# ACMG-ClinVar Penetrance RMarkdown

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#### Abstract

Here, we examine ExAC and the 1000 Genomes Project to investigate the distribution of pathogenic variants across diverse populations. Pathogenic variants were found to be distributed unevenly across ancestral groups, with incidental findings inflated relative to empirical disease prevalences. Quantitative risk estimates were derived by modeling penetrance as a function of disease prevalence, allele frequency, and allelic heterogeneity. Plausible ranges for these parameters were estimated from ExAC, the 1000 Genomes cohort, and the medical literature. Under the most generous assumptions, penetrance estimates for the majority of diseases fall under 50%, with many under 5%. We propose the described model of penetrance as a quantitative framework for evaluating, comparing, and updating clinical interpretations of pathogenic variants.

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# 1 Download, Transform, and Load Data

## 1.1 Collect ACMG Gene Panel

http://www.ncbi.nlm.nih.gov/clinvar/docs/acmg/

## Processed Table from ACMG Website 64 x 4 (selected rows):

	Disease_Name	${\bf Disease\_MIM}$	${\rm Gene\_Name}$	Gene_MIM
<b>A</b> 1	Adenomatous polyposis coli	175100	APC	611731
<b>A2</b>	Aortic aneurysm, familial thoracic 4	132900	MYH11	160745
A5	Arrhythmogenic right ventricular cardiomyopathy, type 5	604400	TMEM43	612048
<b>A10</b>	Breast-ovarian cancer, familial 1	604370	BRCA1	113705
<b>A</b> 11	Breast-ovarian cancer, familial 2	612555	BRCA2	600185
A12	Brugada syndrome 1	601144	SCN5A	600163
A13	Catecholaminergic polymorphic ventricular tachycardia	604772	RYR2	180902
<b>A14</b>	Dilated cardiomyopathy 1A	115200	LMNA	150330
A16	Ehlers-Danlos syndrome, type 4	130050	COL3A1	120180
A17	Fabry's disease	301500	$\operatorname{GLA}$	300644
A18	Familial hypercholesterolemia	143890	APOB	107730
A20	Familial hypertrophic cardiomyopathy 1	192600	MYH7	160760
<b>A28</b>	Familial medullary thyroid carcinoma	155240	RET	164761
A30	Left ventricular noncompaction 6	601494	TNNT2	191045
<b>A31</b>	Li-Fraumeni syndrome 1	151623	TP53	191170
<b>A32</b>	Loeys-Dietz syndrome type 1A	609192	TGFBR1	190181
A37	Long QT syndrome 1	192500	KCNQ1	607542
A40	Lynch syndrome	120435	MLH1	120436
A44	Malignant hyperthermia	145600	RYR1	180901
A46	Marfan's syndrome	154700	FBN1	134797
A48	Multiple endocrine neoplasia, type 1	131100	MEN1	613733
A51	MYH-associated polyposis	608456	MUTYH	604933
A52	Neurofibromatosis, type 2	101000	NF2	607379
A53	Paragangliomas 1	168000	SDHD	602690
A57	Peutz-Jeghers syndrome	175200	STK11	602216
<b>A58</b>	Pilomatrixoma	132600	MUTYH	604933
A59	PTEN hamartoma tumor syndrome	153480	PTEN	601728
<b>A</b> 60	Retinoblastoma	180200	RB1	614041
<b>A</b> 61	Tuberous sclerosis 1	191100	TSC1	605284
A63	Von Hippel-Lindau syndrome	193300	VHL	608537
A64	Wilms' tumor	194070	WT1	607102

### ## ACMG-56 Genes:

##	[1]	APC	MYH11	ACTA2	MYLK	TMEM43	DSP	PKP2	DSG2
##	[9]	DSC2	BRCA1	BRCA2	SCN5A	RYR2	LMNA	MYBPC3	COL3A1
##	[17]	GLA	APOB	LDLR	MYH7	TPM1	PRKAG2	TNNI3	MYL3
##	[25]	MYL2	ACTC1	RET	PCSK9	TNNT2	TP53	TGFBR1	TGFBR2
##	[33]	SMAD3	KCNQ1	KCNH2	MLH1	MSH2	MSH6	PMS2	RYR1
##	[41]	CACNA1S	FBN1	MEN1	MUTYH	NF2	SDHD	SDHAF2	SDHC
##	[49]	SDHB	STK11	PTEN	RB1	TSC1	TSC2	VHL	WT1

#### 1.2 Download ClinVar VCF

ftp://ftp.ncbi.nlm.nih.gov/pub/clinvar/vcf\_GRCh37/clinvar.vcf.gz

ClinVar is the central repository for variant interpretations. Relevant information from the VCF includes:

