

ACMG-ClinVar Penetrance RMarkdown

James Diao, under the supervision of Arjun Manrai

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Contents

| | | |
|----------|---|-----------|
| 1 | Download, Transform, and Load Data | 2 |
| 1.1 | Collect ACMG Gene Panel | 2 |
| 1.2 | Download ClinVar VCF | 3 |
| 1.3 | Download 1000 Genomes VCFs | 4 |
| 1.4 | Import and Process 1000 Genomes VCFs | 5 |
| 1.5 | Import and Process gnomAD/ExAC VCFs | 5 |
| 1.6 | Collect 1000 Genomes Phase 3 Populations Map | 6 |
| 1.7 | Merge ClinVar with gnomAD, ExAC, and 1000 Genomes | 6 |
| 2 | Plot Summary Statistics Across Populations | 7 |
| 2.1 | Distribution of Allele Counts | 7 |
| 2.2 | Overall Non-Reference Sites | 8 |
| 2.3 | Fraction of Individuals with Pathogenic Sites | 10 |
| 2.4 | Common Pathogenic Variants by Ancestry | 12 |
| 3 | Penetrance Estimates | 13 |
| 3.1 | Bayes' Rule as a Model for Estimating Penetrance | 13 |
| 3.2 | Import Literature-Based Disease Prevalence Data | 13 |
| 3.3 | Distribution of Prevalences | 14 |
| 3.4 | Collect and Aggregate Allele Frequencies at the Disease-Level | 15 |
| 3.5 | Penetrance as a Function of $P(V D)$ | 20 |
| 3.6 | Penetrance Estimates by Ancestry | 21 |

Working Directory: /Users/jamesdiao/Documents/Kohane_Lab/2017-ACMG-penetrance/ACMG_Penetrance

1 Download, Transform, and Load Data

1.1 Collect ACMG Gene Panel

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

Table from ACMG SF v2.0 Paper 60 x 8 (selected rows):

| | Phenotype | MIM_disorder | PMID_Gene_Reviews_entry |
|-----------|--------------------------------------|---------------|-------------------------|
| N1 | Hereditary breast and ovarian cancer | 604370 612555 | 20301425 |
| N2 | Hereditary breast and ovarian cancer | 604370 612555 | 20301425 |
| N3 | Li-Fraumeni syndrome | 151623 | 20301488 |
| N4 | Peutz-Jeghers syndrome | 175200 | 20301443 |
| N5 | Lynch syndrome | 120435 | 20301390 |

Table continues below

| | Typical_age_of_onset | Gene | MIM_gene | Inheritance | Variants_to_report |
|-----------|----------------------|-------|----------|-------------|--------------------|
| N1 | Adult | BRCA1 | 113705 | AD | KP&EP |
| N2 | Adult | BRCA2 | 600185 | AD | KP&EP |
| N3 | Child/Adult | TP53 | 191170 | AD | KP&EP |
| N4 | Child/Adult | STK11 | 602216 | AD | KP&EP |
| N5 | Adult | MLH1 | 120436 | AD | KP&EP |

ACMG-59 Genes:

```
## [1] BRCA1 BRCA2 TP53 STK11 MLH1 MSH2 MSH6 PMS2
## [9] APC MUTYH BMPR1A SMAD4 VHL MEN1 RET PTEN
## [17] RB1 SDHD SDHAF2 SDHC SDHB TSC1 TSC2 WT1
## [25] NF2 COL3A1 FBN1 TGFBR1 TGFBR2 SMAD3 ACTA2 MYH11
## [33] MYBPC3 MYH7 TNNT2 TNNI3 TPM1 MYL3 ACTC1 PRKAG2
## [41] GLA MYL2 LMNA RYR2 PKP2 DSP DSC2 TMEM43
## [49] DSG2 KCNQ1 KCNH2 SCN5A LDLR APOB PCSK9 ATP7B
## [57] OTC RYR1 CACNA1S
```

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) CLNREVSTAT = “Review Status, no_assertion, no_criteria, single - criterion provided single submitter, mult - criteria provided multiple submitters no conflicts, conf - criteria provided conflicting interpretations, exp - Reviewed by expert panel, guideline - Practice guideline”

(e) INTERP = Pathogenicity (likely pathogenic or pathogenic; CLNSIG = 4 or 5)

| ## | VAR_ID | CHROM | POS | ID | REF | ALT |
|----|--------|---------------------------------------|-----|-----------|-------------------|--------|
| ## | 59912 | 4_68619662_A_G | 4 | 68619662 | . | A G |
| ## | 86327 | 7_977079_G_A | 7 | 977079 | . | G A |
| ## | 122198 | 10_103530370_C_T | 10 | 103530370 | . | C T |
| ## | 122206 | 10_103534589_G_C | 10 | 103534589 | . | G C |
| ## | 189946 | 17_7579368_A_G | 17 | 7579368 | . | A G |
| ## | 232565 | X_585258_C_A | X | 585258 | . | C A |
| ## | 232567 | X_585263_G_C | X | 585263 | . | G C |
| ## | 232569 | X_591261_G_A | X | 591261 | . | G A |
| ## | 232571 | X_591695_C_T | X | 591695 | . | C T |
| ## | 232573 | X_591752_G_A | X | 591752 | . | G A |
| ## | 232575 | X_591926_T_G | X | 591926 | . | T G |
| ## | 232577 | X_595354_G_T | X | 595354 | . | G T |
| ## | 232579 | X_595379_G_T | X | 595379 | . | G T |
| ## | 232581 | X_595422_A_G | X | 595422 | . | A G |
| ## | 232585 | X_601571_C_T | X | 601571 | . | C T |
| ## | 232587 | X_601577_G_C | X | 601577 | . | G C |
| ## | 232589 | X_601578_C_A | X | 601578 | . | C A |
| ## | 232592 | X_601772_C_T | X | 601772 | . | C T |
| ## | 232595 | X_605321_G_A | X | 605321 | . | G A |
| ## | 232598 | X_605654_A_AAG | X | 605654 | . | A AAG |
| ## | 232600 | X_1407492_T_C | X | 1407492 | . | T C |
| ## | 232602 | X_1409305_G_C | X | 1409305 | . | G C |
| ## | 232604 | X_1428421_G_T | X | 1428421 | . | G T |
| ## | 232700 | X_8700077_T_C | X | 8700077 | . | T C |
| ## | 243456 | Y_535123_N_NTGT | Y | 535123 | . | N NTGT |
| ## | | | | | CLNSIG | INTERP |
| ## | 59912 | | | | Pathogenic | TRUE |
| ## | 86327 | | | | protective | FALSE |
| ## | 122198 | | | | Likely_pathogenic | TRUE |
| ## | 122206 | | | | Likely_pathogenic | TRUE |
| ## | 189946 | Likely_benign, Uncertain_significance | | | | FALSE |
| ## | 232565 | | | | Pathogenic | TRUE |
| ## | 232567 | | | | Pathogenic | TRUE |
| ## | 232569 | Uncertain_significance | | | | FALSE |
| ## | 232571 | Benign, Likely_benign, not_provided | | | | FALSE |
| ## | 232573 | | | | Likely_benign | FALSE |
| ## | 232575 | | | | Benign | FALSE |
| ## | 232577 | | | | Likely_benign | FALSE |
| ## | 232579 | | | | Pathogenic | TRUE |
| ## | 232581 | | | | Likely_pathogenic | TRUE |

```
## 232585                Pathogenic  TRUE
## 232587                Pathogenic  TRUE
## 232589                Pathogenic  TRUE
## 232592                Pathogenic  TRUE
## 232595                Uncertain_significance  FALSE
## 232598                Uncertain_significance  FALSE
## 232600                Benign  FALSE
## 232602                Benign  FALSE
## 232604                Benign  FALSE
## 232700                Pathogenic  TRUE
## 243456                Pathogenic  TRUE
```

Processed ClinVar data frame 224657 x 18 (selected rows/columns):

| VAR_ID | CHROM | POS | ID | REF | ALT | CLNSIG | INTERP |
|--------------|-------|--------|----|-----|-----|------------------------|--------|
| 1_955619_G_C | 1 | 955619 | . | G | C | Likely_benign | FALSE |
| 1_957568_A_G | 1 | 957568 | . | A | G | Uncertain_significance | FALSE |
| 1_957605_G_A | 1 | 957605 | . | G | A | Likely_benign | TRUE |
| 1_957640_C_T | 1 | 957640 | . | C | T | Uncertain_significance | FALSE |

Table continues below

| GOLD_STARS | pathogenic | benign | CLNREVSTAT | CLNDSDBID |
|------------|------------|--------|------------|-----------|
| 1 | FALSE | TRUE | 1 | 1 |
| 1 | FALSE | TRUE | 1 | 1 |
| 0 | TRUE | FALSE | 1 | 1 |
| 1 | FALSE | TRUE | 1 | 1 |

1.3 Download 1000 Genomes VCFs

[ftp://ftp.1000genomes.ebi.ac.uk/vol1/ftp/release/20130502/ALL.\[chrom\].phase3_\[version\].20130502.genotypes.vcf.gz](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/2017-ACMG-penetrance/1000G/

