

# Testing for Adaptive Divergence: $Q_{ST}/F_{ST}$ Comparisons in Populations with Complicated Histories

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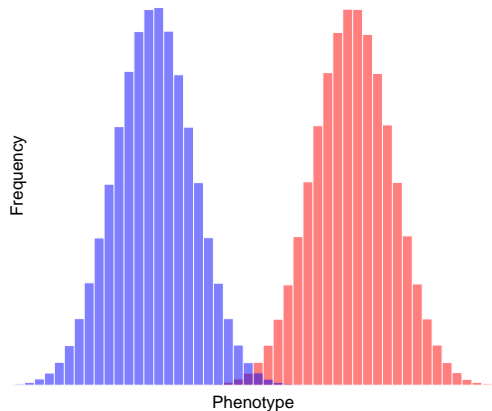
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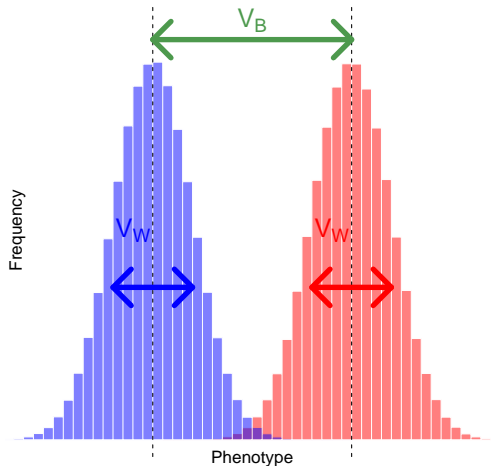
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- ▶ Compute  $Q_{ST}$  and  $F_{ST}$ ; compare them
- ▶ **What if the individuals in our sample can't be fit neatly into a discrete set of populations?**

# The Standard $Q_{ST}/F_{ST}$ Comparison

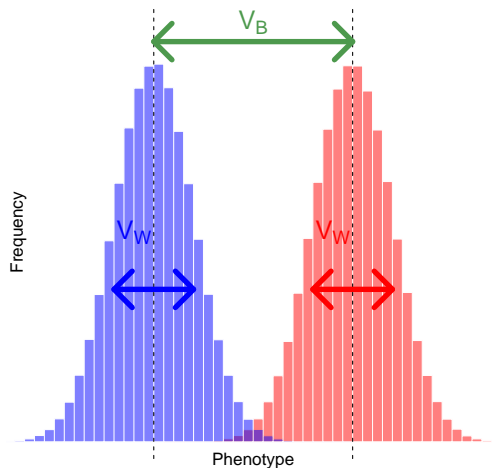


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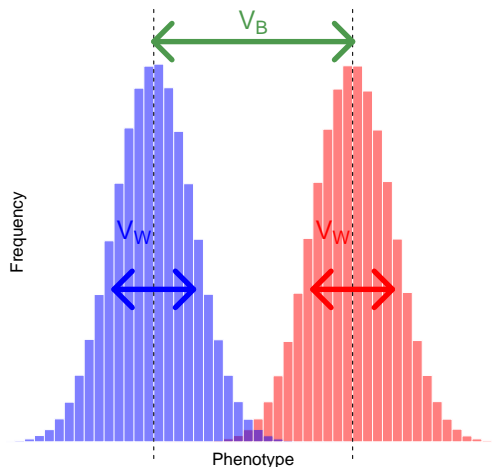


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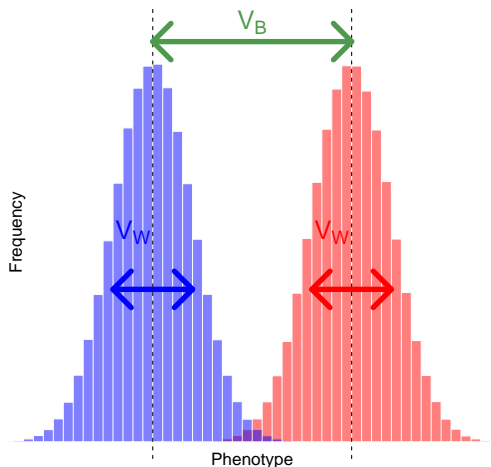


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$$\frac{Q_{ST}}{F_{ST}} = \frac{V_B}{\mathbb{E}[V_B]} \sim \chi^2$$

## LETTER

doi:10.1038/nature09410

### **Hundreds of variants clustered in genomic loci and biological pathways affect human height**

$$Z_k = \sum_{\ell=1}^L \alpha_{\ell} p_{k\ell}$$

$\alpha$  = effect size

$p$  = allele count

# Using GWAS hits to estimate genetic values

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## Evidence of widespread selection on standing variation in Europe at height-associated SNPs

