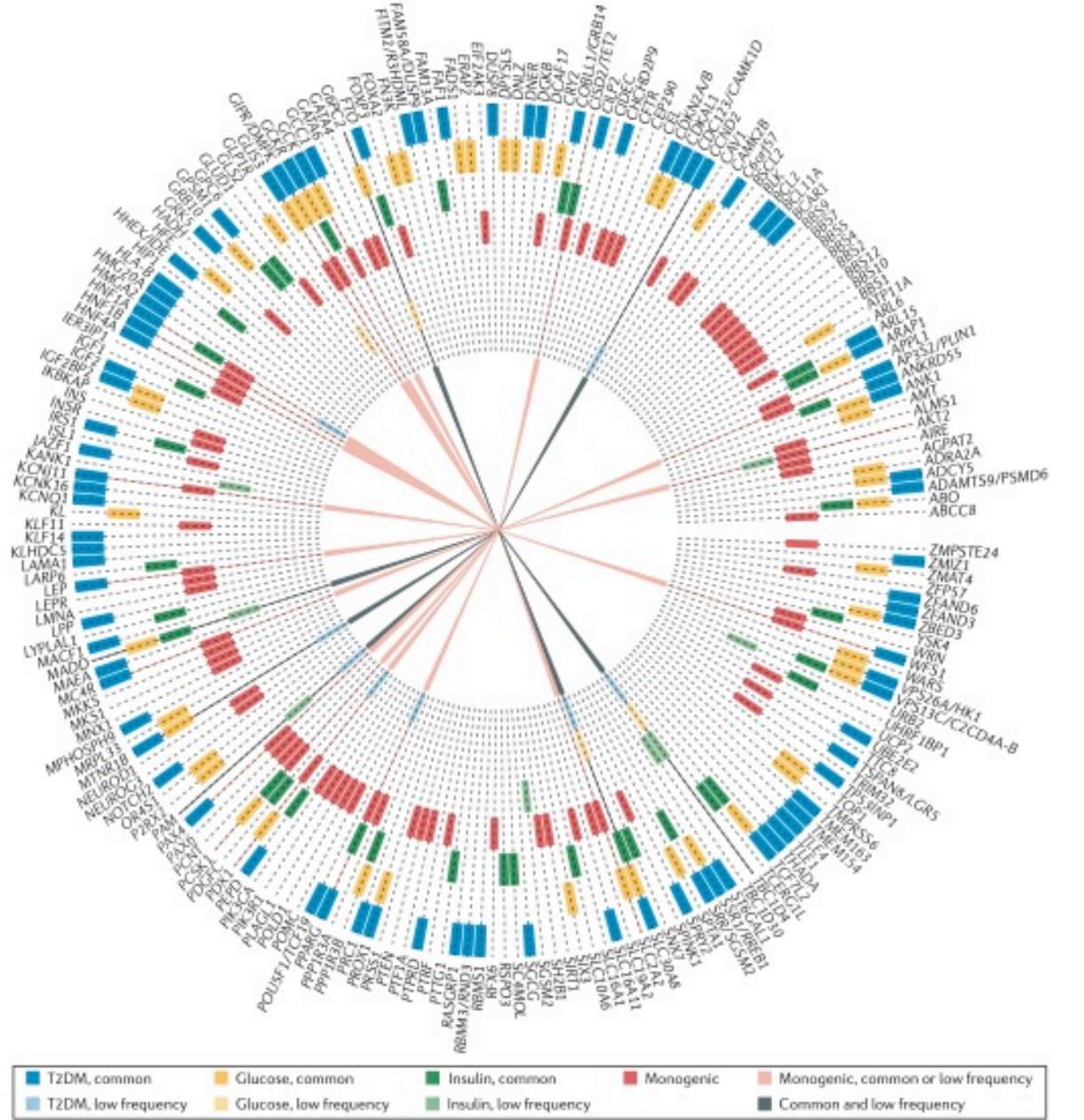


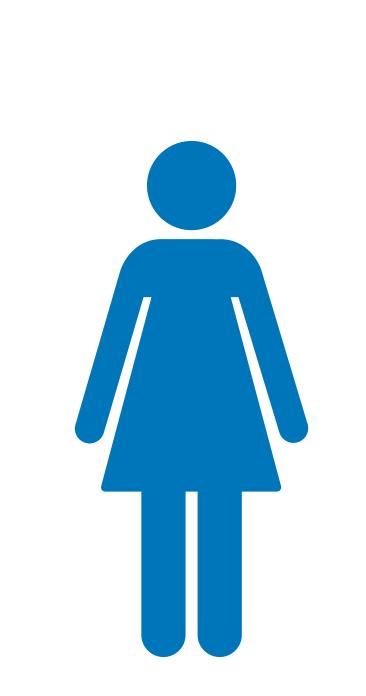


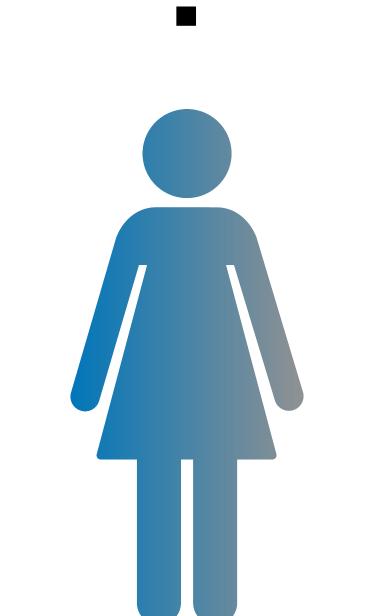
Many damaging mutations in MODY genes are incompletely penetrant

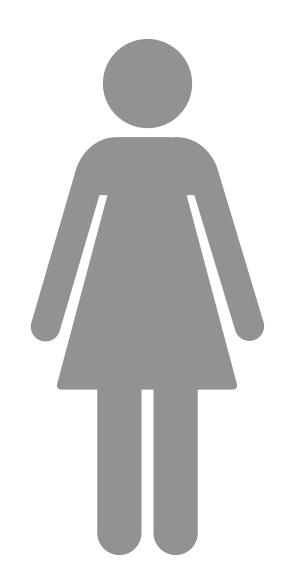


Rare and common forms of diabetes share genes



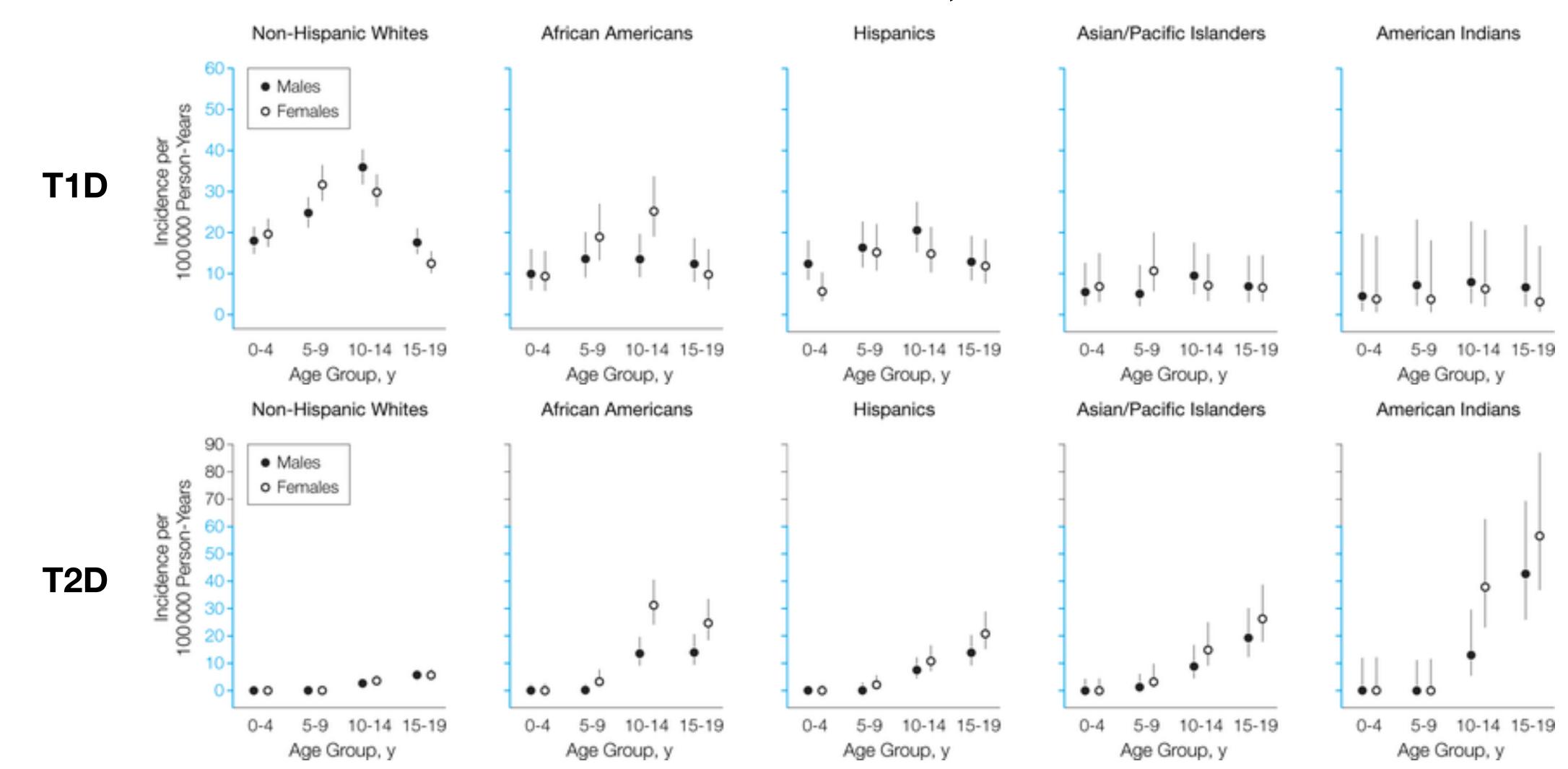






The ProDiGY study of T2D in youth

- Incidence of ~3,700 cases/year and increasing, particularly ages 10-19
 - 15% of new diabetes cases in whites, 46-86% in minorities



Samples





- Longitudinal follow up to assess natural history and complication risk factors
- Active registry of youth diagnosed with diabetes at age < 20
- - Clinical trial of ages 10-17 to compare treatment efficacy of Metformin vs Metformin+Lifestyle Intervention vs Metformin+Rosiglitazone
 - BMI above 85th percentile
- Both studies are multi-ethnic

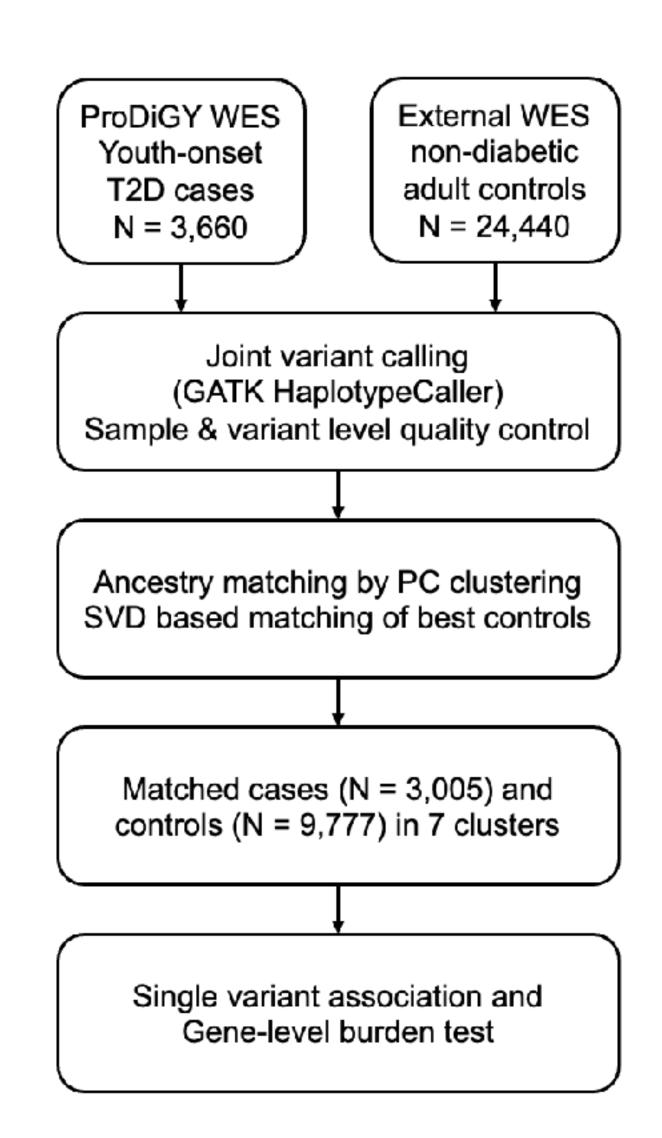


Ancestry	Samples
African-American	1,491 (40.8%)
East-Asian	62 (1.7%)
European	757 (20.7%)
Hispanic	1,306 (35.9%)
NA	34 (0.9%)
Total	3,650

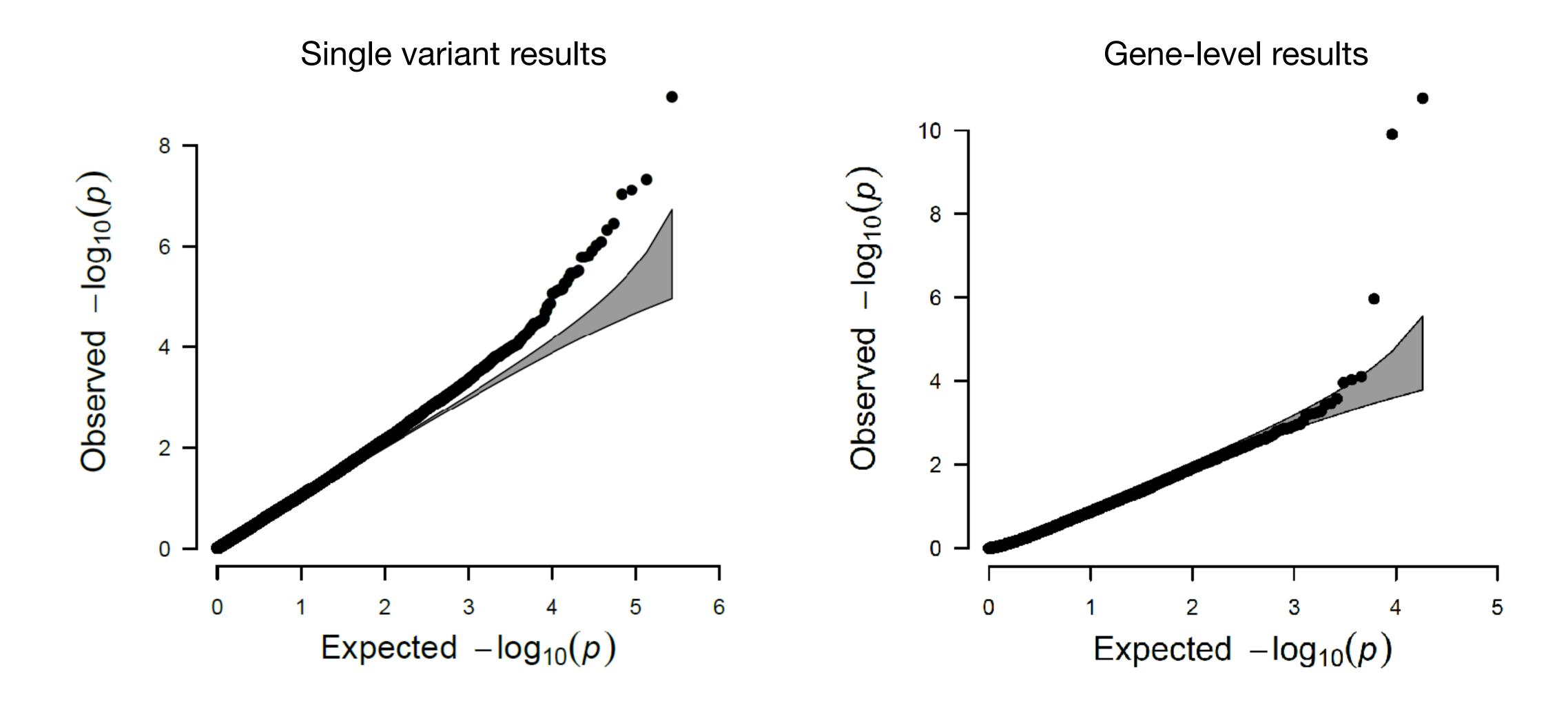
	Total	Male	Female
N	3,650	1,294 (35.4%)	2,356 (64.6%)
Current Age	15.2±3.0	15.1±3.1	15.4±2.8
Age at Onset	13.6±2.3	13.3±2.3	14.1±2.2