Download report: region and successes: 59 x 6 (selected rows):

| gene | name | chrom | start | end | downloaded |
|-------|-----------|-------|----------|----------|------------|
| BRCA1 | NM_007294 | 17 | 41196311 | 41277500 | TRUE |
| BRCA2 | NM_000059 | 13 | 32889616 | 32973809 | TRUE |
| TP53 | NM_000546 | 17 | 7571719 | 7590868 | TRUE |
| STK11 | NM_000455 | 19 | 1205797 | 1228434 | TRUE |
| MLH1 | NM_000249 | 3 | 37034840 | 37092337 | TRUE |

File saved as download_output.txt in Supplementary_Files

1.4 Import and Process 1000 Genomes VCFs

- Unnest the data frames to 1 row per variant_ID key (CHROM_POSITION_REF_ALT).
- Remove all insertions, deletions, CNV, etc, and keep only missense variants (1 REF, 1 ALT)
- 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: 141467 x 2516 (selected rows/columns):

| GENE | AF_1000G | VAR_ID | CHROM | POS | ID | REF | ALT |
|-------|-------------|-----------------|-------|----------|-------------|-----|-----|
| BRCA1 | 0.004193290 | 17_41196363_C_T | 17 | 41196363 | rs8176320 | C | T |
| BRCA1 | 0.008386580 | 17_41196368_C_T | 17 | 41196368 | rs184237074 | C | T |
| BRCA1 | 0.000998403 | 17_41196372_T_C | 17 | 41196372 | rs189382442 | T | C |
| BRCA1 | 0.342252000 | 17_41196408_G_A | 17 | 41196408 | rs12516 | G | A |
| BRCA1 | 0.000399361 | 17_41196409_G_C | 17 | 41196409 | rs548275991 | G | C |

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 |
| 1 | 0 | 1 | 1 | 0 | 2 |
| 0 | 0 | 0 | 0 | 0 | 0 |

1.5 Import and Process gnomAD/ExAC VCFs

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

Processed gnomAD VCFs: 96742 x 48 (selected rows/columns):

| | GENE | AF_GNOMAD | VAR_ID |
|---------------|---------|------------|-----------------|
| 210313 | CACNA1S | 0.00003170 | 1_201047100_A_G |
| 3537 | BRCA2 | 0.00001290 | 13_32914977_A_G |
| 24258 | RB1 | 0.00000397 | 13_49037941_A_C |
| 70823 | KCNQ1 | 0.00000868 | 11_2482624_A_G |
| 53404 | TPM1 | 0.00729000 | 15_63362179_G_A |

Processed ExAC VCFs: 59883 x 45 (selected rows/columns):

| | GENE | AF_EXAC | VAR_ID |
|---------------|---------|-------------|-----------------|
| 22159 | NF2 | 0.000031180 | 22_30069425_G_A |
| 31792 | MYH7 | 0.000024740 | 14_23898940_C_T |
| 269110 | APOB | 0.000041890 | 2_21260121_C_T |
| 161004 | ATP7B | 0.000008299 | 13_52508899_T_G |
| 71415 | CACNA1S | 0.000016470 | 1_201029795_G_A |

1.6 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 |
|---------|-----|-----------|--------|
| HG02702 | GWD | AFR | male |
| NA19309 | LWK | AFR | male |
| HG00530 | CHS | EAS | male |
| NA20785 | TSI | EUR | male |
| NA12046 | CEU | EUR | female |
| HG04219 | ITU | SAS | male |

1.7 Merge ClinVar with gnomAD, ExAC, and 1000 Genomes

Breakdown of ClinVar Variants

| Subset_ClinVar | Number_of_Variants |
|---------------------------|--------------------|
| Total ClinVar | 224657 |
| LP/P | 43321 |
| ACMG LP/P | 9229 |
| ACMG LP/P in gnomAD | 437 |
| ACMG LP/P in ExAC | 283 |
| ACMG LP/P in 1000 Genomes | 27 |

Breakdown of ACMG-gnomAD Variants

| Subset_gnomAD | Number_of_Variants |
|------------------------|--------------------|
| ACMG in gnomAD | 96742 |
| ClinVar-ACMG in gnomAD | 14517 |
| LP/P-ACMG in gnomAD | 437 |

Breakdown of ACMG-ExAC Variants

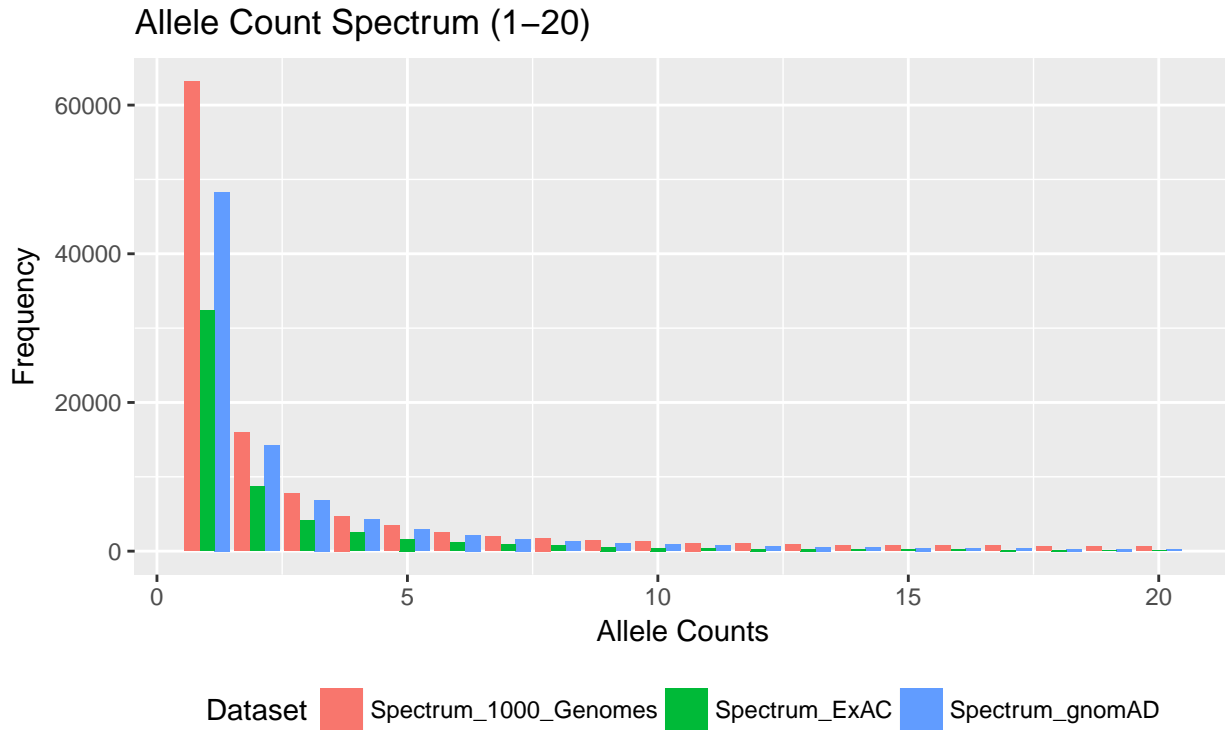
| Subset_gnomAD | Number_of_Variants |
|----------------------|--------------------|
| ACMG in ExAC | 59883 |
| ClinVar-ACMG in ExAC | 11155 |
| LP/P-ACMG in ExAC | 283 |

Breakdown of ACMG-1000G Variants

| Subset_gnomAD | Number_of_Variants |
|-----------------------|--------------------|
| ACMG in 1000G | 141466 |
| ClinVar-ACMG in 1000G | 6080 |
| LP/P-ACMG in 1000G | 27 |

2 Plot Summary Statistics Across Populations

2.1 Distribution of Allele Counts

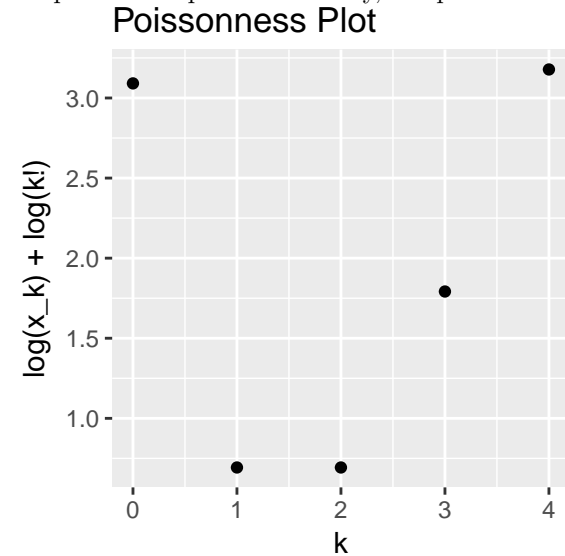


We can model this as a Poisson binomial- the summed occurrence of variants with different allele frequencies. If we assume that the allele frequencies are approximately the same and that variants are independent, (may not be good assumptions), then the distribution follows $\text{Binom}(n, p)$, $n = \# \text{ samples}$ and $p = \text{allele frequency}$. Because n is large and p is small, we can then use a Poisson approximation to the binomial.