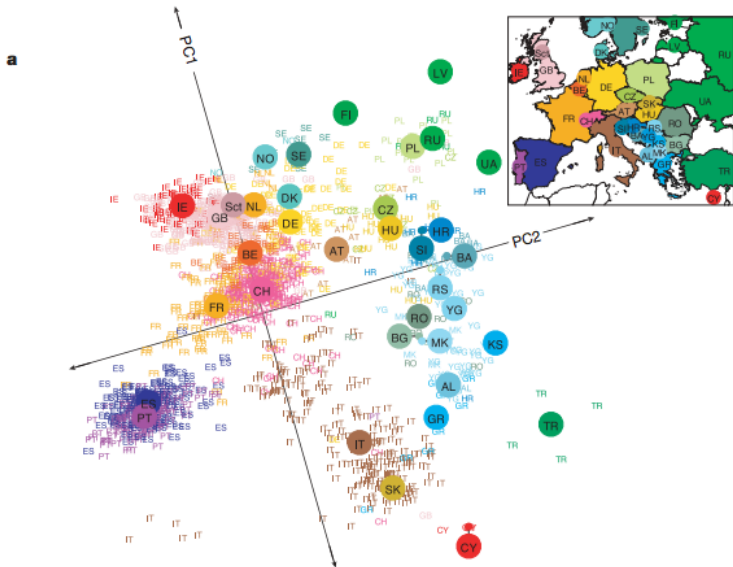
Michael C Turchin<sup>1-5,8</sup>, Charleston WK Chiang<sup>1-6,8</sup>, Cameron D Palmer<sup>1-5</sup>, Sriram Sankararaman<sup>5,6</sup>, David Reich<sup>5,6</sup>, Genetic Investigation of ANthropometric Traits (GIANT) Consortium<sup>7</sup> & Joel N Hirschhorn<sup>1-6</sup>

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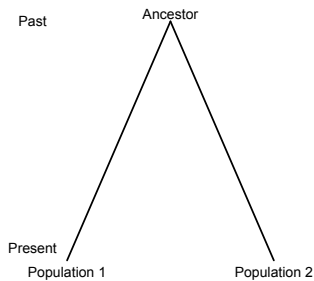
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# What about continuously sampled populations?



# $Q_{ST}/F_{ST}$ on a natural scale



## Variance Partitions

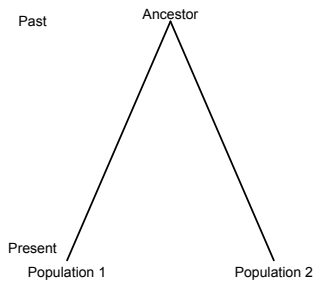
$$Q_{ST} = \frac{V_B}{V_B + V_W}$$

$$F_{ST} = \mathbb{E}[Q_{ST}]$$

## The Kinship Matrix

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_2 \end{bmatrix}$$

# $Q_{ST}/F_{ST}$ on a natural scale



## Variance Partitions

$$V_B = \left( \vec{U}_1 \cdot \vec{Z} \right)^2$$

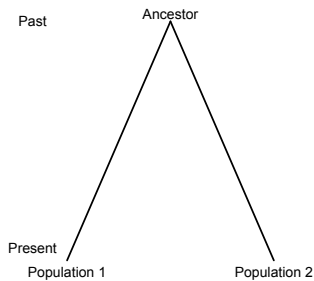
$$V_W = \sum_{i=2}^{K-1} \left( \vec{U}_i \cdot \vec{Z} \right)^2$$

$$F_{ST} = \frac{\lambda_1}{\sum_{i=1}^{K-1} \lambda_i}$$

## The Eigenvalue Decomposition (Principal Components)

$$\mathbf{F} = \begin{bmatrix} \vec{U}_1 & \vec{U}_2 & \dots & \vec{U}_{K-1} \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_{K-1} \end{bmatrix} \begin{bmatrix} \vec{U}_1^T \\ \vec{U}_2^T \\ \dots \\ \vec{U}_{K-1}^T \end{bmatrix}$$