Analysis design

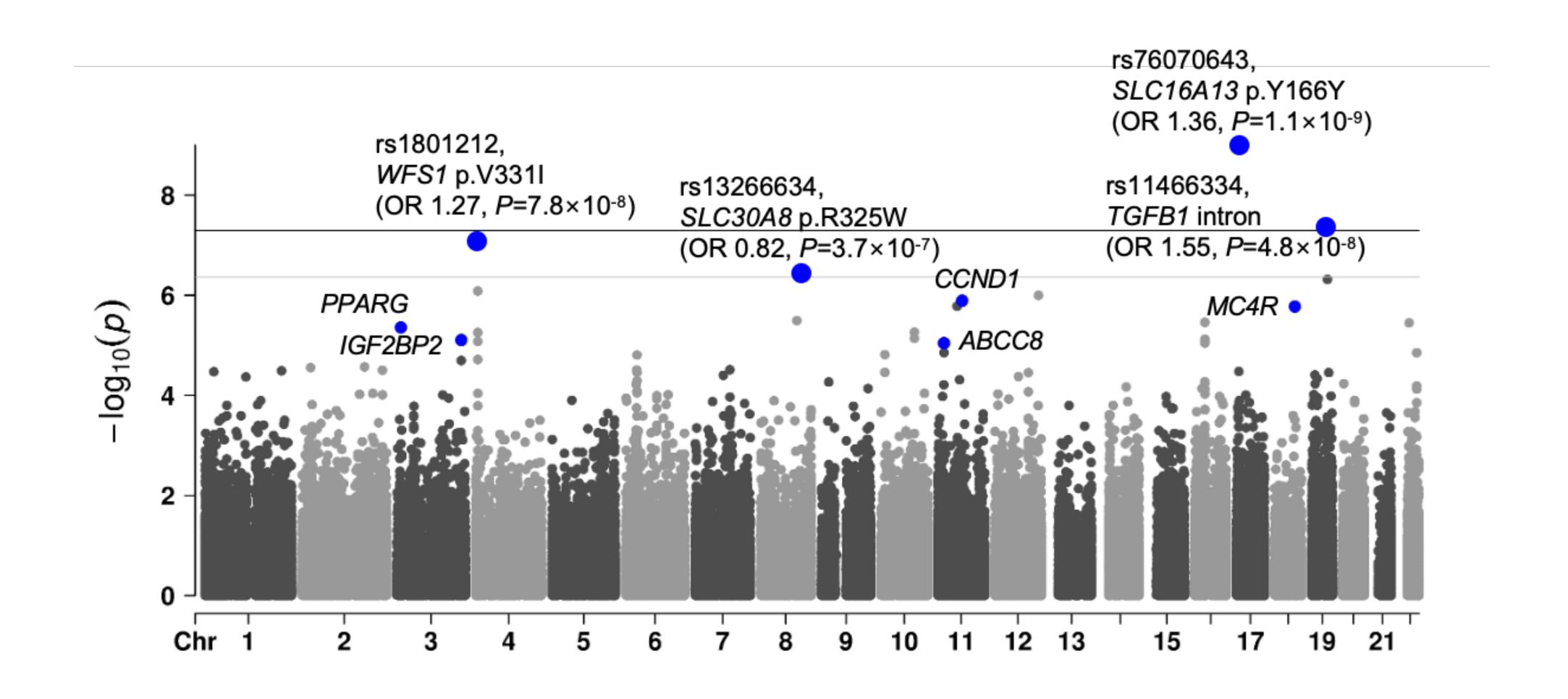
- Whole exome sequencing of 3,650 youth-onset T2D cases
- Match to controls from AMP-T2D exomes
 - Total analysis of 3,005 cases and 9,777 controls
- Single variant analysis (mostly for common variants)
- Gene-level analysis (for rare variants)



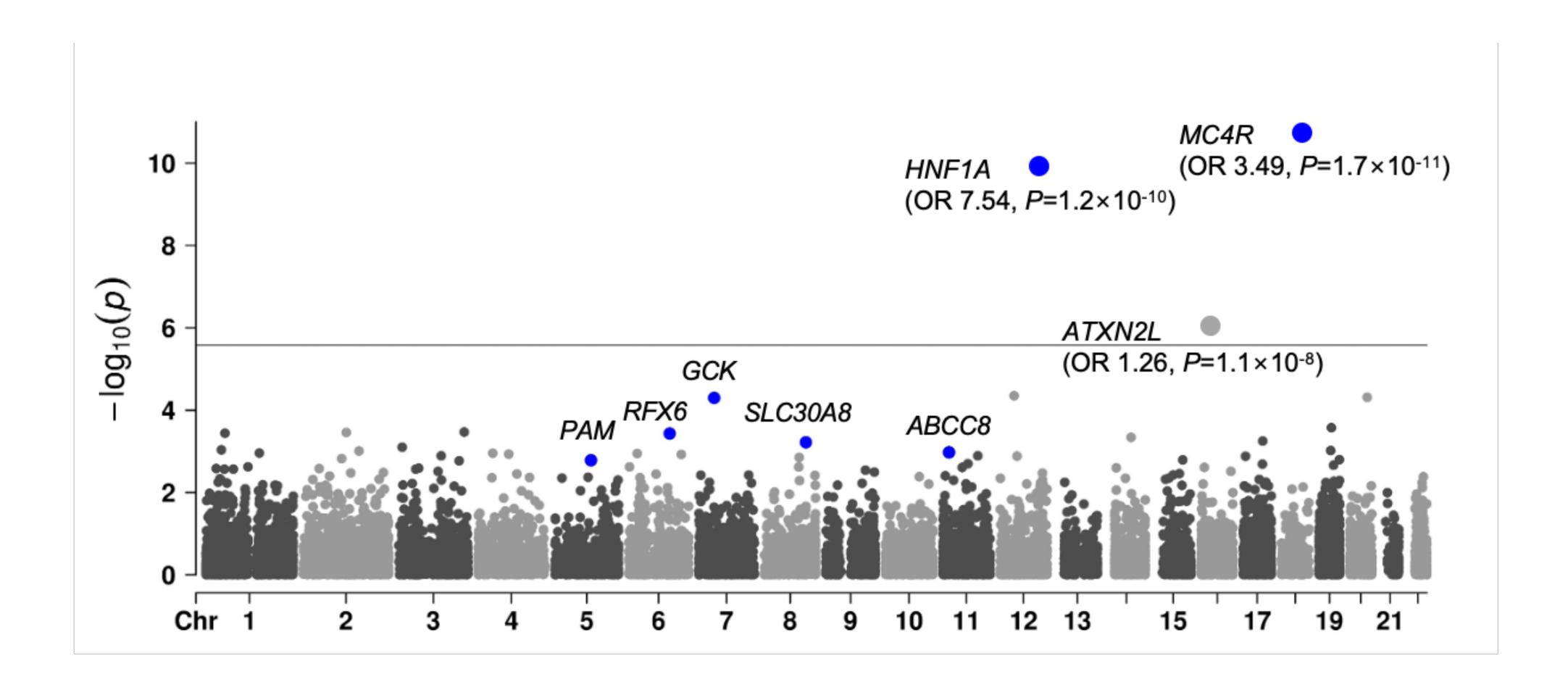
Statistics are well-calibrated



Four exome-wide significant associations



Three exome-wide significant gene-level associations

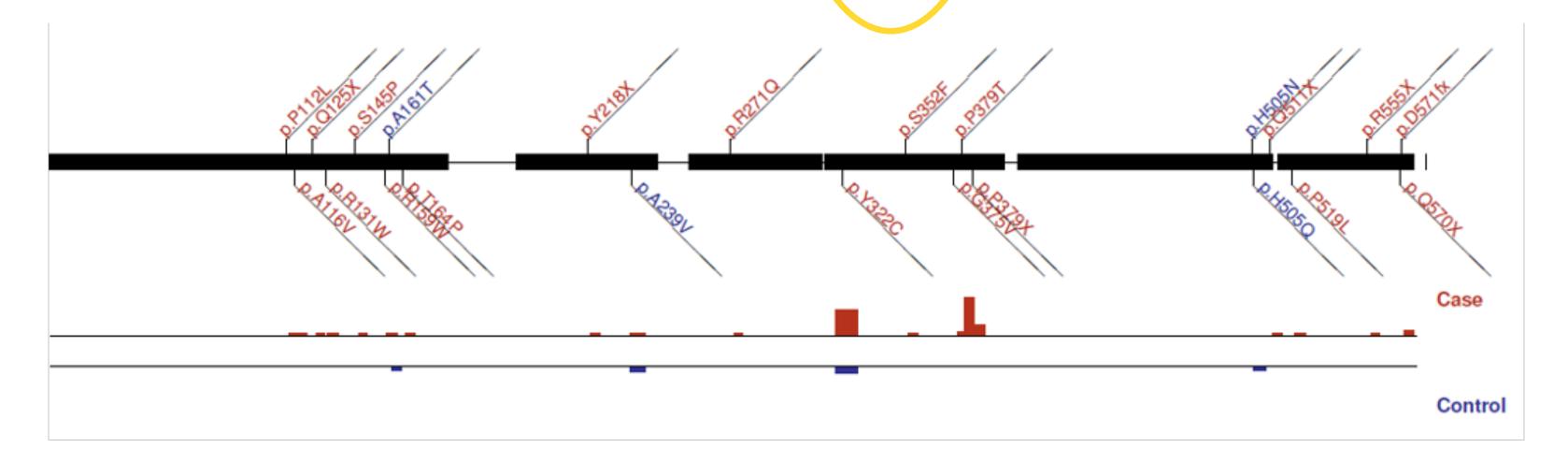


Additionally: 2.1% of cases carry a monogenic diabetes causing variant

Example association: HNF1A



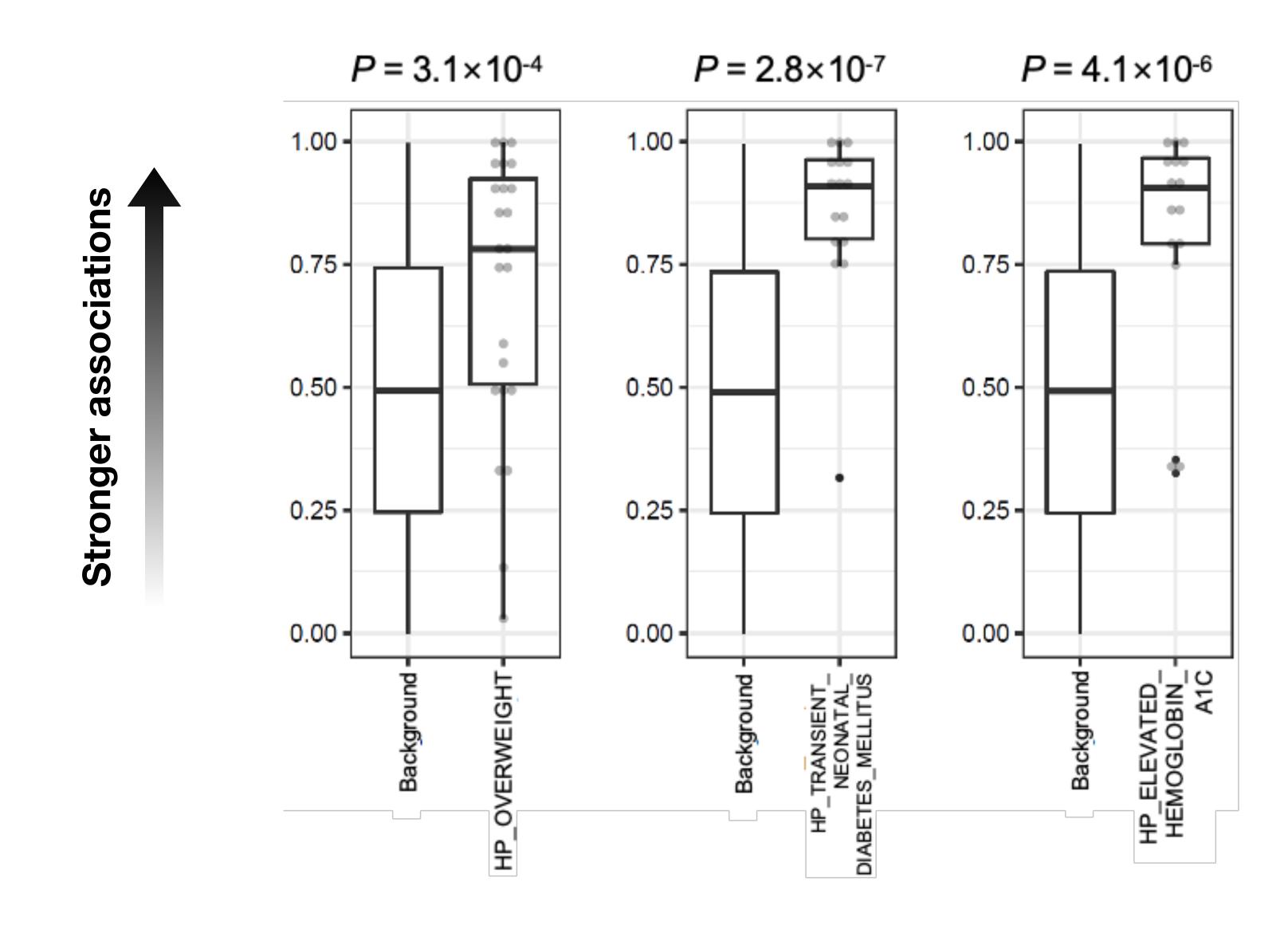
	Total			
MASK	# Var	CAF	OR (95% CI)	Р
LofTee	6	0.00047	46.0 (1.76-1198)	9.55×10 ⁻⁵
16/16	6	0.00047	46.0 (1.76-1198)	9.55×10 ⁻⁵
11/11	21	0.0038	7.51 (3.92-14.4)	2.24×10 ⁻¹¹
5/5	22	0.0039	6.77 (3.63-12.6)	7.59×10 ⁻¹¹
5/5 + LofTee LC 1%	23	0.0040	7.01 (3.77-13.0)	2.41×10 ⁻¹¹
5/5 + 1/5 1%	59	0.018	1.80 (1.41-2.31)	4.21×10 ⁻⁶
5/5 + 0/5 1%	63	0.019	1.82 (1.42-2.32)	2.70×10 ⁻⁶