The fit of this approximation may be tested by the Poissonness plot (Hoaglin 1980), or $\log(x_k) + \log(k!)$ vs. k .

If $x_k = n \Pr(X = k) = n \left(\frac{\lambda^k e^{-\lambda}}{k!} \right)$, then $\ln x_k + \ln k! = \ln n + k \ln \lambda - \lambda = \text{linear function of } k$.

Despite some upward concavity, the plot demonstrates reasonable Poissonness, with correlation = 0.16.



2.2.0.2 For gnomAD/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 | 0.1 | 0.2 | 0 | 0 | 0.3 |
| Variant 2 | 0.2 | 0 | 0.3 | 0 | 0.1 |

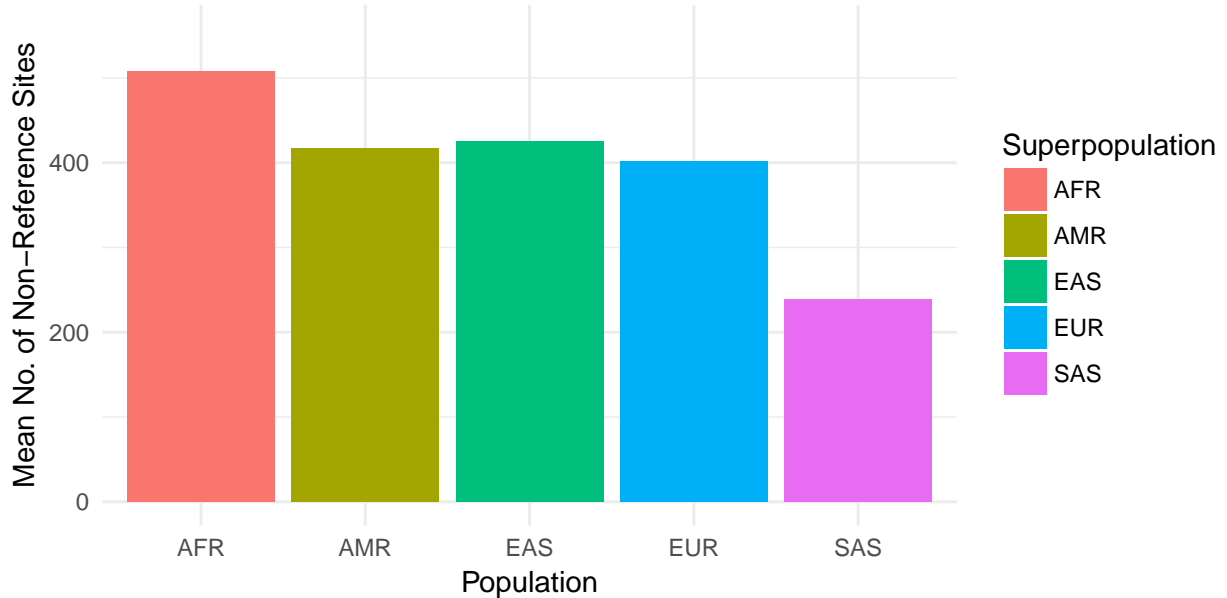
The probability of having at least 1 non-reference site at each variant - (0|1) (1|0) or (1|1) is given by $1 - (1 - AF)^2$. Note that this is approximately $2 * AF$ when AF is small:

| | 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 |

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 |

ACMG-59: Mean in gnomAD



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-59 genes.

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

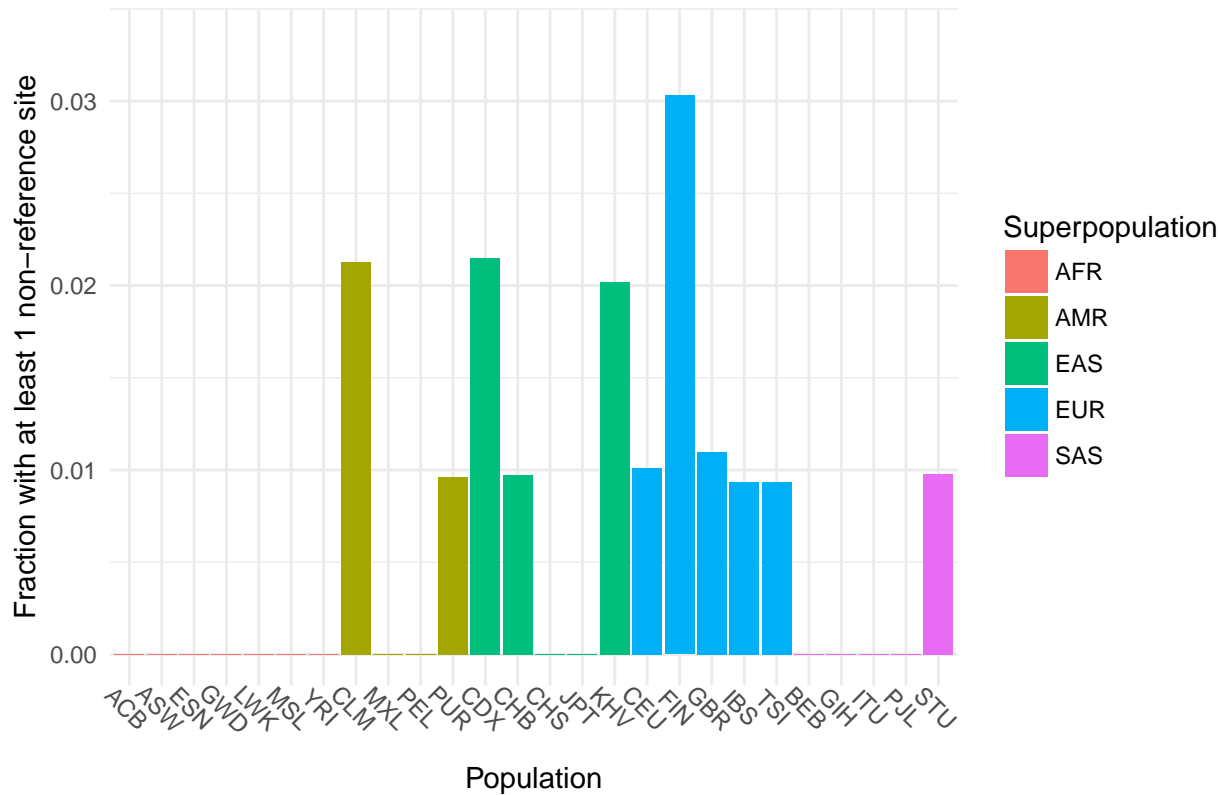
| | HG00366 | HG00367 | HG00368 |
|------------------|---------|---------|---------|
| Variant 1 | 2 | 1 | 1 |
| Variant 2 | 2 | 1 | 1 |
| Variant 3 | 1 | 0 | 0 |

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

| HG00366 | HG00367 | HG00368 |
|---------|---------|---------|
| 1 | 1 | 1 |

Mean = 1

ACMG-59 Pathogenic: Fraction in 1000 Genomes



2.3.0.2 For gnomAD/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:

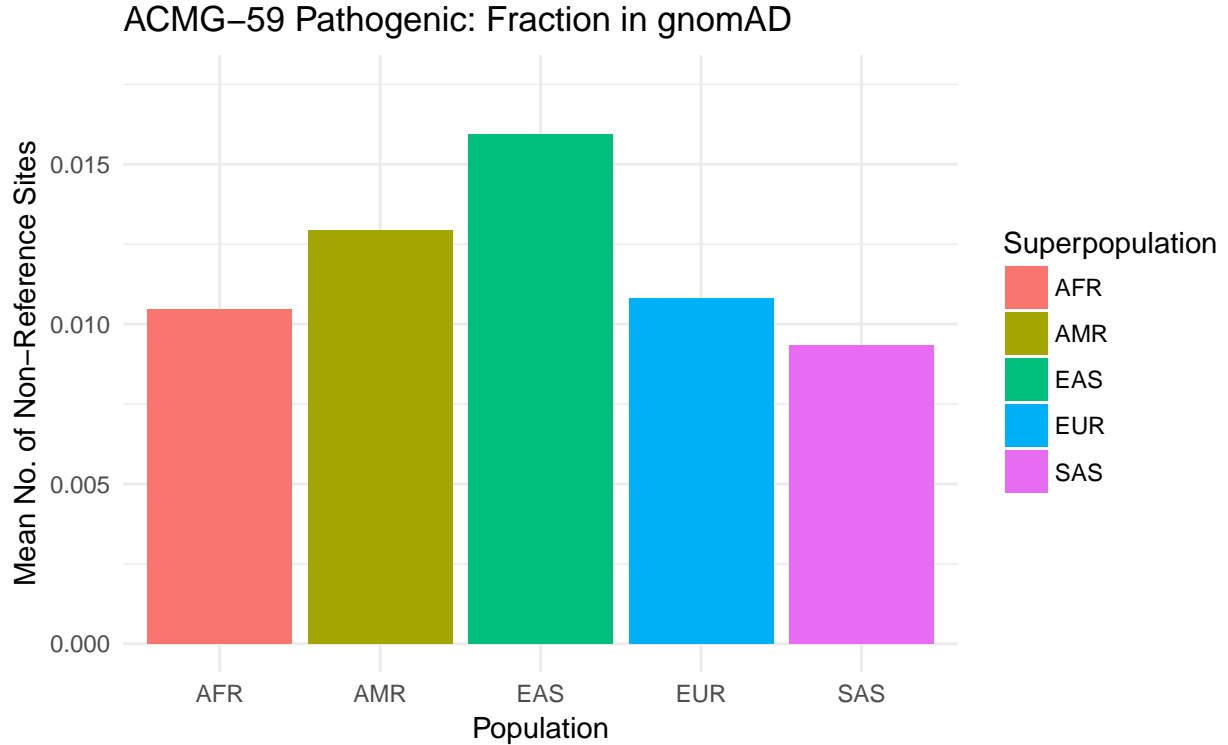
| | AFR | AMR | EAS | EUR | SAS |
|------------------|-----|-----|-----|-----|-----|
| Variant 1 | 0.1 | 0.2 | 0 | 0 | 0.3 |
| Variant 2 | 0.2 | 0 | 0.3 | 0 | 0.1 |