- (a) CLNSIG = "Variant Clinical Significance, 0 Uncertain, 1 Not provided, 2 Benign, 3 Likely benign, 4
- Likely pathogenic, 5 Pathogenic, 6 Drug response, 7 Histocompatibility, 255 Other"
- (b) CLNDBN = "Variant disease name"
- (c) CLNDSDBID = "Variant disease database ID"
- (d) INTERP = Pathogenicity (likely pathogenic or pathogenic; CLNSIG = 4 or 5)
- ## Processed ClinVar data frame 117420 x 14 (selected rows/columns):

VAR_ID	CHROM	POS	ID	REF	ALT	CLNSIG
1_955597_G_T	1	955597	rs115173026	G	${ m T}$	2
$1_{955619}G_{C}$	1	955619	rs201073369	G	$\mathbf{C}$	255
$1\_957605\_G\_A$	1	957605	$\mathrm{rs}756623659$	G	A	5

Table continues below

CLNDBN	CLNDSDBID	INTERP
not_specified	CN169374	FALSE
not_specified	CN169374	FALSE
Congenital_myasthenic_syndrome	C0751882:ORPHA590	TRUE

### 1.3 Download 1000 Genomes VCFs

 $\label{lem:condition} $$ftp://ftp.1000genomes.ebi.ac.uk/vol1/ftp/release/20130502/ALL.[chrom].phase3\_[version].20130502.genotypes.vcf.gz Downloaded 1000 Genomes VCFs are saved in: /Users/jamesdiao/Documents/Kohane\_Lab/2016-paper-ACMG-penetrance/1000G/$ 

## Download report: region and successes: 56 x 6 (selected rows):

gene	name	chrom	start	end	downloaded
APC	NM_001127511	5	1.12e + 08	112181936	TRUE
MYH11	NM_001040113	16	15796991	15950887	TRUE
ACTA2	$NM\_001141945$	10	90694830	90751154	TRUE
MYLK	$NM\_001321309$	3	123331142	123603149	TRUE
TMEM43	$\mathrm{NM}\_024334$	3	14166439	14185180	TRUE

## File saved as download\_output.txt in Supplementary\_Files

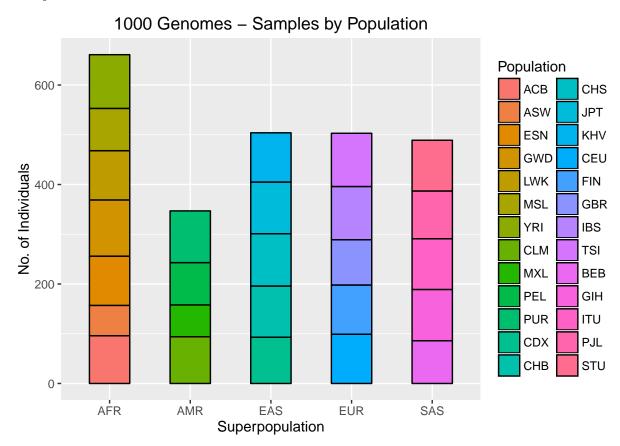
## 1.4 Collect 1000 Genomes Phase 3 Populations Map

This will allow us to assign genotypes from the 1000 Genomes VCF to ancestral groups. From: ftp://ftp.1000genomes.ebi.ac.uk/vol1/ftp/release/20130502/integrated\_call\_samples\_v3.20130502. ALL.panel

## Phase 3 Populations Map Table: 2504 x 4 (selected rows)

sample	pop	super_pop	gender
NA19121	YRI	AFR	male
HG02813	$\operatorname{GWD}$	AFR	$_{\mathrm{male}}$
NA19036	LWK	AFR	female
NA19037	LWK	AFR	female
HG02339	ACB	AFR	female
HG01323	PUR	AMR	female
HG00533	CHS	EAS	male
HG00133	GBR	EUR	female
NA20854	GIH	SAS	female
HG03016	PJL	SAS	female

## Population Distribution



### 1.5 Import and Process 1000 Genomes VCFs

- (a) Unnest the data frames to 1 row per variant\_ID key (CHROM\_POSITION\_REF\_ALT).
- (b) Remove all insertions, deletions, CNV, etc, and keep only missense variants (1 REF, 1 ALT)
- (c) For 1000 Genomes: convert genomes to allele counts. For example: (0|1) becomes 1, (1|1) becomes 2. Multiple alleles are unnested into multiple counts. For example: (0|2) becomes 0 for the first allele (no 1s) and 1 for the second allele (one 2).