Substantial enrichment in diabetes-relevant gene sets

 Gene sets defined by HP_ABNORMAL_WAIST_TO_HIP_RATIO -Three categories HP_INSULIN_RESISTANCE HP_OVERWEIGHT HPO terms HP_INCREASED_BODY_WEIGHT HP_PANCREATIC_HYPOPLASIA -HP_ABNORMAL_PANCREAS_SIZE -HP_TRANSIENT_NEONATAL_DIABETES_MELLITUS -HP_HYPOINSULINEMIA • HP_NEONATAL_INSULIN_DEPENDENT_DIABETES_MELLITUS -HP_MATURITY_ONSET_DIABETES_OF_THE_YOUNG -HP_ABNORMAL_PANCREAS_MORPHOLOGY = HP_ABNORMALITY_OF_ENDOCRINE_PANCREAS_PHYSIOLOGY HP_HYPERGLYCEMIA • HP_GLUCOSE_INTOLERANCE -HP_ELEVATED_HEMOGLOBIN_A1C -HP_ABNORMAL_ORAL_GLUCOSE_TOLERANCE -HP_TYPE_II_DIABETES_MELLITUS -HP_ABNORMAL_C_PEPTIDE_LEVEL · Fraction of overlap Othe HP_IMPAIRED_GLUCOSE_TOLERANCE -HP_ABNORMAL_BLOOD_GLUCOSE_CONCENTRATION -5% HP_MATERNAL_DIABETES -10% HP_INSULIN_RESISTANT_DIABETES_MELLITUS 15% HP_GLYCOSURIA -HP_ABNORMAL_INSULIN_LEVEL 20% HP_PANCREATIC_ISLET_CELL_HYPERPLASIA --log10(p)

Enrichments are due to many genes



Tiers of candidate genes

• Tier 1: Exome-wide significant genes (MC4R, HNF1A, ATXN2L)

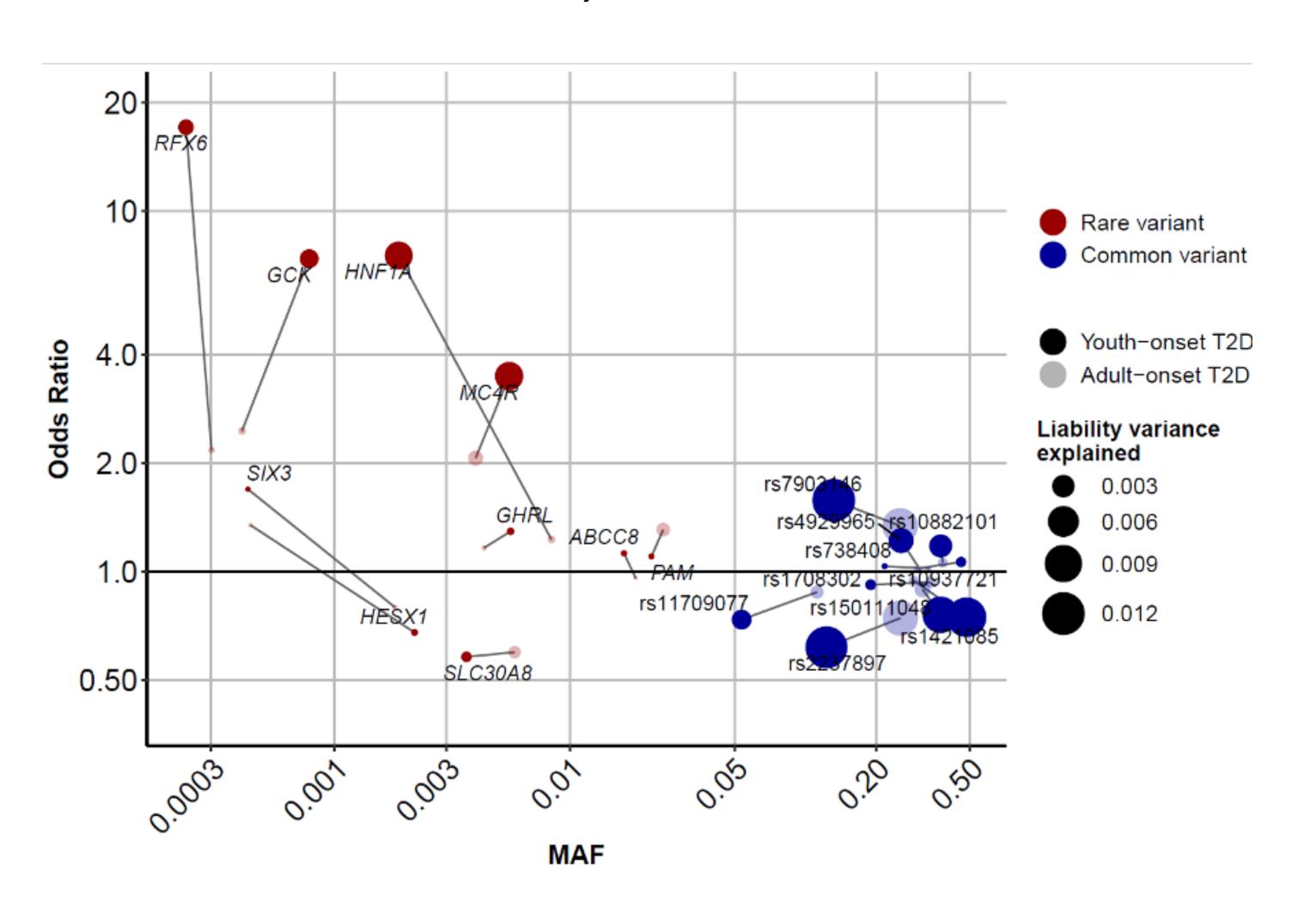
 Tier 2: among top 50 and causal for monogenic diabetes or T2D (GCK, SLC30A8, ABCC8, PAM)

• **Tier 3:** among the top 50 and in an enriched HPO gene set (*RFX6*, *GHRL*, *HESX1*, *SIX3*)

Tier 4: p<0.05 and in a diabetes-relevant gene set (38 additional genes)

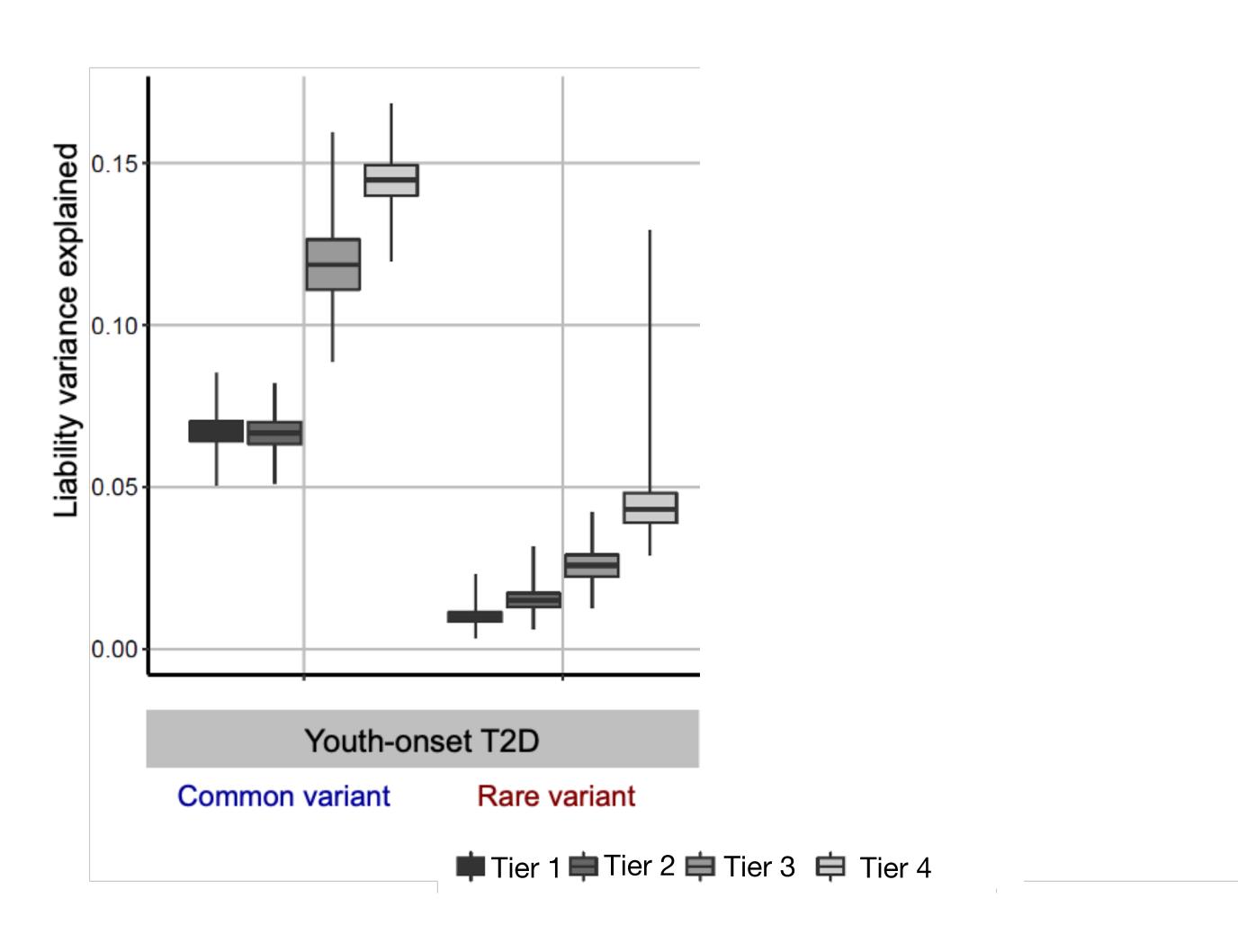
Both common and rare variants are enriched in ProDiGY

(relative to adult-onset T2D cases)



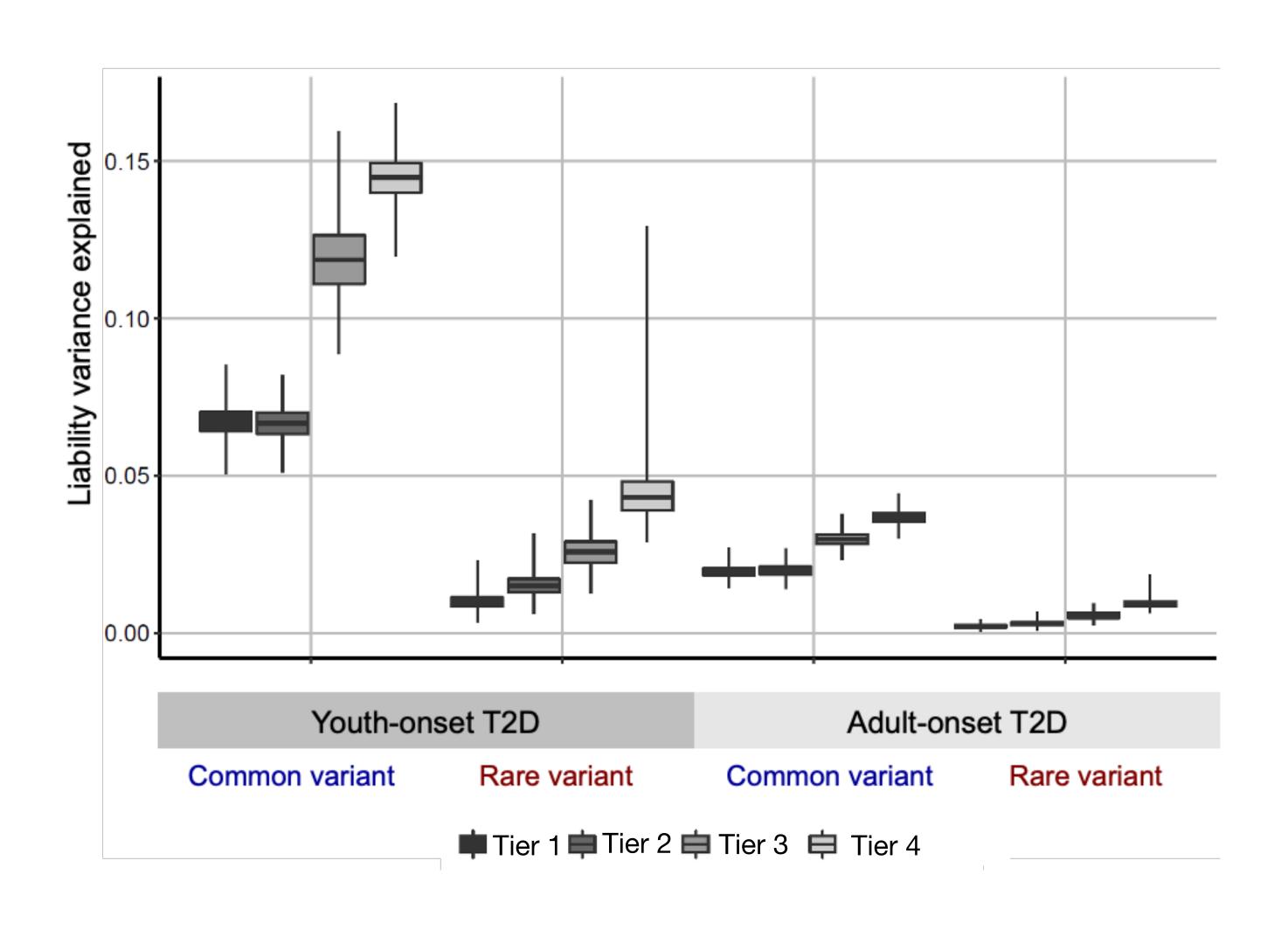
Both common and rare variants explain more heritability

(relative to adult-onset T2D cases)



Both common and rare variants explain more heritability

(relative to adult-onset T2D cases)

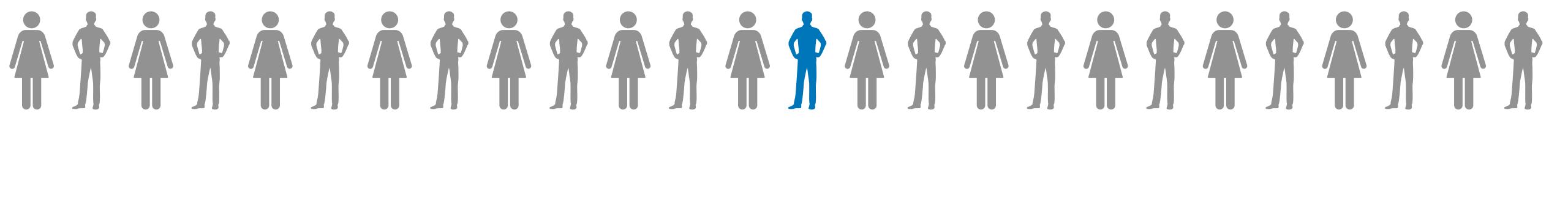


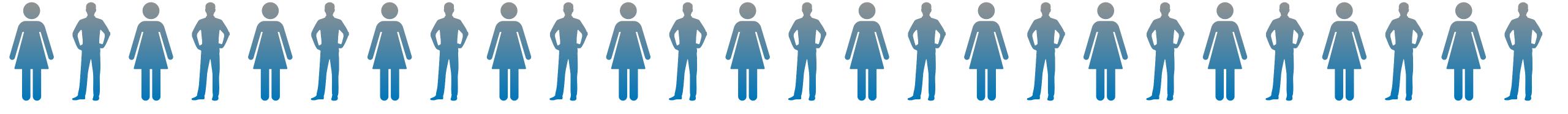
As a **population**, youth-onset T2D cases are enriched for all types of genetic risk factors