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:

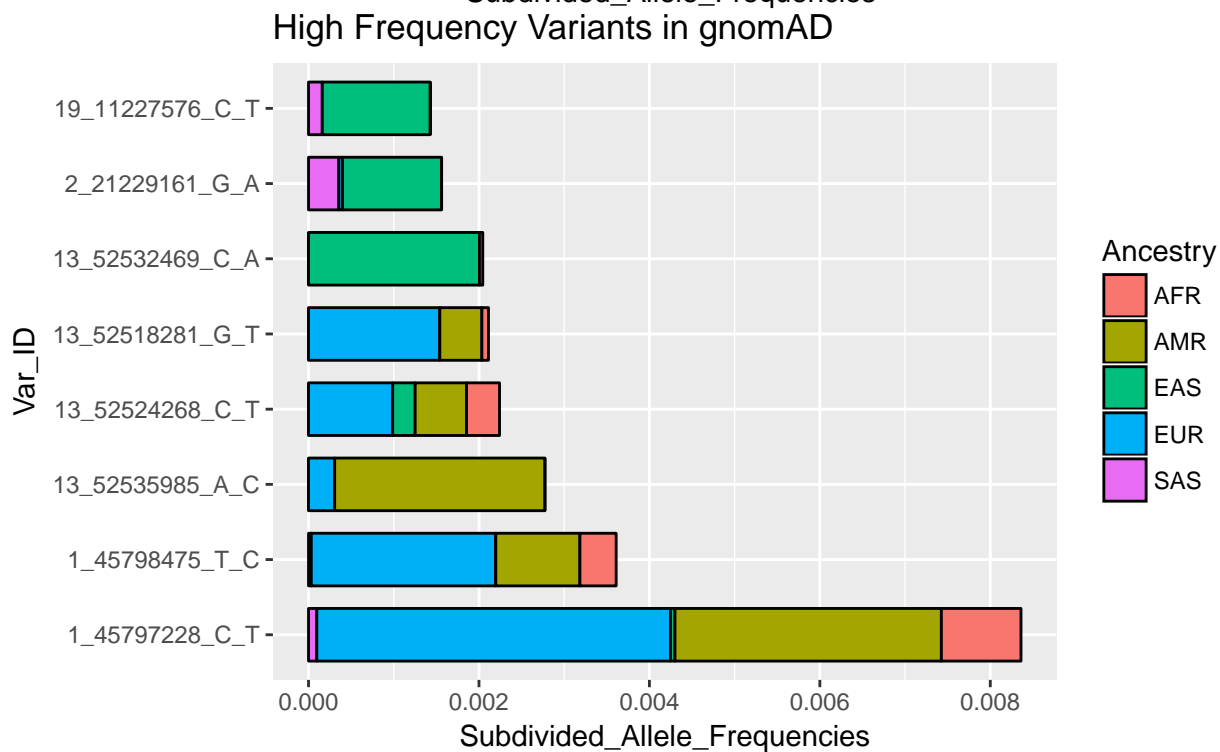
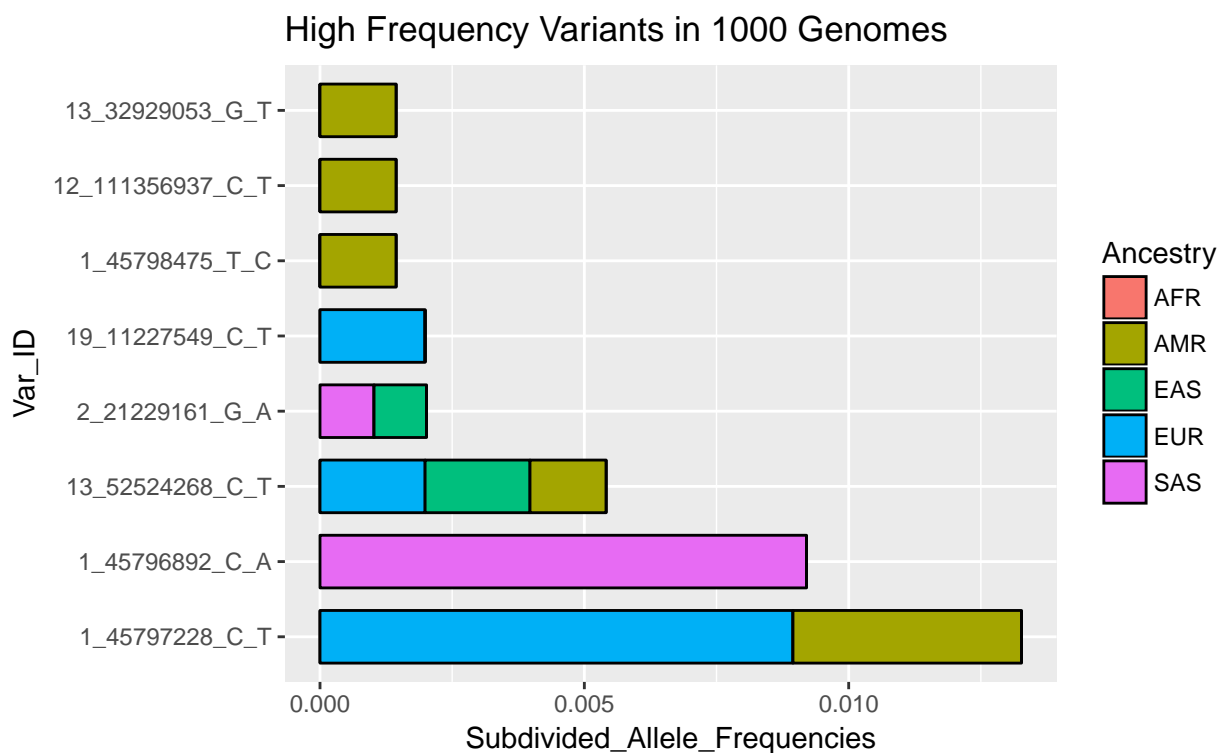
| | AFR | AMR | EAS | EUR | SAS |
|------------------|------|------|------|-----|------|
| Variant 1 | 0.19 | 0.36 | 0 | 0 | 0.51 |
| Variant 2 | 0.36 | 0 | 0.51 | 0 | 0.19 |

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 Common Pathogenic Variants by Ancestry



3 Penetrance Estimates

3.1 Bayes' Rule as a Model for Estimating Penetrance

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. Population Allele Frequency (PAF) = $P(V_x)$
3. Case Allele Frequency (CAF) = $P(V_x|D_x)$
4. Penetrance = $P(D_x|V_x)$

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

$$P(D_x|V_x) = \frac{P(D_x) * P(V_x|D_x)}{P(V_x)} = \frac{(Prevalence)(Population\ Allele\ Frequency)}{(Case\ Allele\ Frequency)}$$

To compute penetrance estimates for each of the diseases related to the ACMG-59 genes, we will use the prevalence data we collected into `Literature_Prevalence_Estimates.csv`, allele frequency data from 1000 Genomes/ExAC/gnomAD, and a broad range of values for case allele frequency.

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 59 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.