## Processed 1000 Genomes VCFs: 139335 x 2516 (selected rows/columns):

GENE	AF_1000G	VAR_ID	CHROM	POS	ID	REF	ALT
APC	0.0001997	5_112043211_A_0	F 5	1.12e+08	rs554351451	A	G
APC	0.0001997	5_112043231_G_A	5	1.12e + 08	rs575784409	G	A
APC	0.005391	$5\_112043234\_C\_T$	5	1.12e + 08	rs115658307	$\mathbf{C}$	${ m T}$
APC	0.0001997	5_112043252_G_A	5	1.12e + 08	rs558562104	G	A
APC	0.008786	$5\_112043263\_C\_T$	5	1.12e+08	rs138386816	$\mathbf{C}$	${ m T}$

Table continues below

HG00096	HG00097	HG00099	HG00100	HG00101	HG00102
 0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
 0	0	0	0	0	0

### 1.6 Import and Process ExAC VCFs

- (a) Unnest the data frames to 1 row per variant\_ID key (CHROM\_POSITION\_REF\_ALT).
- (b) Remove all insertions, deletions, CNV, etc, and keep only missense variants (1 REF, 1 ALT)
- (c) Collect superpopulation-level allele frequencies: African = AFR, Latino = AMR, European (Finnish + Non-Finnish) = EUR, East.Asian = EAS, South.Asian = SAS.

## Processed ExAC VCFs: 58873 x 45 (selected rows/columns):

GENE	AF_EXAC	AF_EXAC_AFR	AF_EXAC_AMR	AF_EXAC_EAS	AF_EXAC_EUR
APC	8.13e-05	0	0	0	0
APC	8.131e-05	0	0	0	0
APC	0.1112	0.07979	0.1022	0	0.1063
APC	8.131e-05	0	0	0	0
APC	8.134 e-05	0	0	0	0

Table continues below

AF_EXAC_SAS	VAR_ID	CHROM	POS	ID	REF	ALT
0.0001313	5_112043365_G_C	5	1.12e + 08		G	С
0.0001313	$5\_112043382\_A\_G$	5	1.12e + 08		A	G
0.1185	5_112043384_T_G	5	1.12e + 08	rs78429131	${ m T}$	G
0.0001313	$5\_112043392\_C\_T$	5	1.12e + 08		$\mathbf{C}$	Τ
0.0001313	5_112043412_C_G	5	1.12e+08	•	С	G

## 1.7 Merge ClinVar with 1000 Genomes and ExAC

### ## Breakdown of ClinVar Variants

Subset_ClinVar	Number_of_Variants
Total ClinVar	117420
LP/P-ClinVar	33633
LP/P-ClinVar & ACMG	6971
LP/P-ClinVar & ACMG & ExAC	964
LP/P-ClinVar & ACMG & 1000	147
Genomes	

### ## Breakdown of ACMG-1000 Genomes Variants

Subset_1000_Genomes	Number_of_Variants
Total 1000_Genomes & ACMG	139335
1000_Genomes & ACMG & ClinVar	4339
1000_Genomes & ACMG &	147
LP/P-ClinVar	

### ## Breakdown of ACMG-ExAC Variants

Subset_ExAC	Number_of_Variants
Total ExAC & ACMG	58873
ExAC & ACMG & ClinVar	9347
ExAC & ACMG & LP/P-ClinVar	964

### 1.8 Comparison with ClinVar Browser Query Results

clinvar\_query.txt contains all results matched by the search query: "(APC[GENE] OR MYH11[GENE]... OR WT1[GENE]) AND (clinsig\_pathogenic[prop] OR clinsig\_likely\_pathogenic[prop])" from the ClinVar website. The exact query is saved in /Supplementary\_Files/query\_input.txt This presents another way of collecting data from ClinVar.

Intermediate step: convert hg38 locations to hg19 using the Batch Coordinate Conversion tool (liftOver) from UCSC Genome Browser Utilities.

## ClinVar Query Results Table (substitutions only): 6714 x 13 (selected rows/columns)

VAR_ID	Gene(s)	Condition(s)	Frequency
X_100652891_C_G	GLA	Fabry disease	GMAF:0.00050(G)
11_47374186_C_G	MYBPC3	Primary familial hypertrophic cardiomyopathy	GMAF:0.00020(G)
11_47355233_C_G	MYBPC3	Familial hypertrophic cardiomyopathy 4	GMAF:0.00020(G)
11_47364162_C_G	MYBPC3	Familial hypertrophic cardiomyopathy 4	GMAF:0.00020(G)
$14\_23886482\_G\_C$	MYH7	not specified	GMAF:0.00020(C)
14_23893148_C_G	MYH7	Primary dilated cardiomyopathy	GO-ESP:0.00046(G)
$1\_17355075\_A\_T$	SDHB	Gastrointestinal stromal tumor	GMAF:0.00120(T)
1_17380507_G_C	SDHB	Cowden syndrome 2	GO-ESP:0.01323(C)