2.1% carry monogenic variants (MODY cases)5.0-fold more rare variants than adult-onset cases3.4-fold more common variants than adult-onset cases

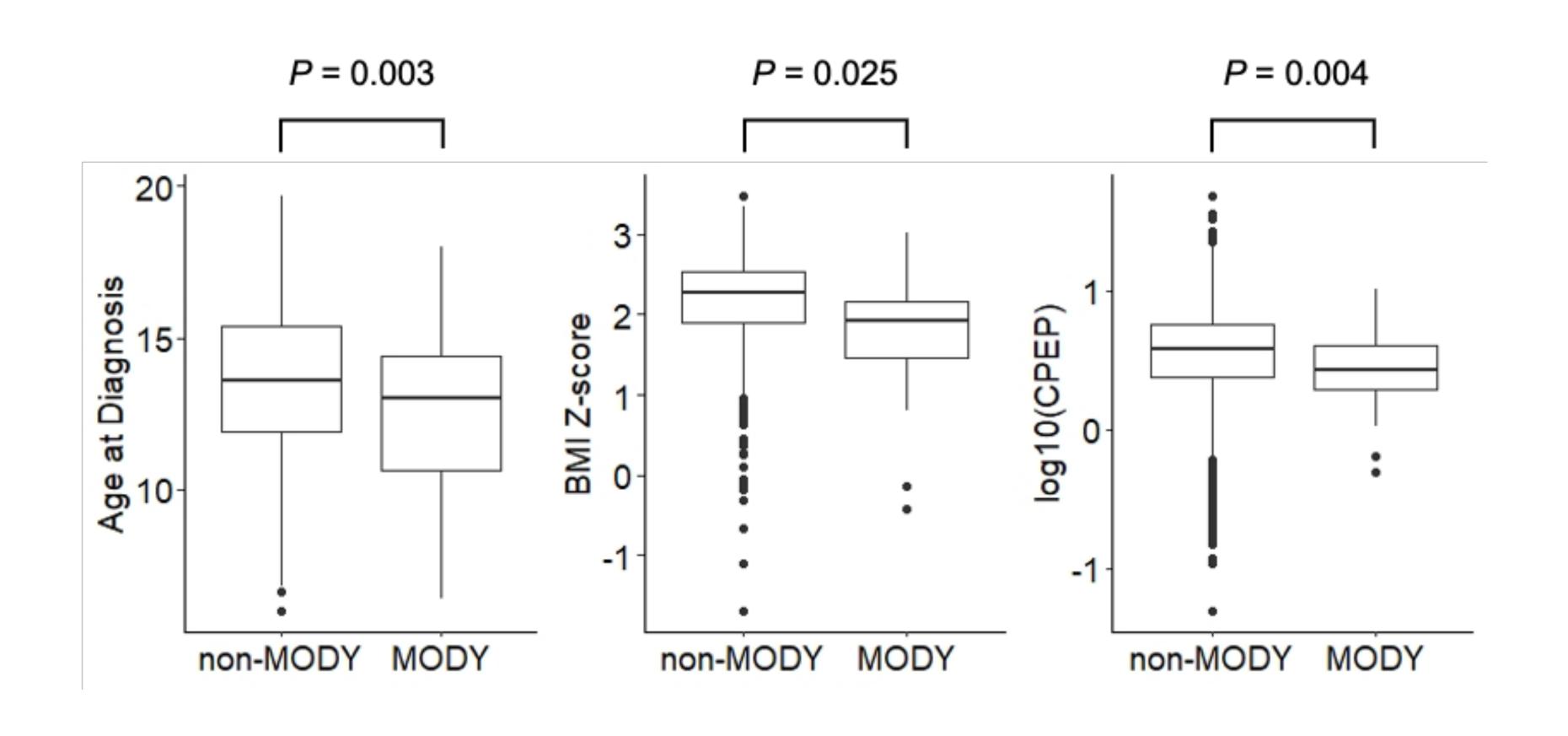
skew towards **common variants in absolute** terms skew towards **rare variants relative** to adult-onset T2D

What about individually?