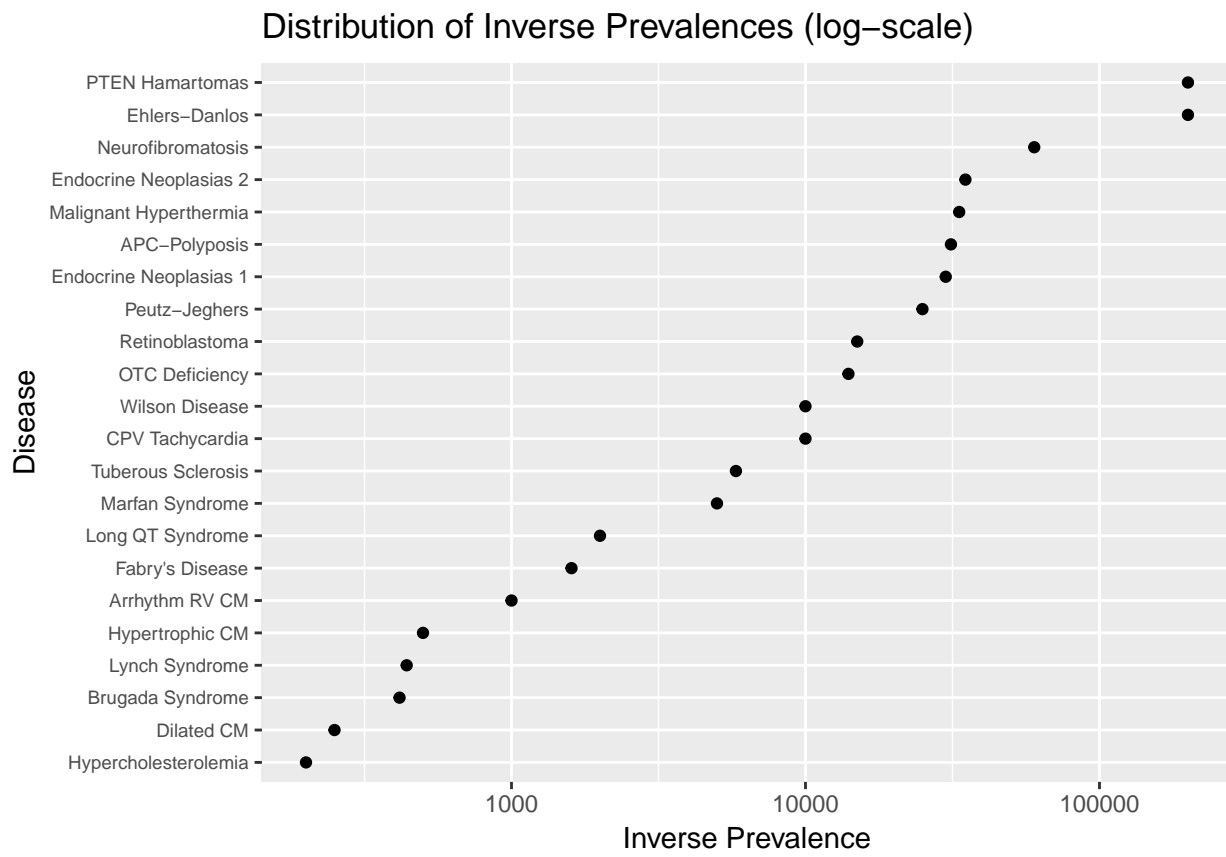
Table of Literature-Based Estimates 22 x 20 (selected rows/columns):

| Gene | Phenotype |
|---|-------------------------------------|
| APC | Familial adenomatous polyposis |
| MEN1 | Multiple endocrine neoplasia type 1 |
| MYH7 TPM1 MYBPC3 PRKAG2 TNNT3 MYL3 MYL2 ACTC1 | Hypertrophic cardiomyopathy |
| STK11 | Peutz-Jeghers syndrome |

Table continues below

| Inverse_Prevalence | Case_Allele_Frequency |
|--------------------|-----------------------|
| 31250 | 0.9 |
| 30000 | 0.9 |
| 500 | 0.6 |
| 25000 | 0.96 |

3.3 Distribution of Prevalences



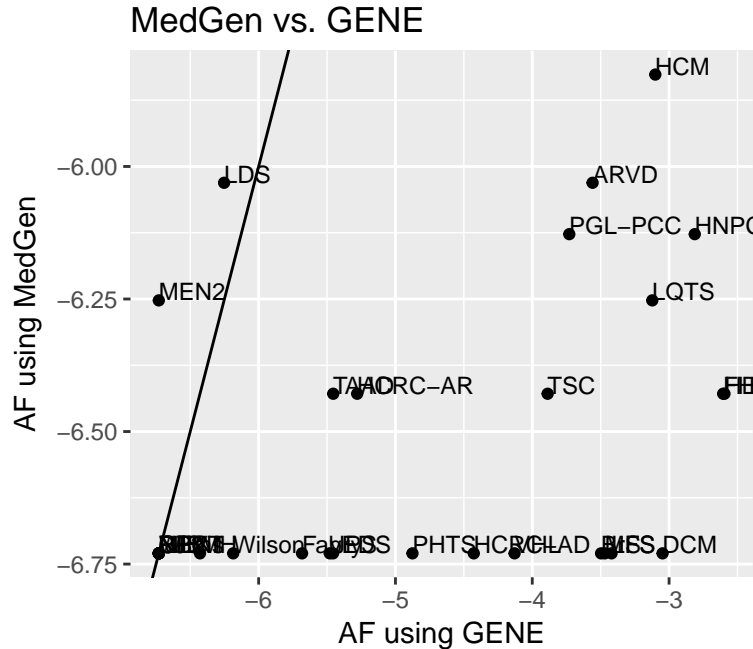
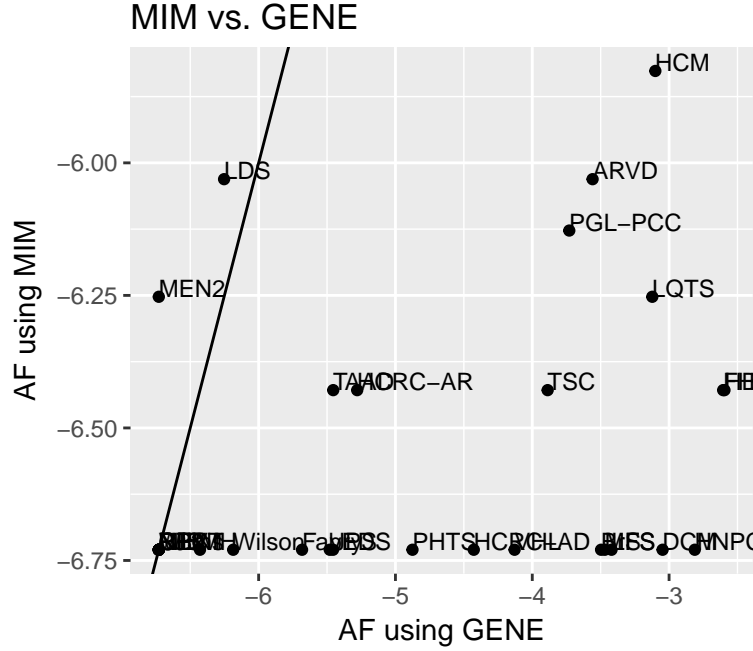
3.4 Collect and Aggregate Allele Frequencies at the Disease-Level

We define $AF(disease)$ as the probability of having at least 1 variant associated with the disease. The variants can be assigned to diseases in two ways:

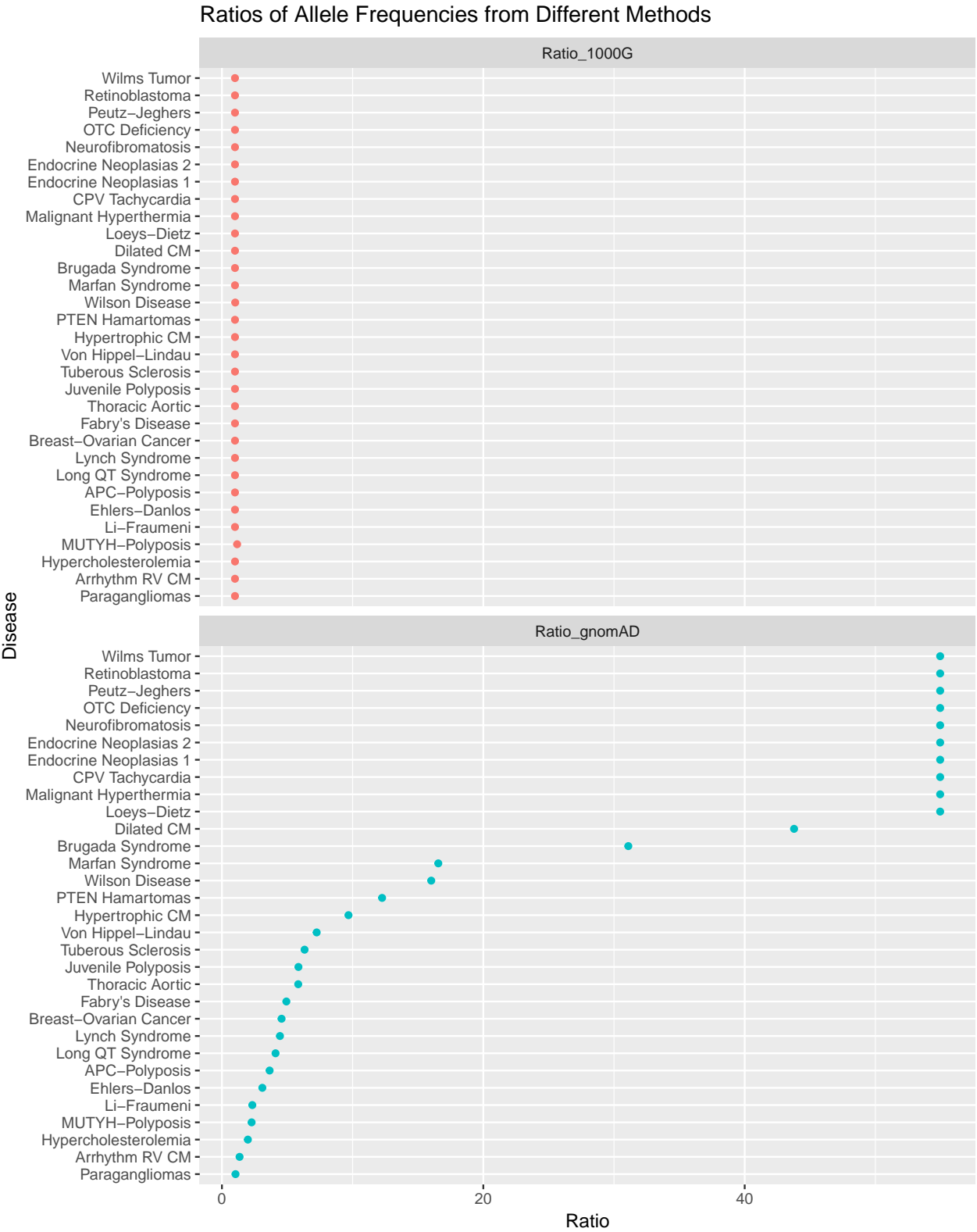
- (1) By associating it by MIM. An MIM code is assigned for around 31% of assertions in each dataset.
- (1) By associating it by MedGen. An MIM code is assigned for around 22% of assertions in each dataset.
- (2) By associating it by gene. All variants are associated with genes, but some variants may be designated as pathogenic for non-ACMG conditions.

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 1000 Genomes, ExAC, or gnomAD (assumes independence).

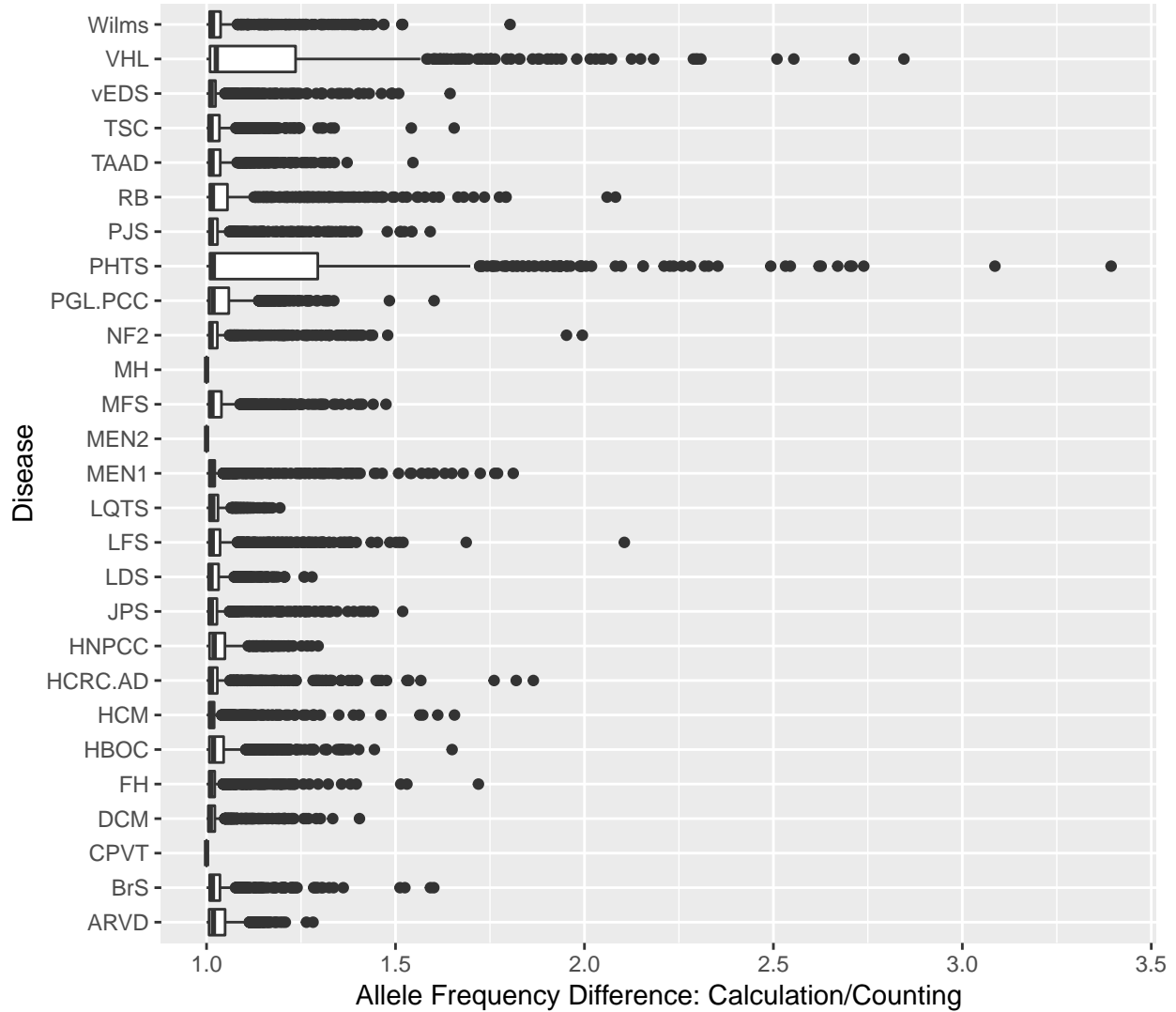


Ratio_1000G (red, top) computes $AF(\text{calculation in 1000 Genomes}) / AF(\text{counting in 1000 Genomes})$.
 Ratio_gnomAD (blue, bottom) computes $AF(\text{calculation in gnomAD}) / AF(\text{calculation in 1000 Genomes})$.