#### ## Breakdown of ClinVar Query Results Table:

Subset	$Number\_of\_Variants$
Initial Count	12525
Filter Substitutions (N>N')	6732
Filter Coupling/Bad-Locations	6714
In ClinVar VCF	508
In LP/P-ClinVar VCF	504
^ & ACMG & ExAC	48
& ACMG & 1000 Genomes	9
^ & ACMG & ExAC & 1000 Genomes	8

<sup>##</sup> Note the 12-fold reduction after merging the online query results with the VCF.

## 2 Plot Summary Statistics Across Populations

### 2.1 Overall Non-Reference Sites

#### 2.1.0.1 For 1000 Genomes

Each individual has n non-reference sites, which can be found by counting. The mean number is computed for each population.

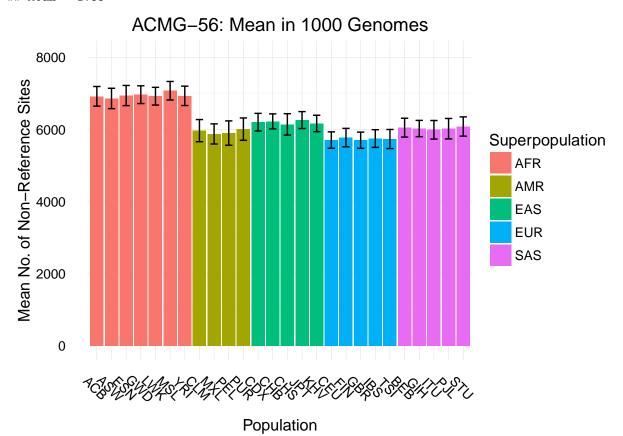
Ex: the genotype of 3 variants in 3 people looks like this:

	HG00097	HG00099	HG00100
Variant 1	0	2	1
Variant 2	0	0	1
Variant 3	0	0	1

Count the number of non-reference sites per individual:

HG00097	HG00099	HG00100
0	1	3

## Mean = 1.33



Note: the error bars denote standard deviation, not standard error.

#### 2.1.0.2 For ExAC

The mean number of non-reference sites is E(V), where  $V = \sum_{i=1}^{n} v_i$  is the number of non-reference sites at all variant positions  $v_1$  through  $v_n$ .

At each variant site, the probability of having at least 1 non-reference allele is  $P(v_i) = P(v_{i,a} \cup v_{i,b})$ , where a and b indicate the 1st and 2nd allele at each site.

If the two alleles are independent,  $P(v_{i,a} \cup v_{i,b}) = 1 - (1 - P(v_{i,a}))(1 - P(v_{i,b})) = 1 - (1 - AF(v_i))^2$ 

If all variants are independent,  $E(V) = \sum_{i=1}^{n} 1 - (1 - AF(v_i))^2$  for any set of allele frequencies.

Ex: the allele frequencies of 3 variants across the 5 superpopulations looks like this:

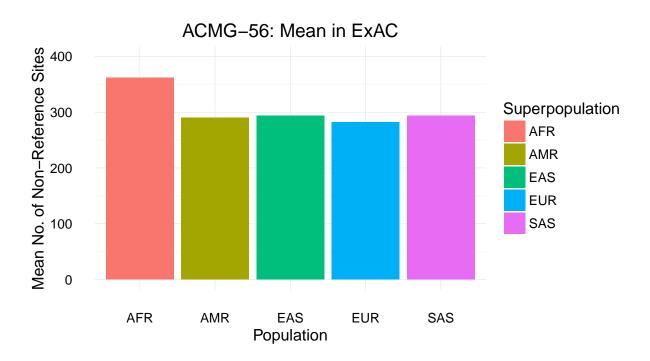
	AFR	AMR	EAS	EUR	SAS
Variant 1 Variant 2	0.1	0.2	0	0	0.3
variant 2	0.2	U	0.3	U	0.1

The probability of having at least 1 non-reference site at each variant - (0|1) (1|0) or (1|1) is given by  $1 - (1 - AF)^2$ . Note that this is approximately 2 \* AF when AF is small:

	AFR	AMR	EAS	EUR	SAS
Variant 1	0.19	0.36	0	0	0.51
Variant 2	0.36	0	0.51	0	0.19

By linearity of expectation, the expected (mean) number of non-reference sites is  $\sum E(V_i) = \sum (columns)$ .