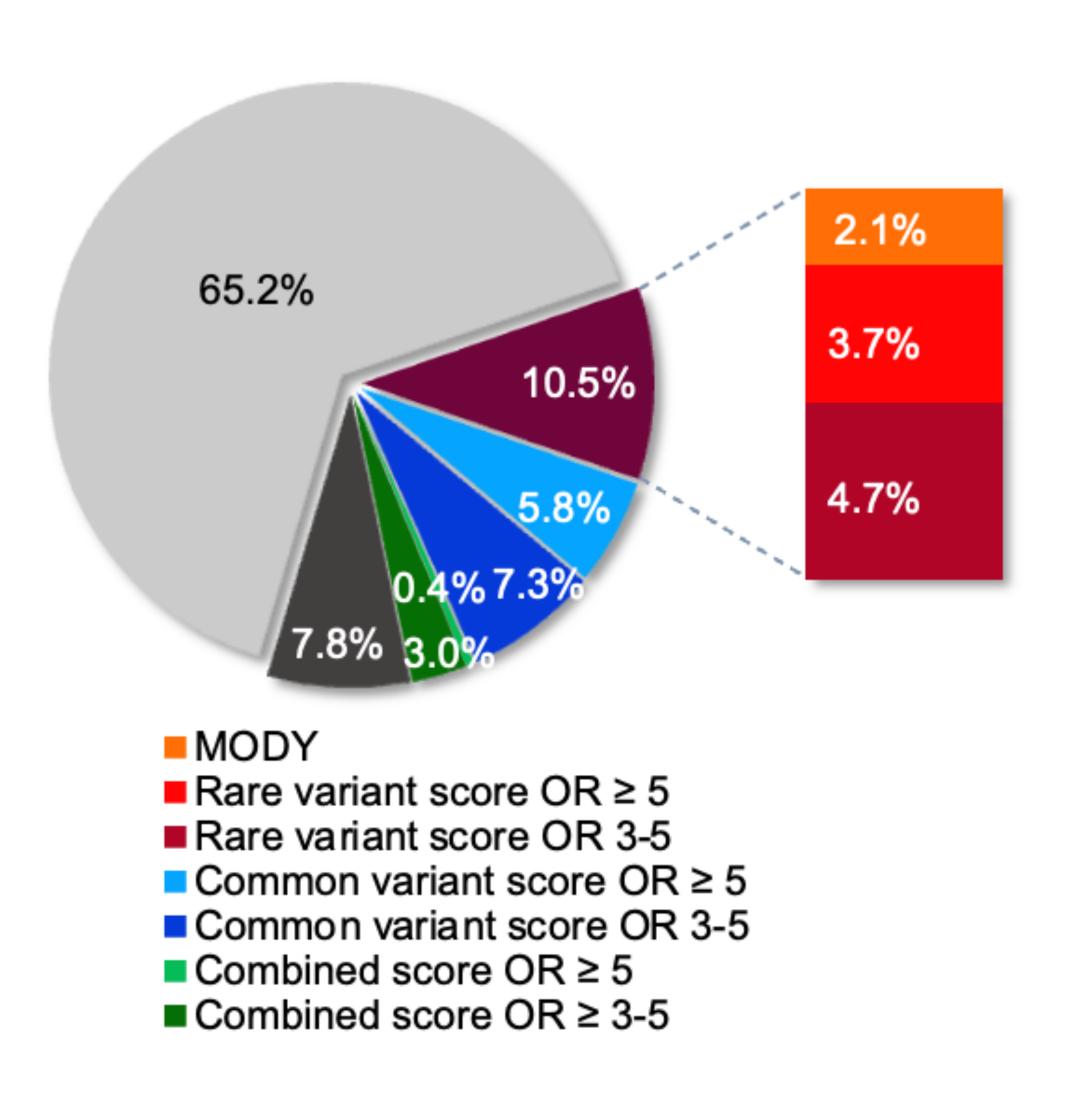




Cases due to MODY mutations are phenotypically different

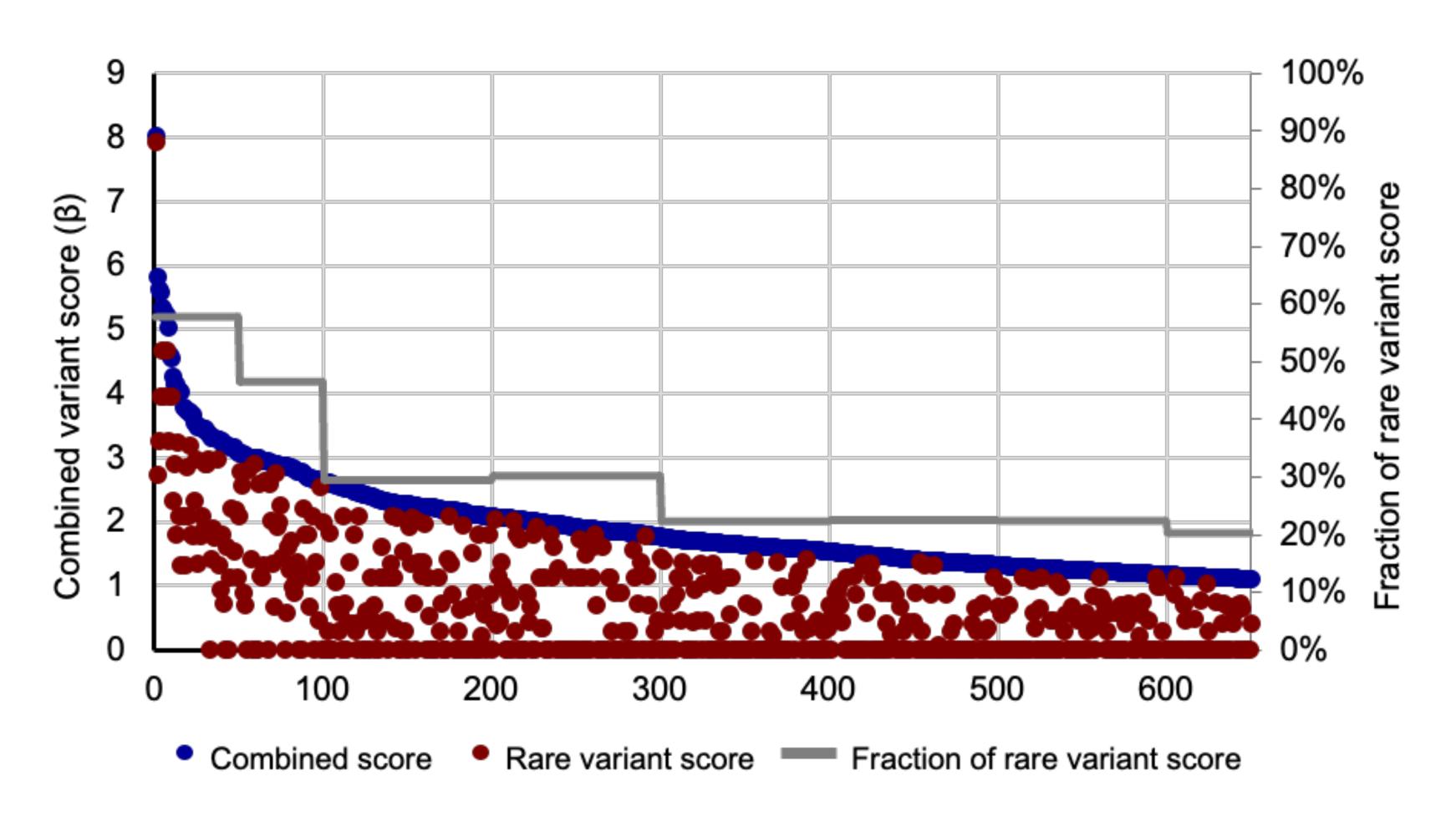


Start with cases "explained" by rare or common variants

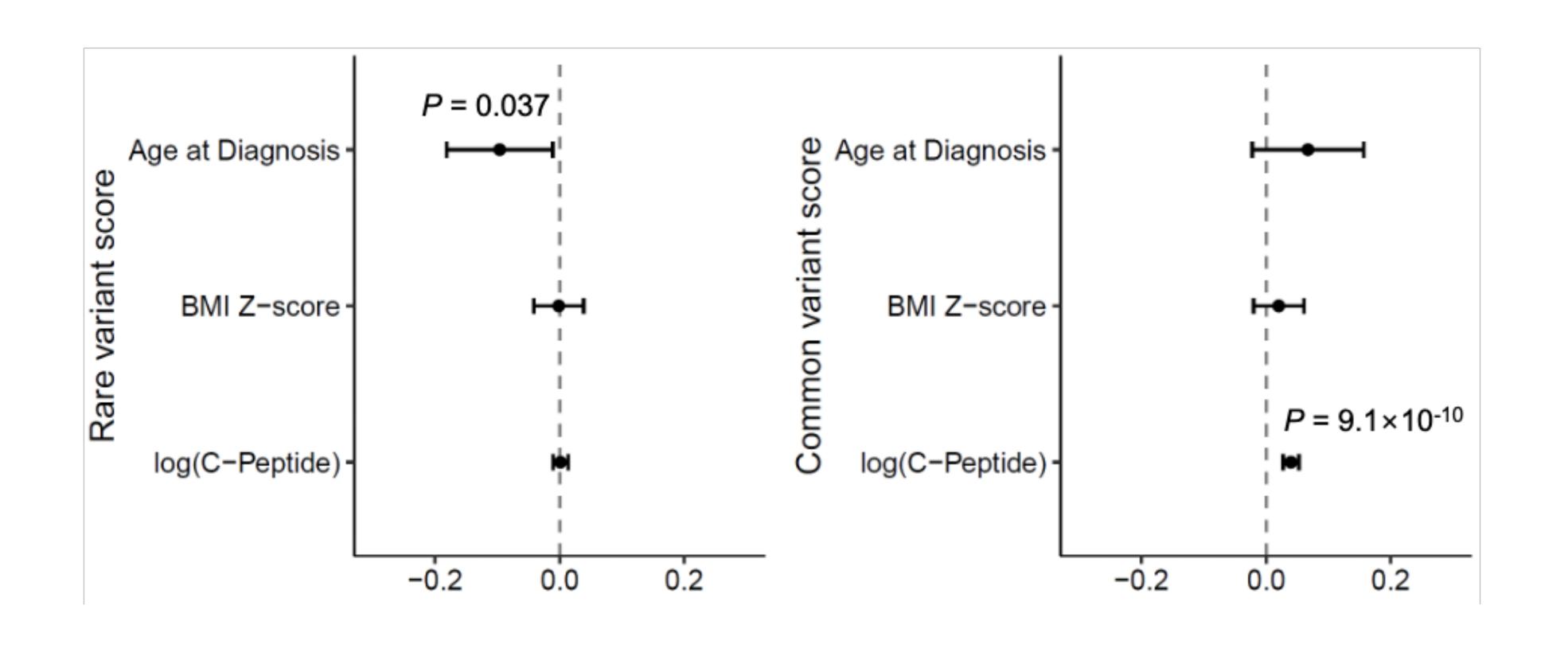


No clear dividing line between cases due to rare vs. common variants

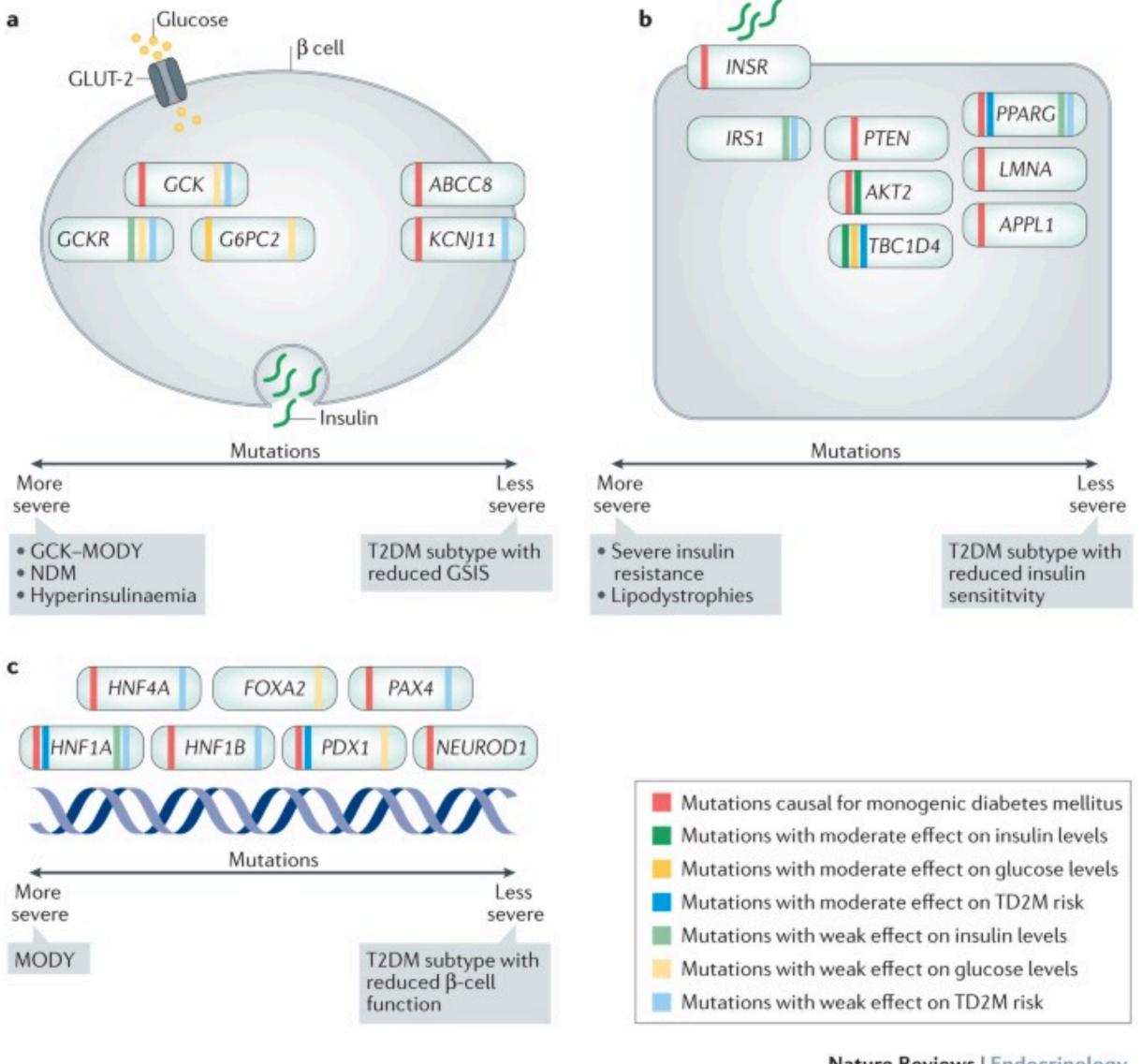
But, a substantial amount of heterogeneity across cases



Cases due to rare vs. common variants are phenotypically different

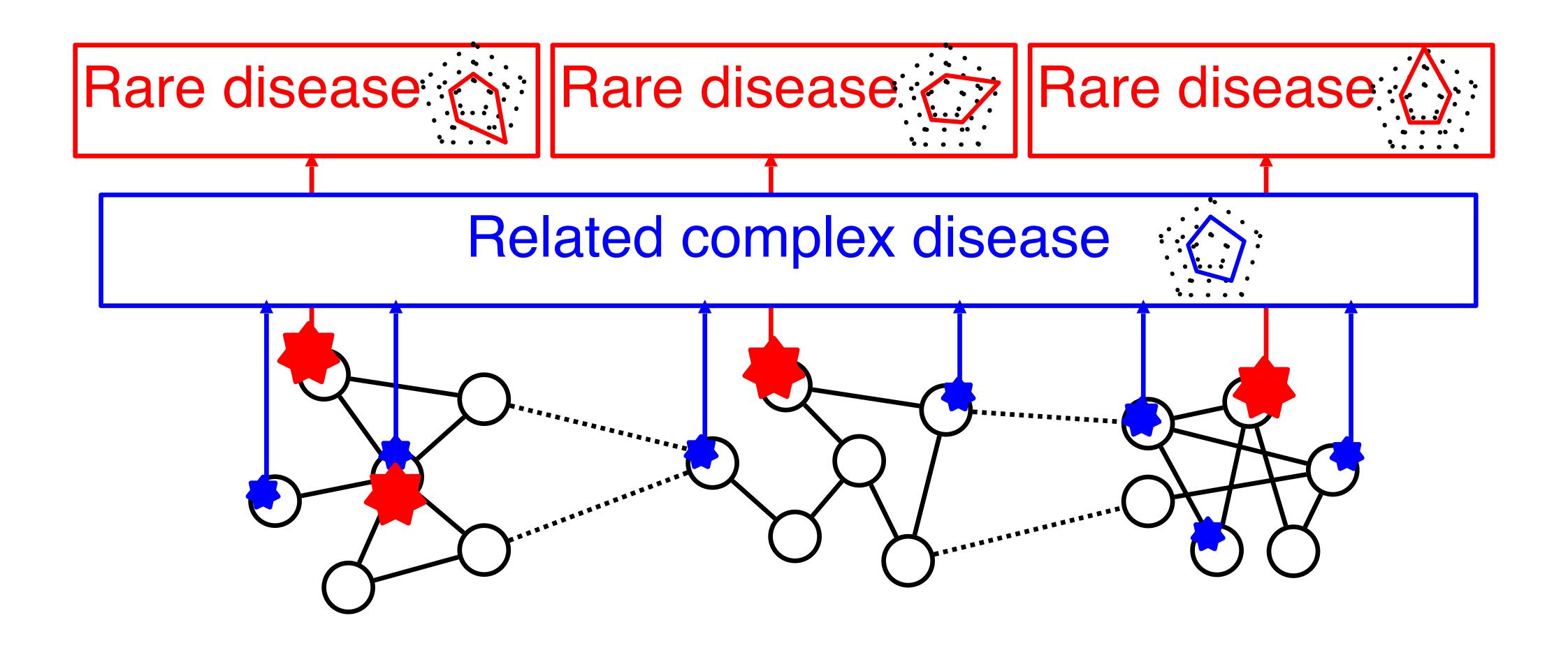


Model: allelic series are pervasive across genes and pathways

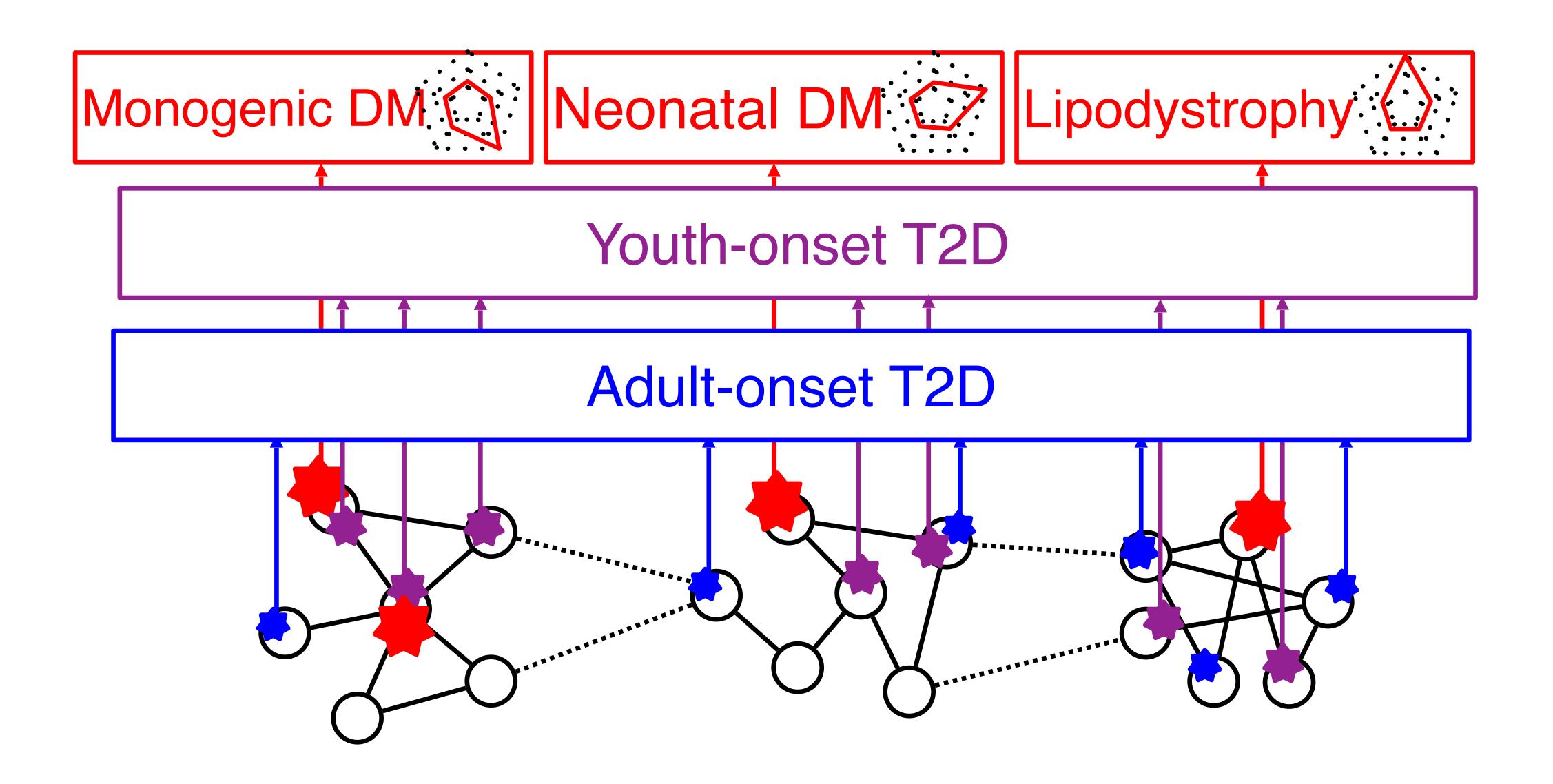


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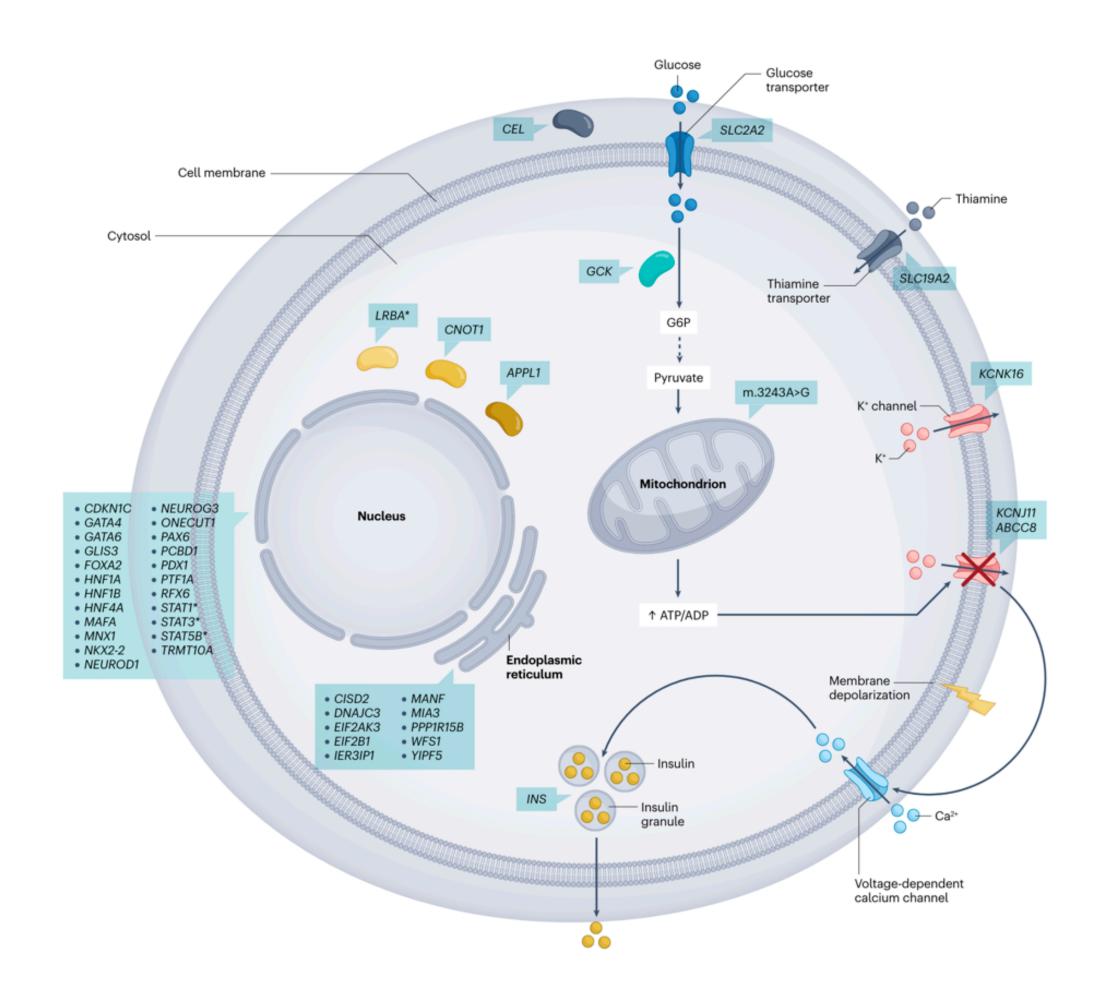
Model: allelic series are pervasive across genes and pathways

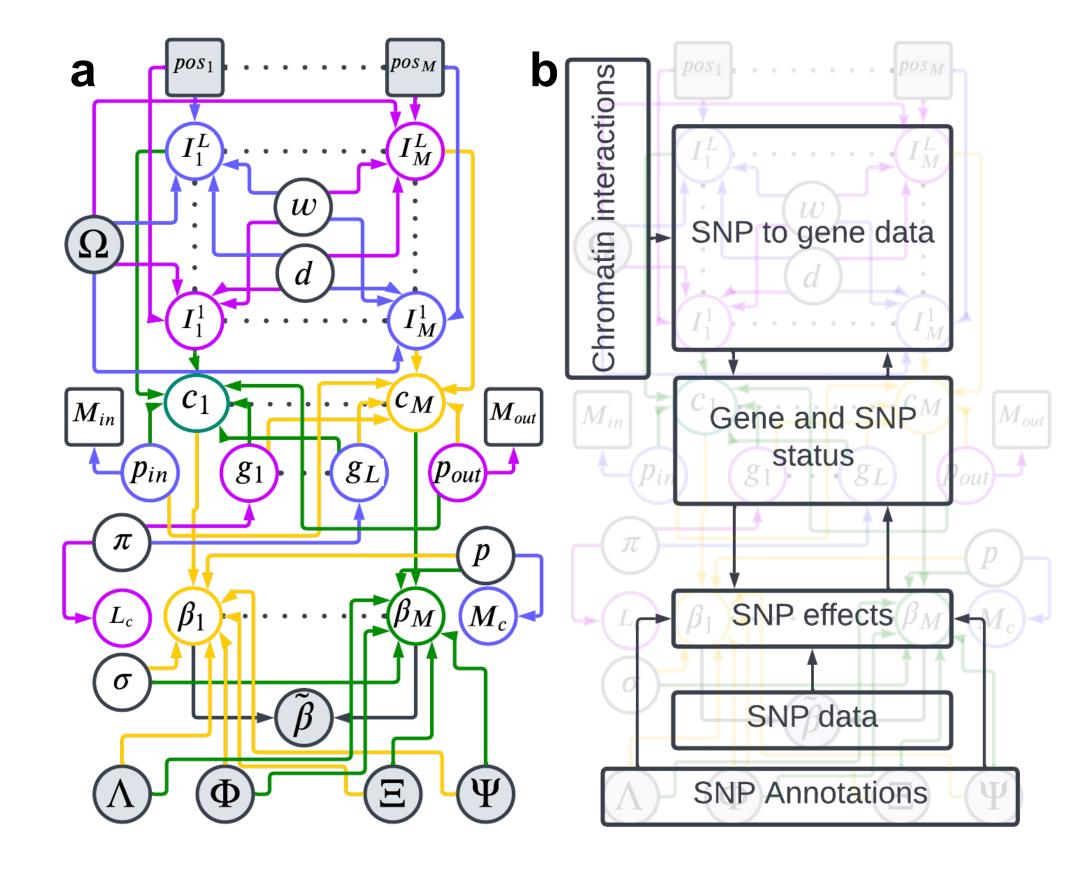


Model: allelic series are pervasive across genes and pathways



What's next?