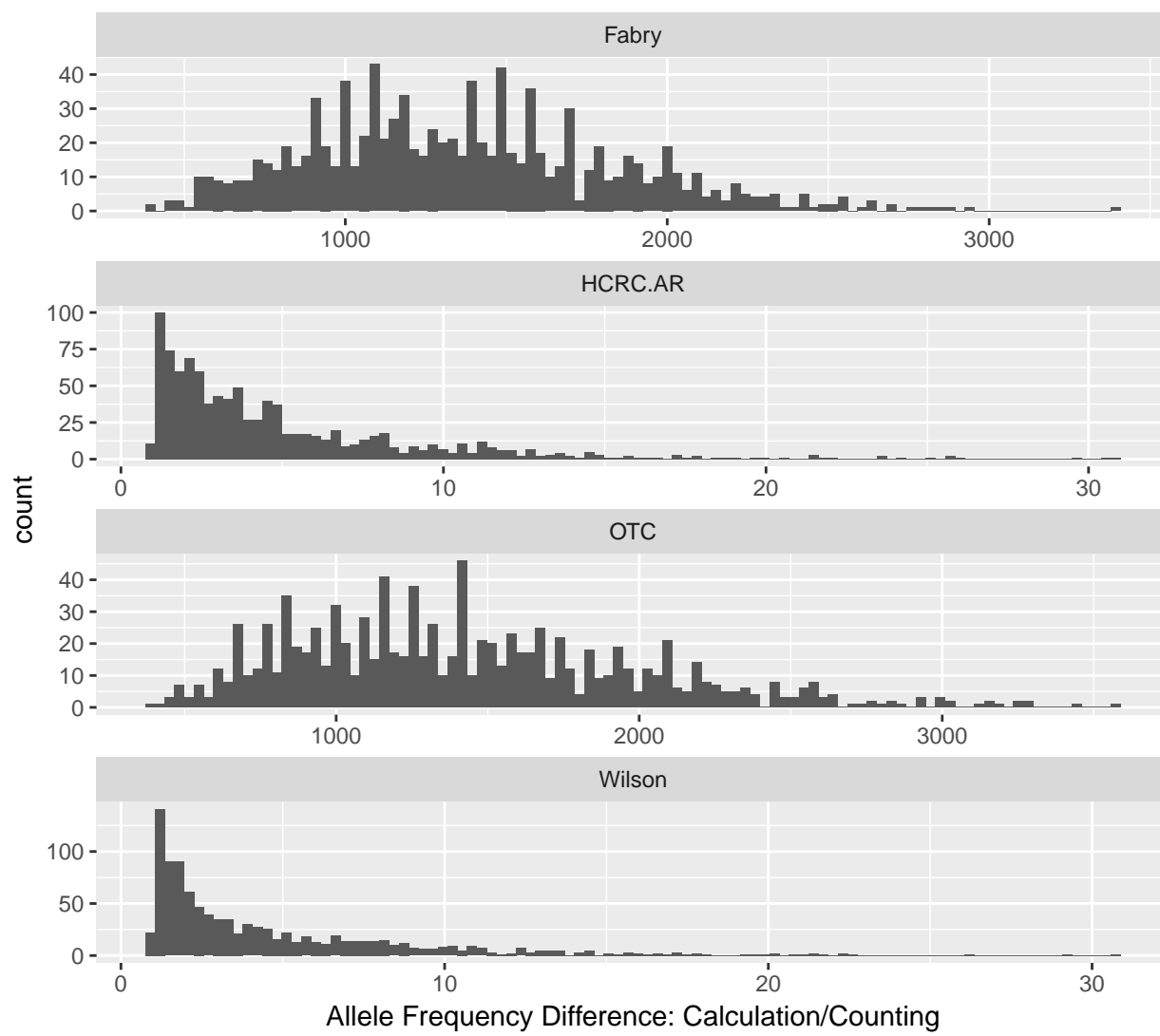


Sampling 1000 variants from all variants in 1000 Genomes to test deviations from independence assumptions. Repeat for 1000 trials and plot the distribution of disease-level allele frequencies (1000 points per disease). Only variants with allele frequency $< 1\%$ are evaluated. Since we look at 17 variants per disease, the maximum is approximately $1 - (1 - 0.01)^{34} \approx 0.29$

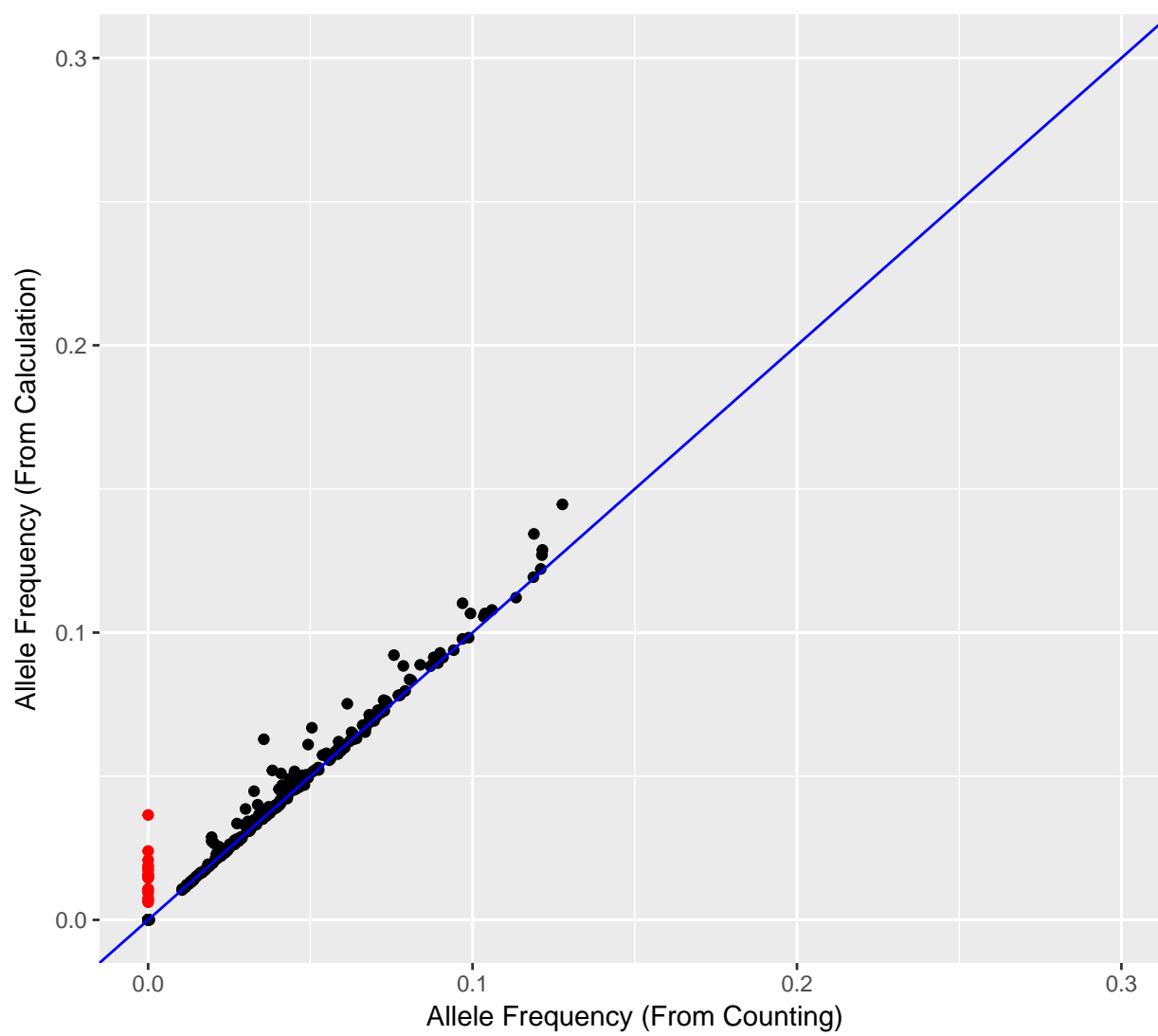
Differences in AF Methods: by Disease



Differences in AF Methods: by Disease (Outliers)



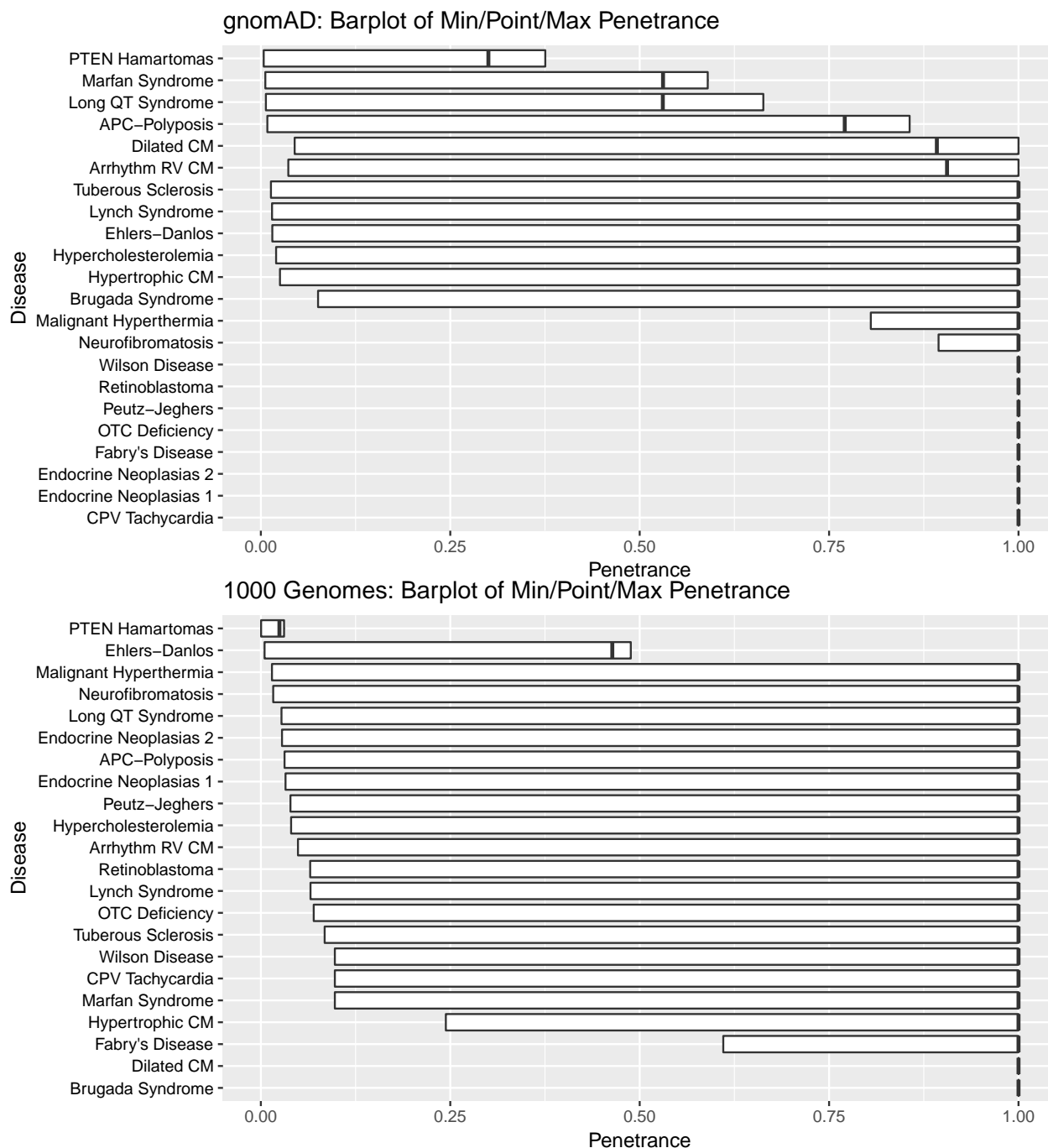
Testing Independence with Random Sampling



```
## 31 diseases x 1000 points = 31,000 points.  
## This plot has been downsampled 100x and contains 310 points.  
## AR (autosomal recessive) and XL (X-linked) diseases are colored in red.  
## Pearson correlation: 0.989
```