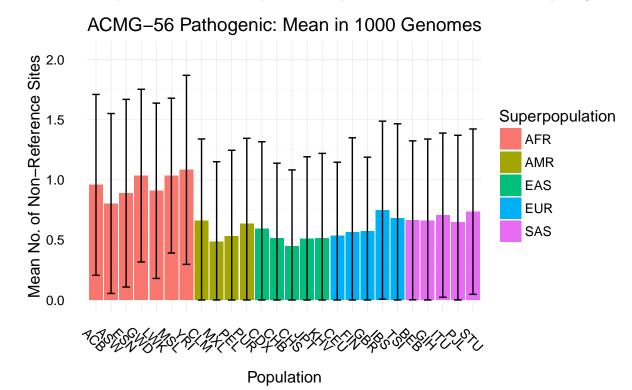
AFR	AMR	EAS	EUR	SAS
0.55	0.36	0.51	0	0.7

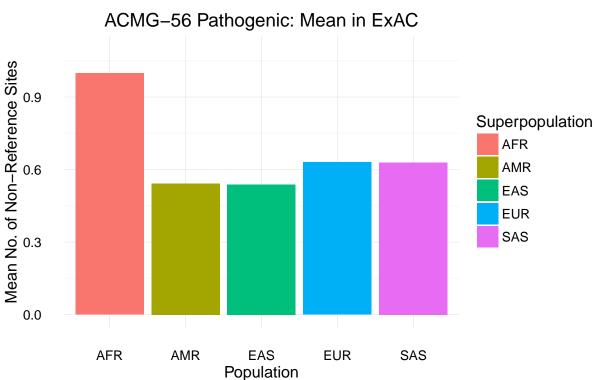


## 2.2 Pathogenic Non-Reference Sites

### 2.2.0.1 For 1000 Genomes and ExAC

This is the same procedure as above, but performed only on the subset of variants that are pathogenic.





## 2.3 Fraction of Individuals with Pathogenic Sites

#### 2.3.0.1 For 1000 Genomes

We can count up the fraction of individuals with 1+ non-reference site(s) in each population. This is the fraction of individuals who would receive a positive genetic test result in at least 1 of the ACMG-56 genes.

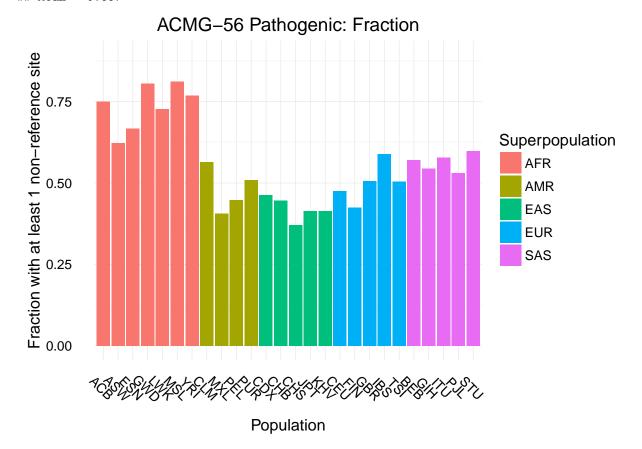
Ex: the genotype of 3 variants in 3 people looks like this:

	HG00097	HG00099	HG00100
Variant 1	0	2	1
Variant 2	0	0	1
Variant 3	0	0	1

Count each individual as having a non-reference site (1) or having only reference sites (0):

HG00097	HG00099	HG00100
0	1	1

## Mean = 0.667



#### 2.3.0.2 For ExAC

The probability of having at least 1 non-reference site is P(X), where X indicates a non-reference site at any variant position  $v_1$  through  $v_n$ .

Recall that  $P(v_i) = P(v_{i,a} \cup v_{i,b}) = 1 - (1 - AF(v))^2$  when alleles are independent.

If all alleles are independent,  $P(X) = P(\bigcup_{i=1}^n v_i) = 1 - \prod_{i=1}^n (1 - AF(v_i))^2$ 

Ex: the allele frequencies of 3 variants across the 5 superpopulations looks like this:

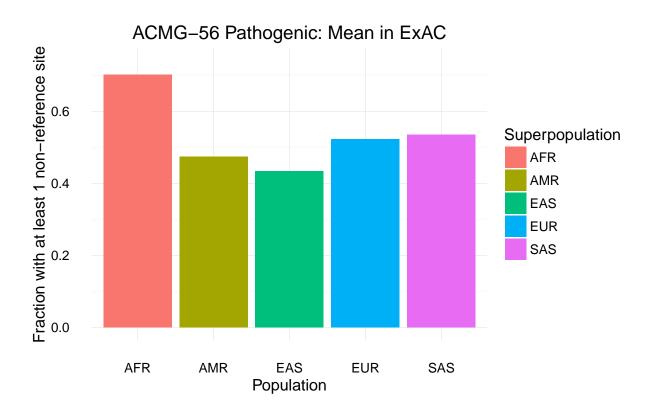
	AFR	AMR	EAS	EUR	SAS
Variant 1	0.1	0.2	0	0	0.3
Variant 2	0.2	0	0.3	0	0.1

The probability of having at least 1 non-reference site at each variant - (0|1) (1|0) or (1|1) is given by  $1 - (1 - AF)^2$ . Note that this is approximately 2 \* AF when AF is small:

	AFR	AMR	EAS	EUR	SAS
Variant 1	0.19	0.36	0	0	0.51
Variant 2	0.36	0	0.51	0	0.19

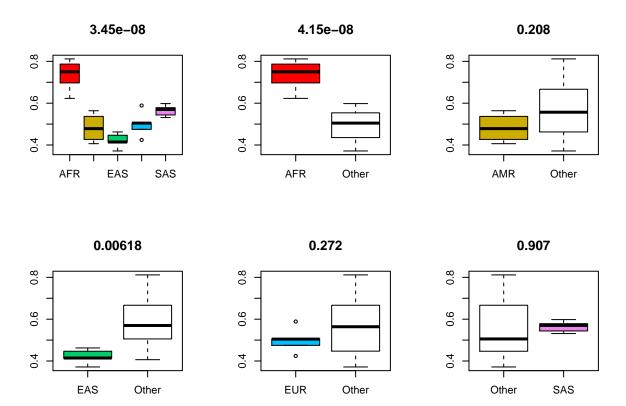
The expected (mean) number of non-reference sites is given by  $1 - \prod (1 - AF)^2$ .

AFR	AMR	EAS	EUR	SAS
0.4816	0.36	0.51	0	0.6031



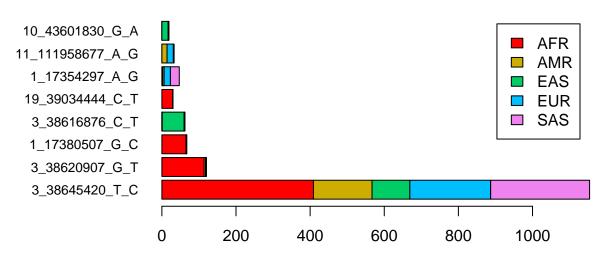
### 2.4 Test Statistics for Ancestral Differences

F-statistic/T-statistic: probability that the different groups are sampled from distributions with the same mean. These plots are from 4(a) - 1000 Genomes Fraction with 1+ Non-Reference Site, but can be replicated for plots 2(ab) and 3(ab) as well.



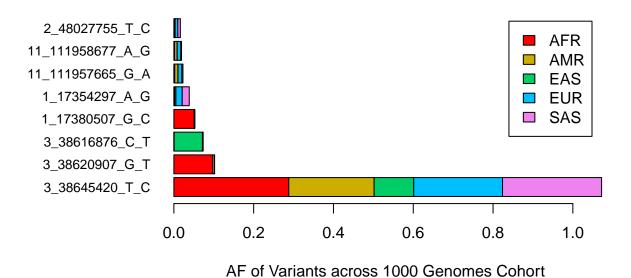
## 2.5 Common Pathogenic Variants by Ancestry

## In 1000 Genomes



Proportion of Variants across 1000 Genomes Cohort

### In ExAC



14

### 3 Penetrance Estimates

### 3.1 Bayes' Rule as a Model for Estimating Penetrance Using

Let  $V_x$  be the event that an individual has 1 or more variant related to disease x, and  $D_x$  be the event that the individual is later diagnosed with disease x.

In this case, we can define the following probabilities:

- 1. Prevalence =  $P(D_x)$
- 2. Allele Frequency =  $P(V_x)$
- 3. Allelic Heterogeneity =  $P(V_x|D_x)$
- 4. Penetrance =  $P(D_x|V_x)$

By Bayes' Rule, the penetrance of a variant related to disease x may be defined as:

$$P(D_x|V_x) = \frac{P(D_x) * P(V_x|D_x)}{P(V_x)} = \frac{Prevalence * Allelic - Heteogeneity}{Allele - Frequency}$$

To compute penetrance estimates for each of the diseases related to the ACMG-56 genes, we will use the prevalence data we collected into Literature\_Prevalence\_Estimates.csv, allele frequency data from 1000 Genomes and ExAC, and a broad range of values for allelic heterogeneity.