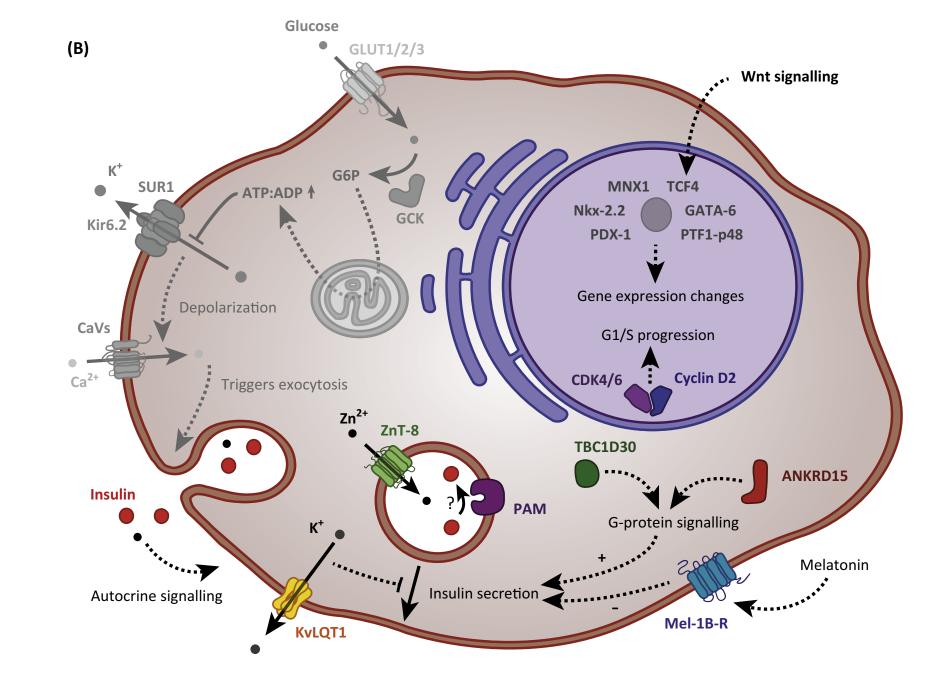




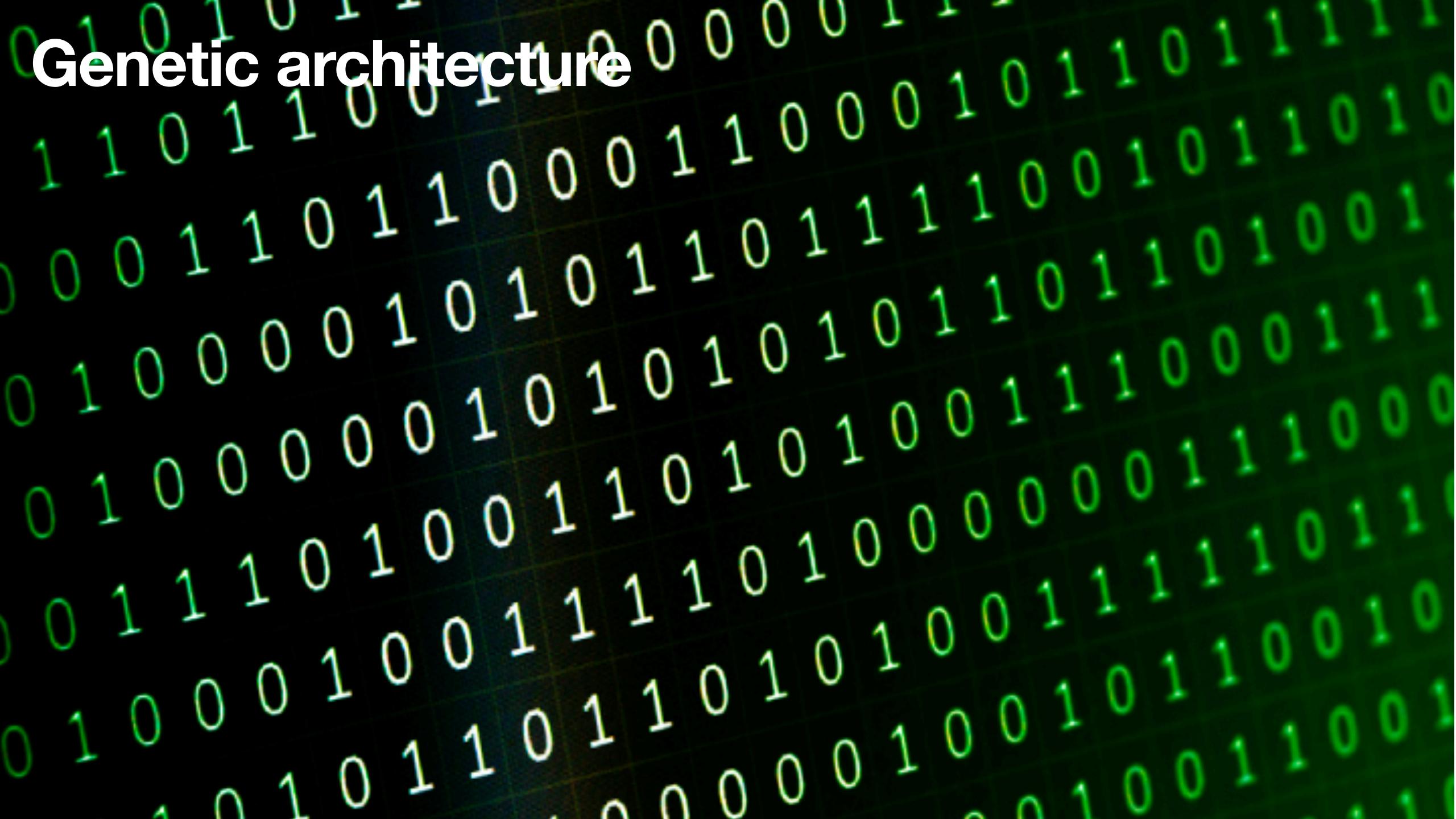
Biological insights

VS.

Genetic architecture

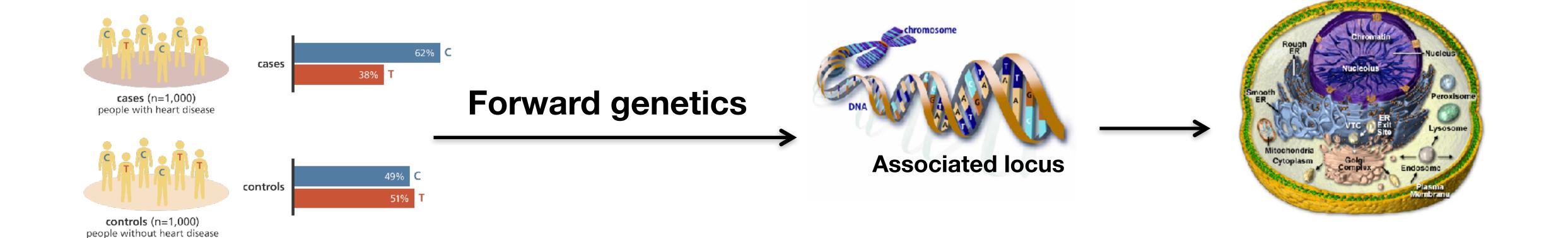




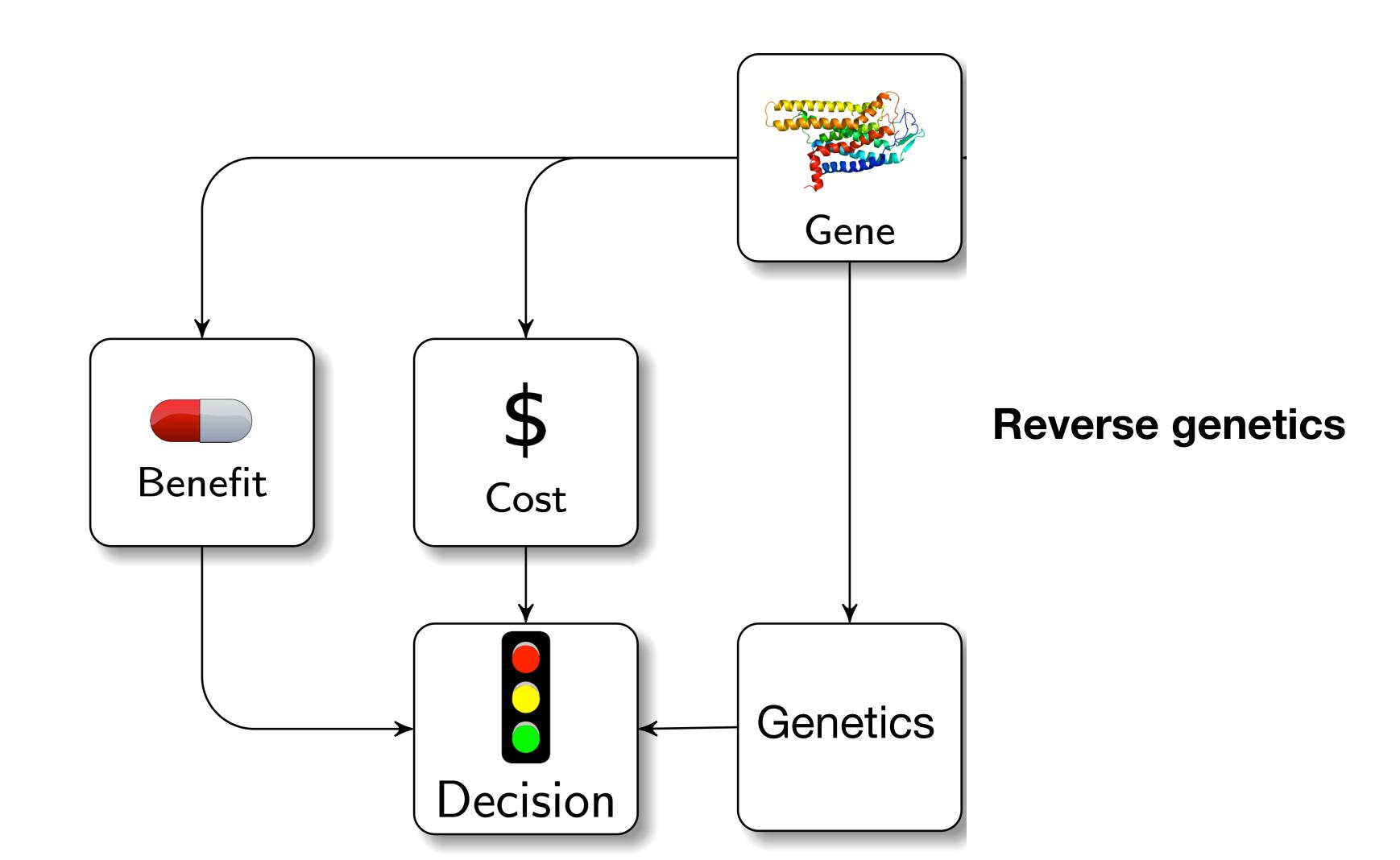


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ke sk	41.6	26:23:40.49	601	2151	Apple	0.0	0.00	0	root
	27.8	11:47:16.65	29	268	Apple	19.3	2:14:13.01	386	_win
mas_stores	19.9	7:28:41.39	5	1	Apple	0.0	0.00	542	root
Google Chrome Helper (GPU) Stop	12.0	3:29:07.62	33	103	Apple	8.2	31:53.17	757	flanr
© Google Chrome	9.4	4:53:08.90	48	68	Apple	0.0	0.00	558	flanr
screencapture	6.0	0.48	2	0	Apple	0.0	0.00	46086	flanr
Zotero	5.4	3:37:59.23	71	2	Intel	0.0	12.95	31740	flanr
Google Chrome Helper (Renderer)	5.3	1.12	23	14	Apple	0.0	0.00	46022	flann
Slack Helper (Renderer)	3.2	3:40:56.17	18	5	Apple	0.0	0.00	2228	flanr
Google Chrome Helper	2.5	2:52:45.36	31	43	Apple	0.0	0.00	758	flanr
Activity Monitor	2.3	7.76	5	2	Apple	0.0	0.00	45817	flanr
Slack Helper (GPU)	2.2	45:24.27	11	130	Apple	0.2	8:11.00	2221	flanr
Google Chrome Helper (Renderer)	1.5	32.79	25	0	Apple	0.0	0.00	97973	flanr
S Cisco AnyConnect Secure Mobility Client	1.2	8:07:36.75	7	4	Intel	0.0	0.00	74765	flanr
se_agent	1.1	3:41:14.86	7	1	Apple	0.0	0.00	750	root
com.cisco.anyconnect.macos.acsockext	1.0	2:35:20.73	8	0	Apple	0.0	0.00	524	root
ServiceDaemon	1.0	5:40:31.87	16	0	Intel	0.0	0.00	363	root
repmgr	0.8	16:29.45	24	10	Apple	0.0	0.00	3614	root
bluetoothd	0.7	15:27.91	10	0	Apple	0.0	0.00	375	root
JamfDaemon	0.7	1:45:11.20	6	0	Apple	0.0	0.00	323	root
httpd	0.7	5:24.92	1	0	Apple	0.0	0.00	19369	_ww
mdworker_shared	0.6	0.08	4	0	Apple	0.0	0.00	46075	flanr
Screen Shot	0.6	0.10	3	0	Apple	0.0	0.00	46087	flanr
sysmond	0.6	5:27.07	2	0	Apple	0.0	0.00	1084	root
sharingd	0.4	11:13.38	4	0	Apple	0.0	0.00	621	flanr
Google Chrome Helper (Renderer)	0.4	1:53.20	25	2	Apple	0.0	0.00	819	flanr
airportd	0.4	1:01:05.84	9	0	Apple	0.0	0.00	400	root
mds	0.3	1:27:40.12	6	7	Apple	0.0	0.00	336	root
fseventsd	0.3	34:34.76	12	11	Apple	0.0	0.00	310	root
logd	0.3	27:33.59	4	0	Apple	0.0	0.00	306	root
http://localhost	0.3	13:56.65	6	3	Apple	0.0	9.12	1852	flanr
🔼 Adobe Acrobat Synchronizer	0.3	42:04.38	12	1	Apple	0.0	0.00	814	flanr
Acrobat Reader Synchronizer	0.3	42:28.93	12	1	Apple	0.0	0.00	847	flanr
ForeScout SecureConnector	0.3	28:36.14	4	0	Intel	0.0	0.00	344	root
mDNSResponder	0.2	21:38.17	4	8	Apple	0.0	0.00	428	_md
Toolkit	0.2	20:36.72	38	0	Intel	0.0	0.00	5131	flanr
	2.2	40.45.04	-			0.0	0.00	670	

Where will genetic associations lead us?