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

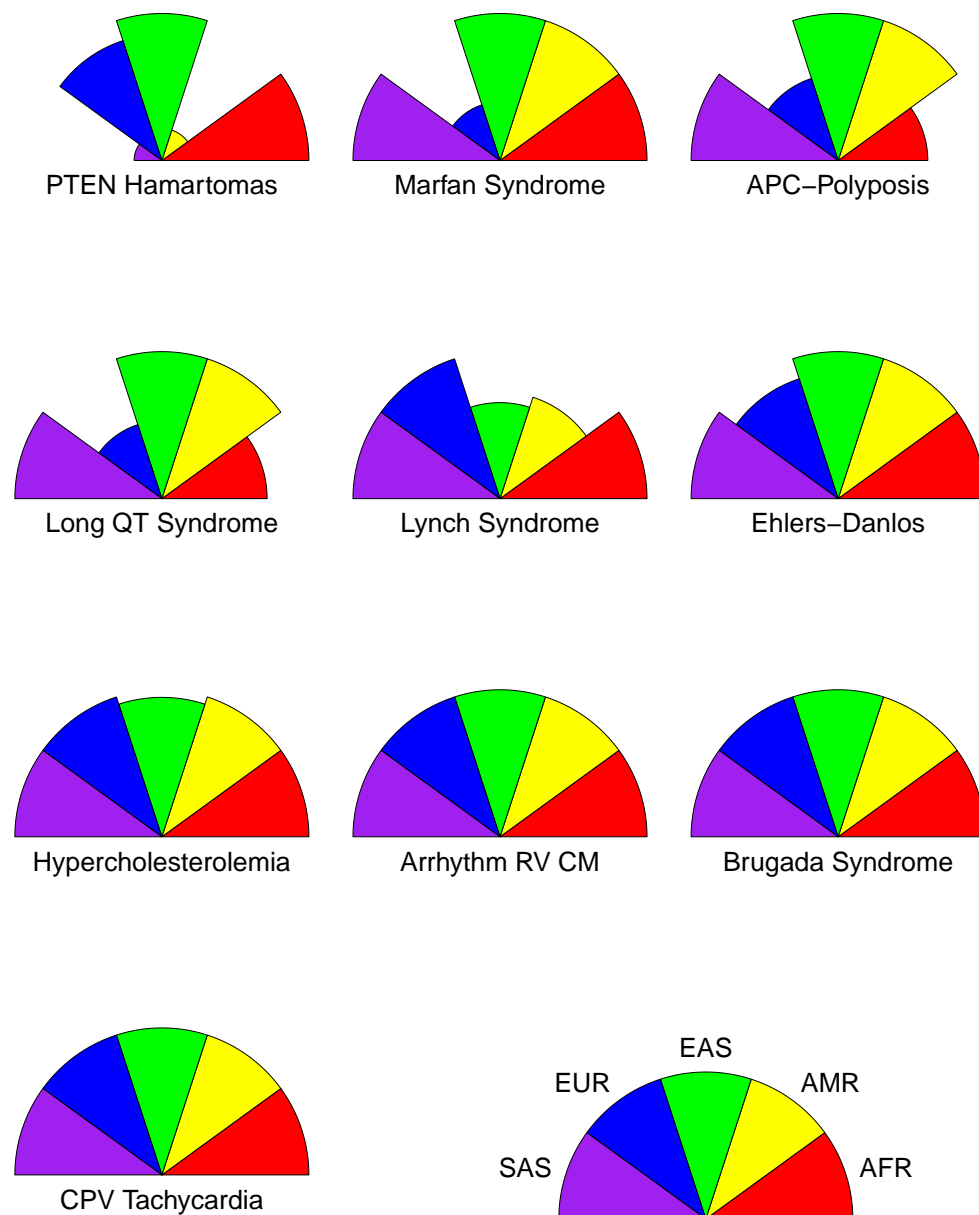
The left end of the boxplot indicates $P(V|D) = 0.01$,
the bold line in the middle indicates $P(V|D) = \text{point value}$,
the right end of the boxplot indicates $P(V|D) = 1$.



Note: Some diseases have mean theoretical penetrance = 1 because the assumed allelic heterogeneity is greater than is possible, given the observed prevalence and allele frequencies.

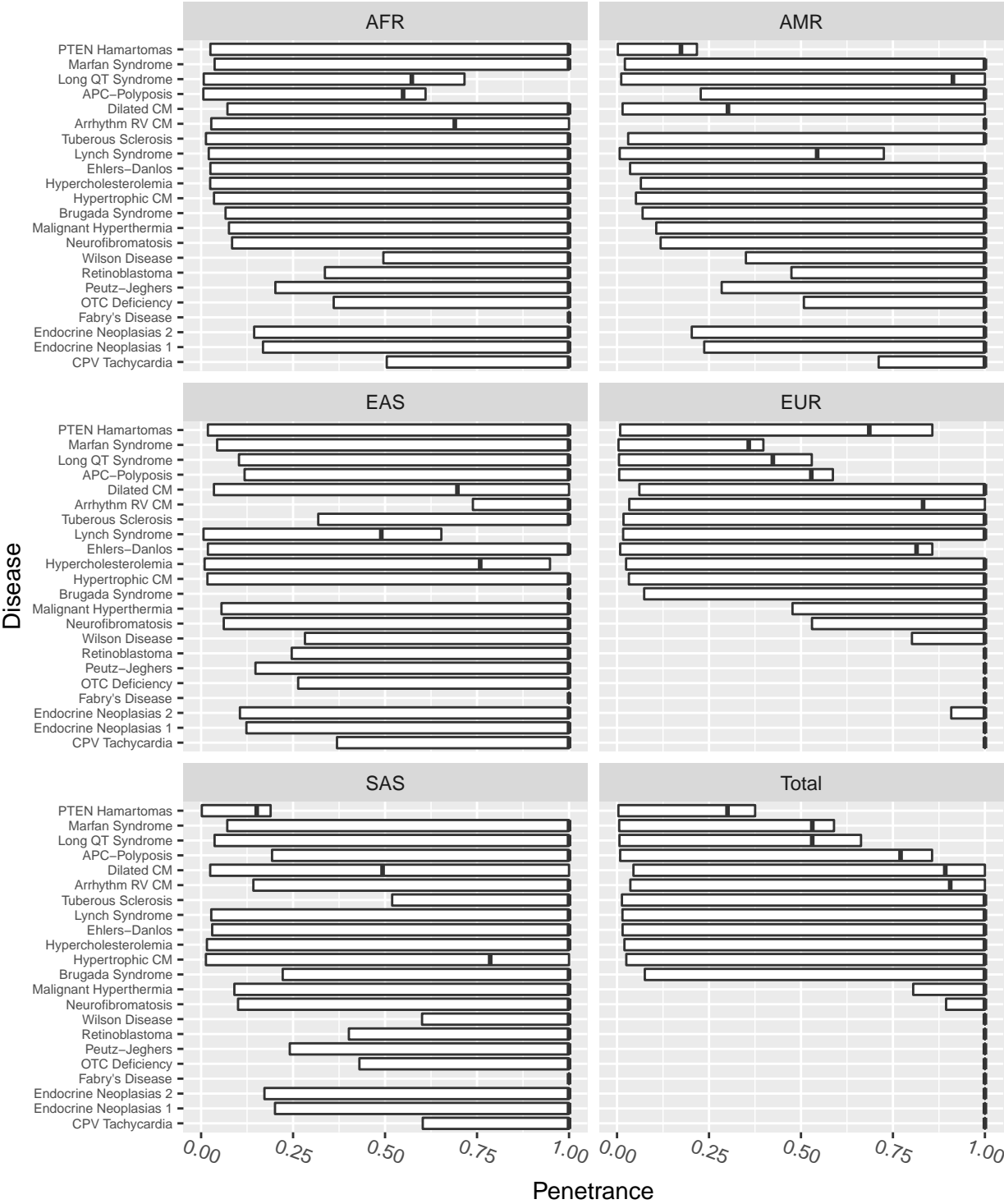
3.6 Penetrance Estimates by Ancestry

Radar Plot: Max Penetrance by Ancestry (gnomAD)



[1] These are the top 10 diseases by summed allele frequencies. NULL values are not plotted.
 ## [1] Each radius is proportional to the penetrance of the disease in the given population.

Barplot: Penetrance by Ancestry (gnomAD)



Heatmap: Max Penetrance by Ancestry (gnomAD)