### 3.2 Import Literature-Based Disease Prevalence Data

Data Collection: 1. Similar disease subtypes were grouped together (e.g., the 8 different types of familial hypertrophic cardiomyopathy), resulting in 30 disease categories across 56 genes.

- 2. The search query "[disease name] prevalence" was used to find articles using Google Scholar.
- 3. Prevalence estimates were recorded along with URL, journal, region, publication year, sample size, first author, population subset (if applicable), date accessed, and potential issues. Preference was given to studies with PubMed IDs, more citations, and larger sample sizes.

Prevalence was recorded as reported: either a point estimate or a range. Values of varying quality were collected across all diseases.

## Table of Literature-Based Estimates of Disease Prevalence 30 x 16 (selected rows/columns):

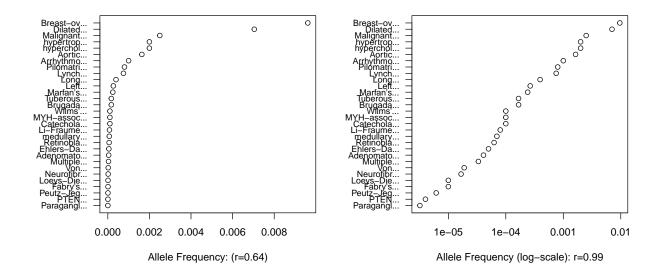
Gene	Disease	Disease_MIM	Tags
BRCA1;BRCA2	Breast-ovarian cancer familial	604370;612555	breast;ovarian
SCN5A	Brugada syndrome	601144	brugada
COL3A1	Ehlers-Danlos syndrome	130050	ehler;danlos
TP53	Li-Fraumeni syndrome	151623	fraumeni

Table continues below

Inverse. Prevalence. 1	Inverse. Prevalence. 2	year	first.author	citations
104	NA	2013	NA	NA
10000	2000	2006	Antzelevitch	11
20000	NA	2010	Malfait	116
20000	5000	1999	Schneider	47

### 3.3 Distribution of Prevalences

Later, we face the question of how to compute point estimates for penetrance, which requires a point estimate of prevalence. We decided to combine the upper and lower bounds of prevalence ranges using the geometric-mean, or log-average, because the prevalences seem to be distributed most uniformly on a logarithmic-scale.



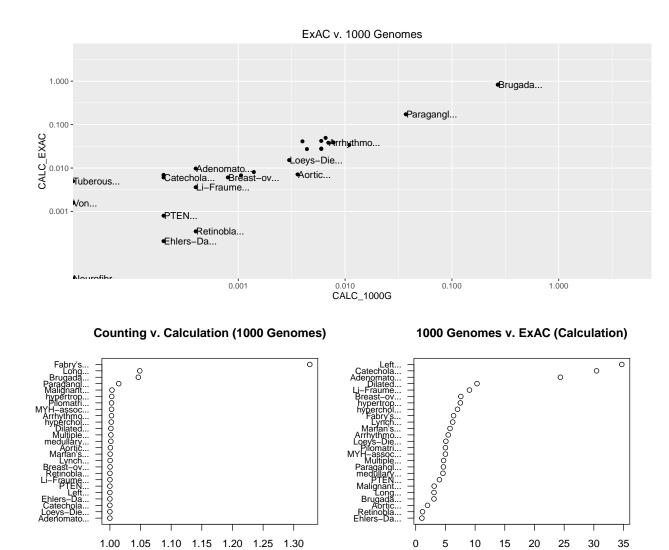
## 3.4 Collect and Aggregate Allele Frequencies at the Disease-Level

We define AF(disease) as the probability of having at least 1 variant associated with the disease. The frequencies across the relevant variants can be aggregated in two ways:

- (1) By direct counting, from genotype data in 1000 Genomes.
- (2) AF(disease) =  $1 \prod_{variant} (1 AF_{variant})$ , from population data in ExAC (assumes independence).

Correlation Table:

	COUNT_1000G	$\rm CALC\_1000G$	CALC_EXAC
COUNT_1000G	1	1	0.9979
${ m CALC\_1000G}$	1	1	0.9981
$CALC\_EXAC$	0.9979	0.9981	1



Ratio (larger/smaller)

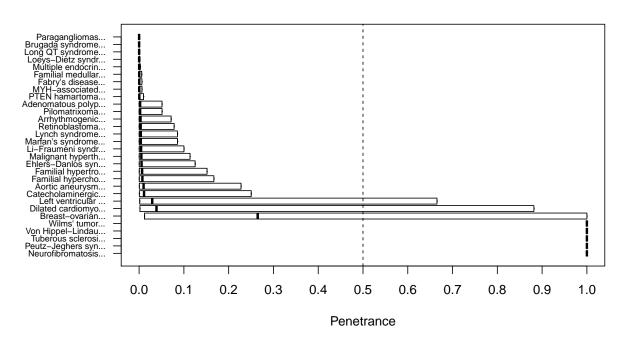
The median AF(disease) ratio between counting and calculation is: 1.002. The median AF(disease) ratio between ExAC and 1000 Genomes is: 5.078.