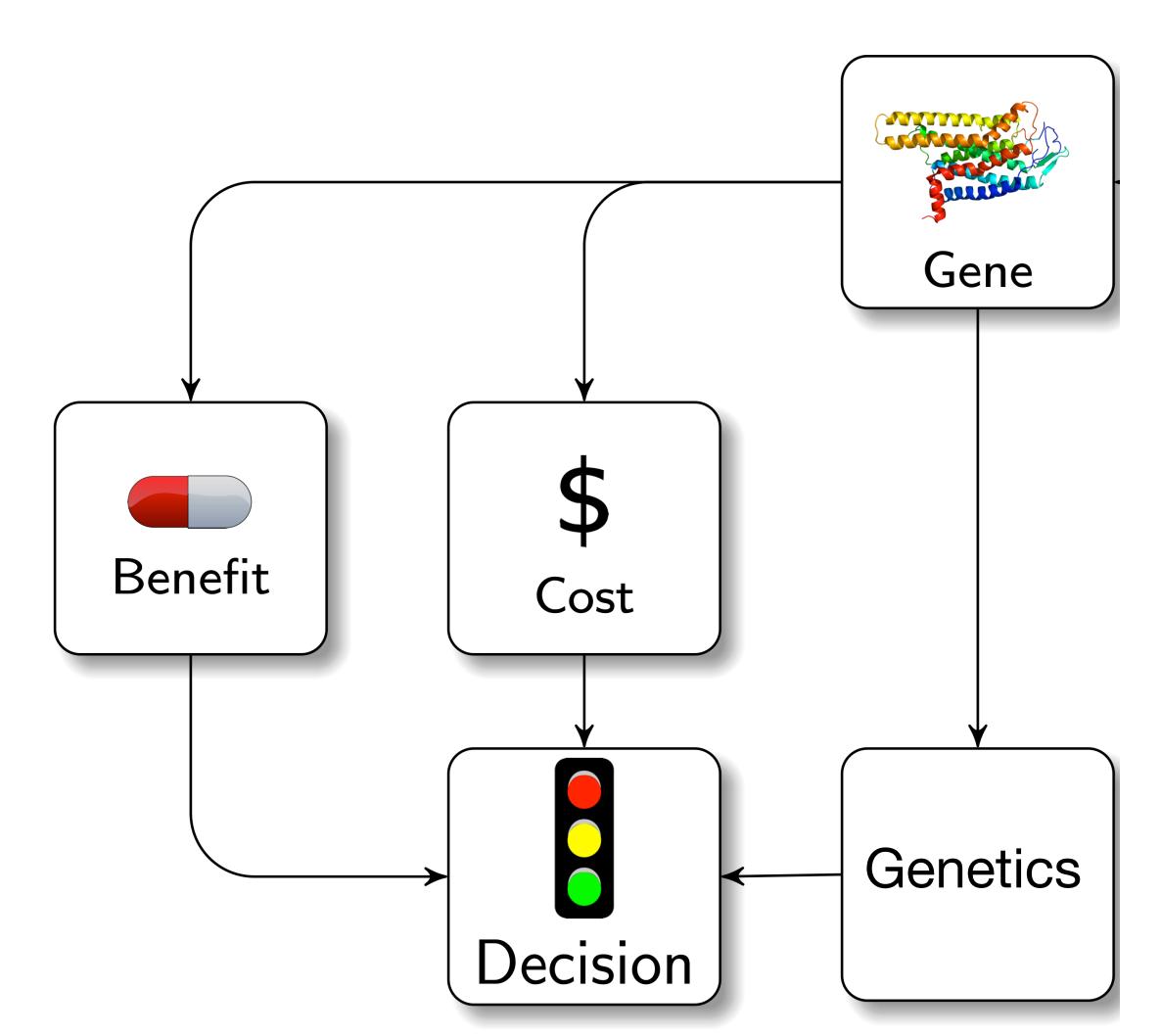
Can we lead human genetics instead?



Our organizing question

What does human genetic data tell us about a gene?

explicitly or implicitly



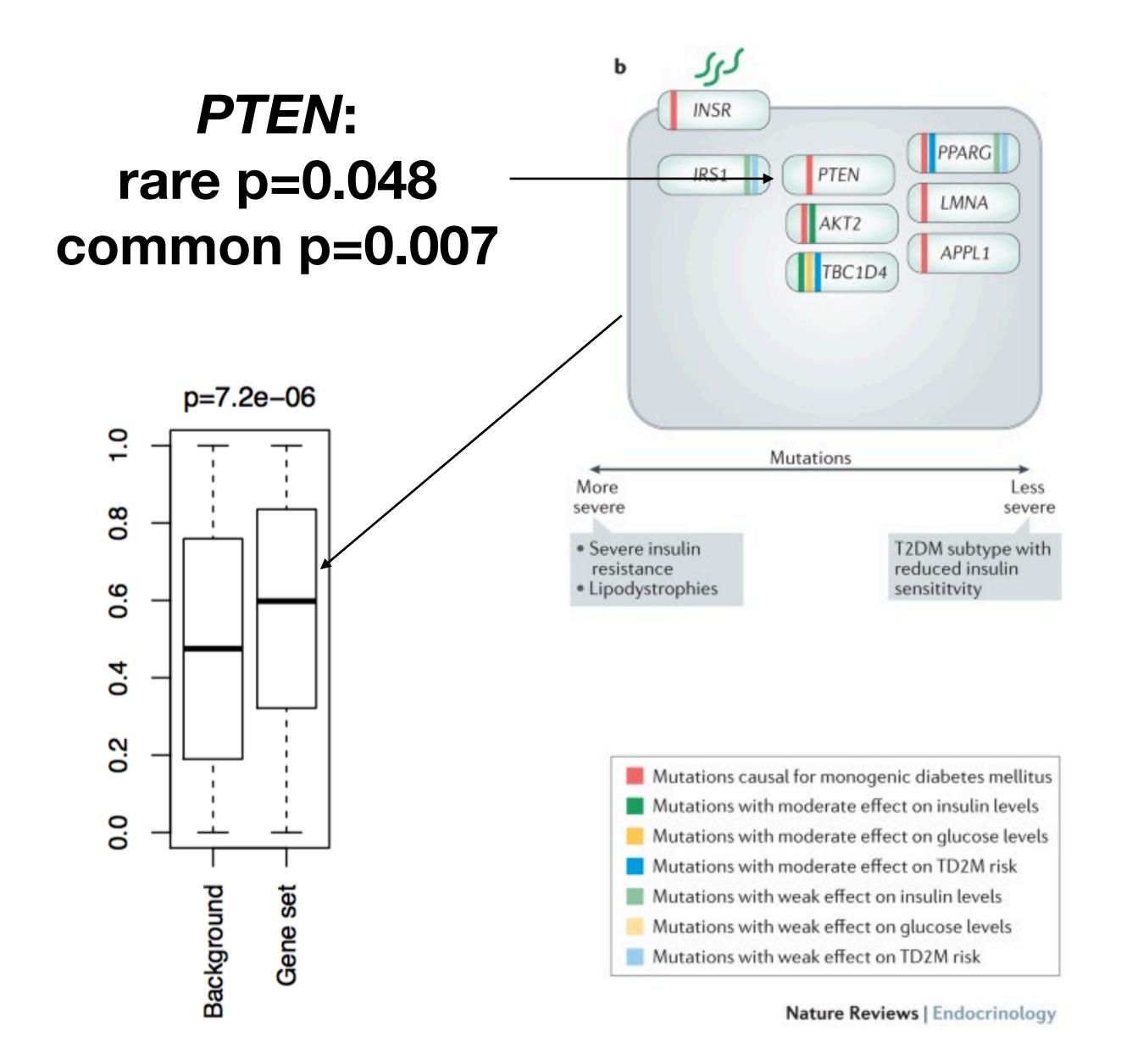




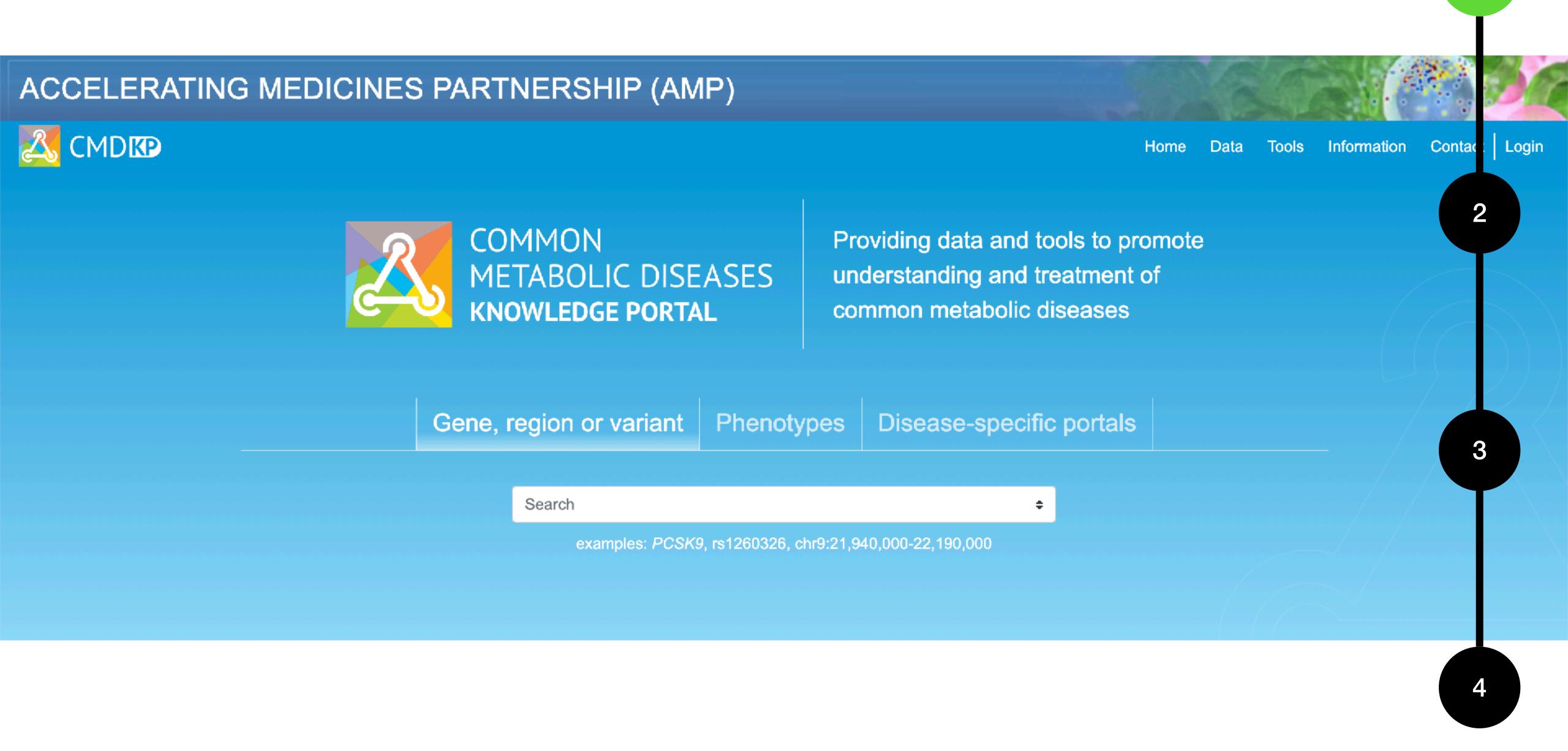




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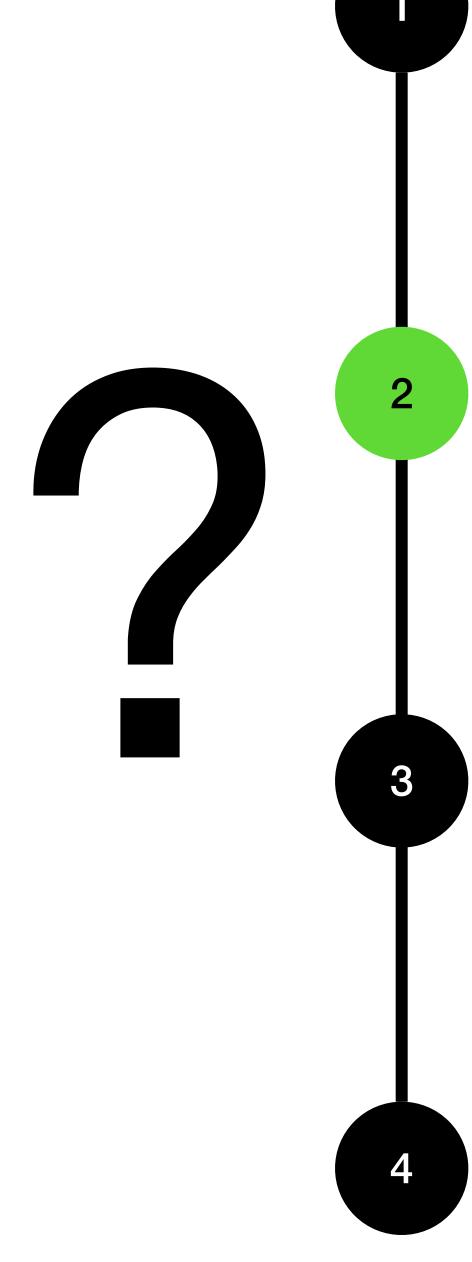


1. Make the data available



2. Help interpret the data

Gene	GWAS	Exome
SIN3A	Minimum p=9.2e-16	p=0.59
FOXO1	Minimum p=1.91e-5	p=0.036

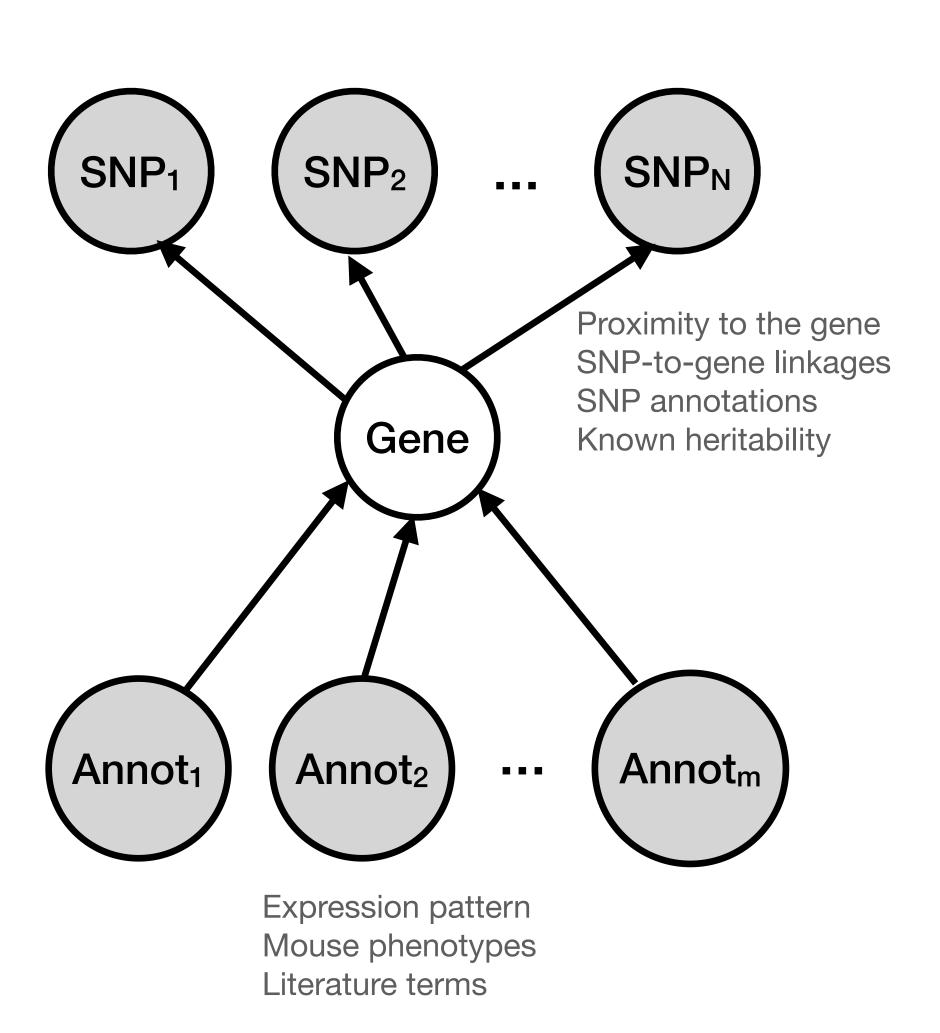


2. Help interpret the data

Compelli 95% 99	Causal coding variant	
Very Stro 70% 90	Nearest gene Coding variant	
Strong 50% 85	Coding variant	
Modera 15% 40	GWAS locus	
No evide 5% 209	No evidence	

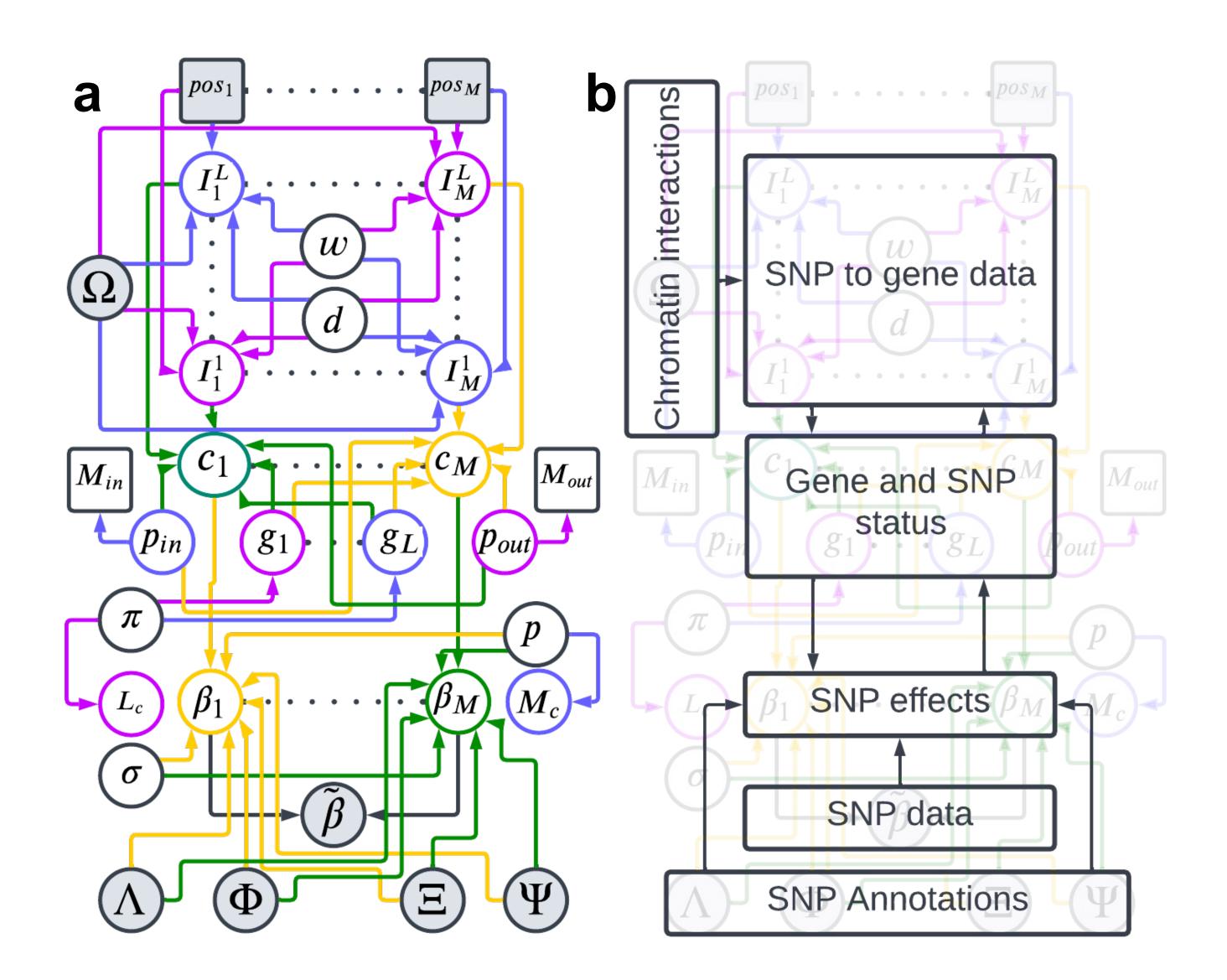
Compelling	Compelling	Compelling	Compelling	Compelling		
95% 99%	95% 99%	99% 9%	99% 99%	99% 99%		
Very Strong	Very Strong	Extreme	Compelling	Compelling		
70% 90%	80% 95%	90% 95%	99% 99%	99% 99%		
Strong	Very Strong	Very Strong	Compelling	Compelling		
50% 85%	60% 90%	75% 95%	95% 99%	99% 99%		
Moderate	Moderate	Moderate	Very Strong	Compelling		
15% 40%	20% 55%	30% 70%	75% 95%	99% 99%		
No evidence	Anecdotal	Moderate	Strong	Compelling		
5% 20%	5% 25%	15% 45%	50% 85%	95% 99%		
No evidence <i>p</i> ≥0.1	Weak <i>p</i> <0.1	Nominal <i>p</i> <0.05	Strong <i>p</i> <1x10 ⁻³	Exome-wide p<2.5x10 ⁻⁶		
Rare Variation						

3. Build ever more sophisticated models

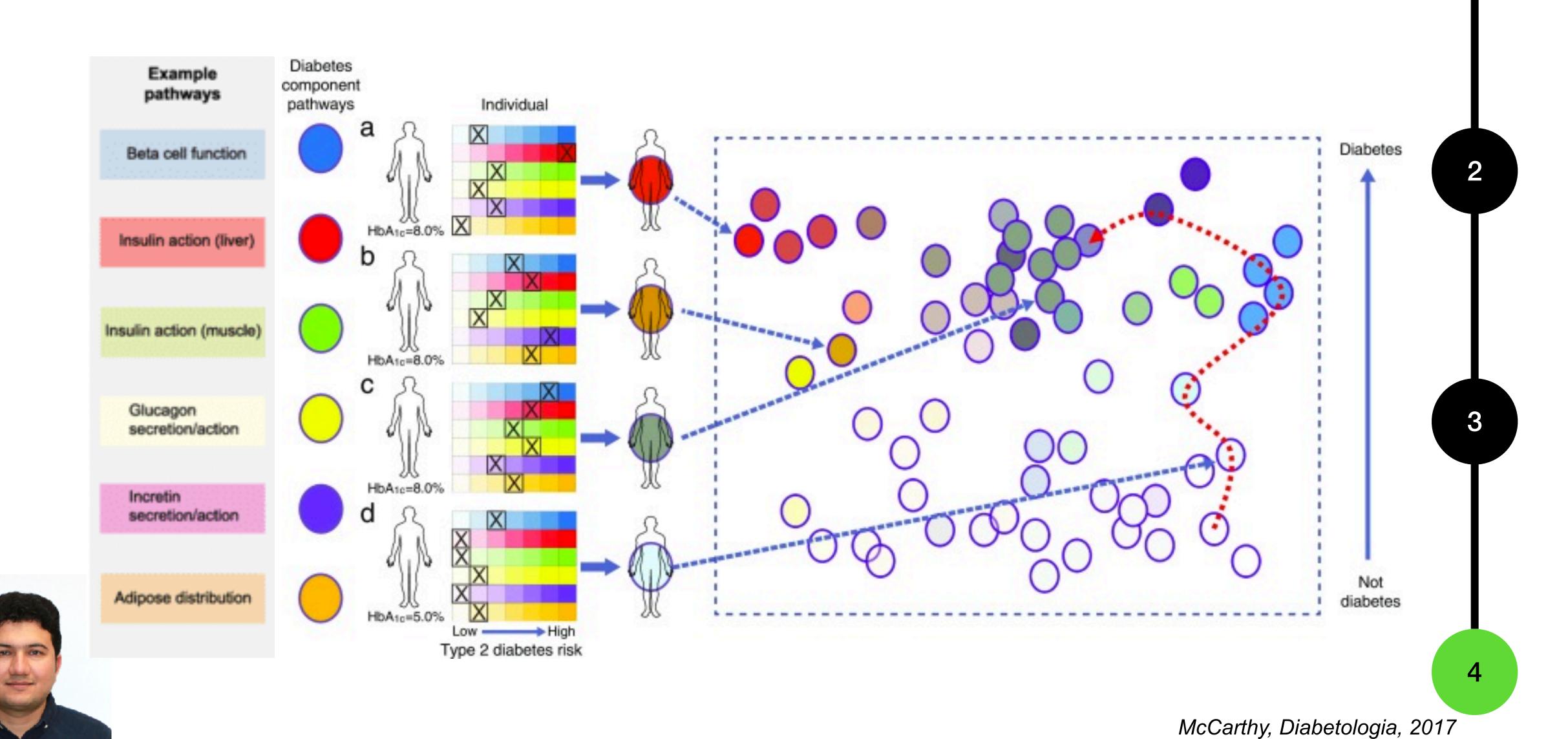




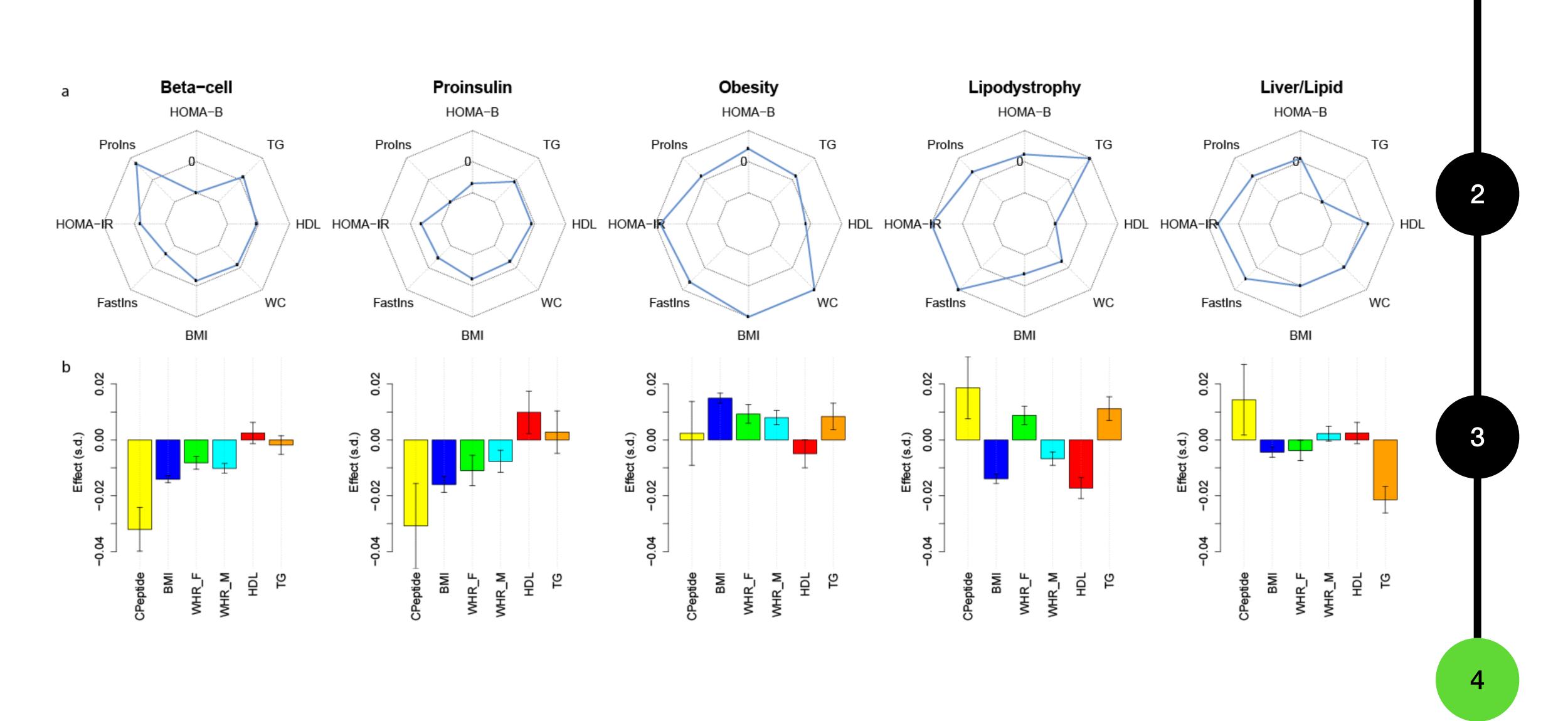
3. Build ever more sophisticated models



4. Extend beyond genes to pathways



4. Extend beyond genes to pathways



Statistical Genetics

Data integration and dissemination

> Rare coding variants

Type 2 Diabetes

Computer Science

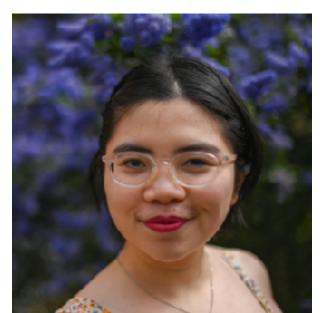
Computational Biology

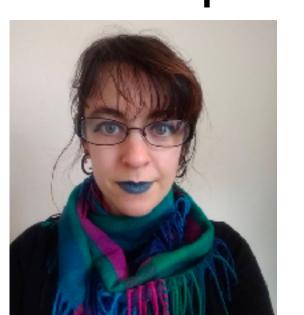
























We are always seeking collaborators and motivated new members!

Contact flannick@broadinstitute.org or http://flannicklab.org