Ratio (larger/smaller)

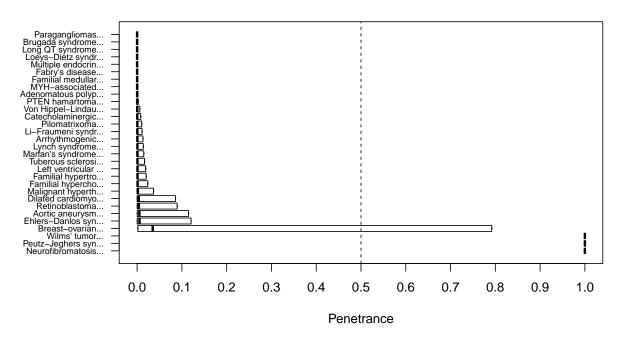
### 3.5 Penetrance as a Function of P(V|D)

The left end of the boxplot indicates P(V|D) = 0.001, the bold line in the middle indicates P(V|D) = 0.022, the right end of the boxplot indicates P(V|D) = 0.5.

#### 1000 Genomes



#### **ExAC**



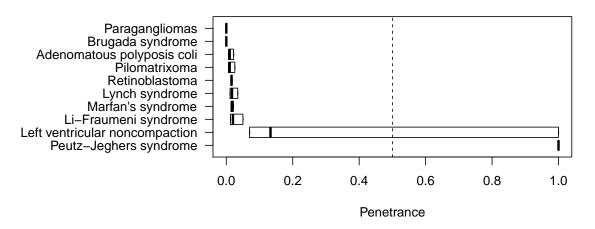
Note: the bold black lines at 1.0 all indicate no allele frequency (disease\_AF) data. (Disease\_AF = 0 returns "infinite penetrance", which is capped at 1).

### 3.6 Penetrance as a Function of P(D)

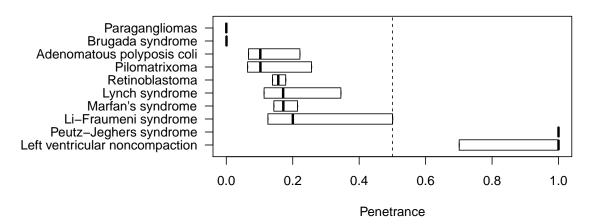
The left end of the boxplot indicates P(D) = upper value, the bold line in the middle indicates  $P(D) = \text{mean}(\log(\text{values}))$ , the right end of the boxplot indicates P(D) = lower value.

Disease	$Prevalence\_Ratio$
Retinoblastoma	1.3
Marfan's syndrome	1.5
Lynch syndrome	3.0
Adenomatous polyposis coli	3.3
Li-Fraumeni syndrome	4.0
Paragangliomas	4.0
Pilomatrixoma	4.0
Brugada syndrome	5.0
Peutz-Jeghers syndrome	12.0
Left ventricular noncompaction	18.6

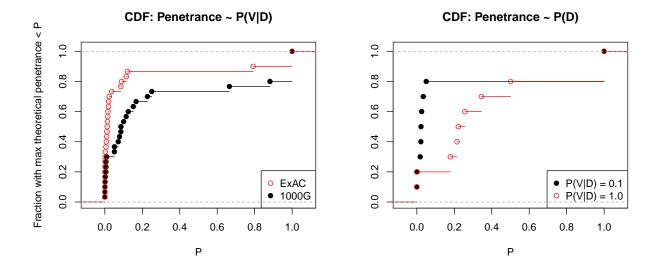
### Penetrance Estimates for Prevalence Ranges, P(V|D) = 0.1



### Penetrance Estimates for Prevalence Ranges, P(V|D) = 1



This can only be computed in 10 cases where a prevalence range was given, rather than a point estimate.



## 3.7 Penetrance ranges given P(D) and P(V|D):

The left end of the boxplot indicates P(D) AND P(V|D) = lower value, the bold line in the middle indicates P(D) AND P(V|D) = mean(log(values)), the right end of the boxplot indicates P(D) AND P(V|D) = upper value.