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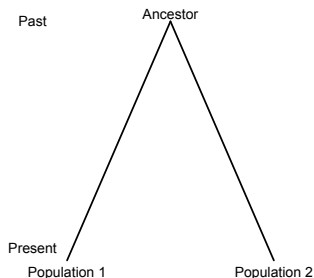
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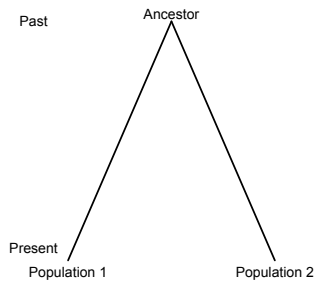
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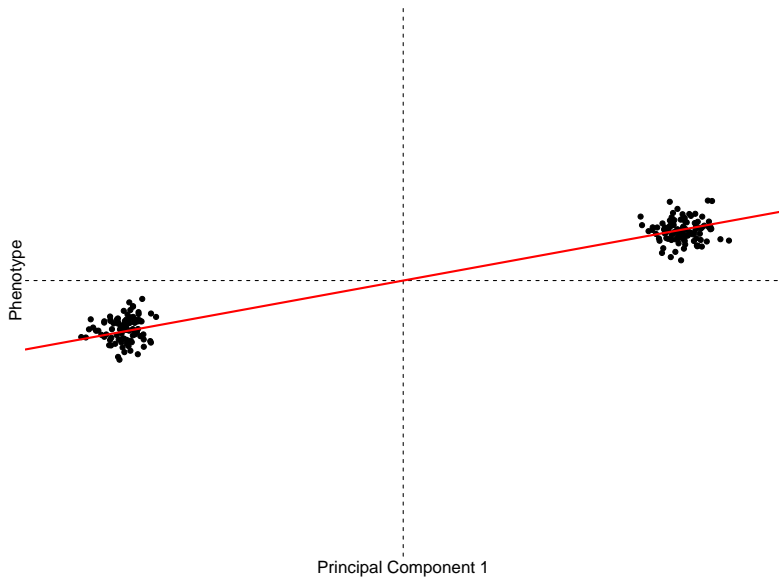
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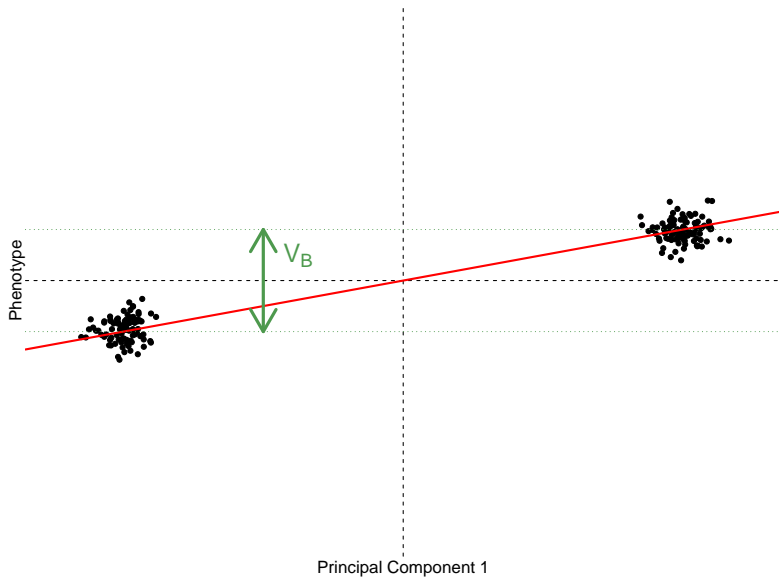
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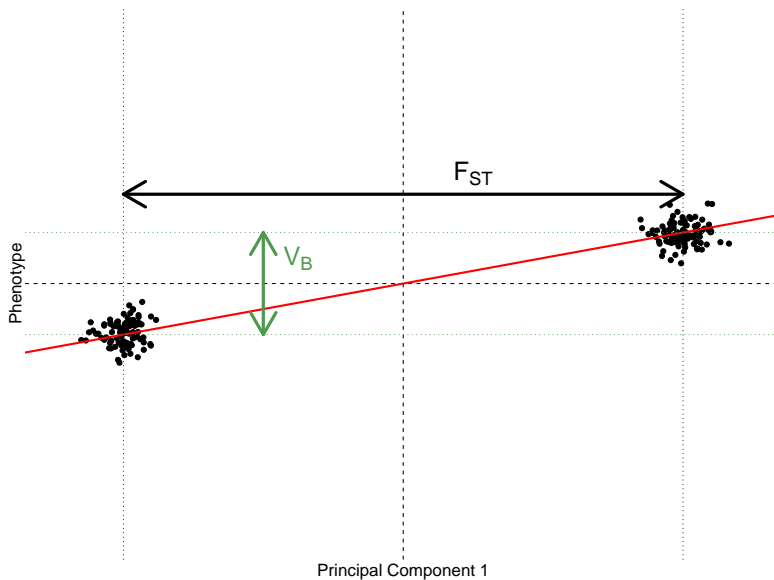
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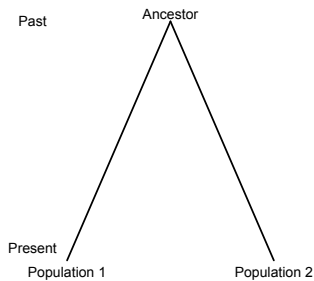
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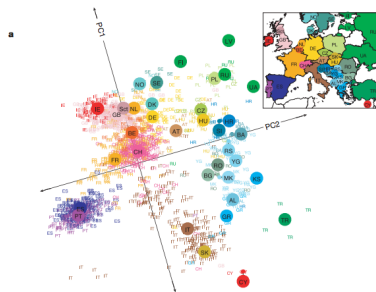
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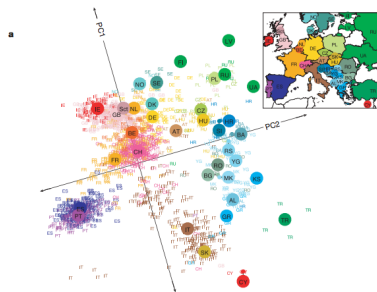
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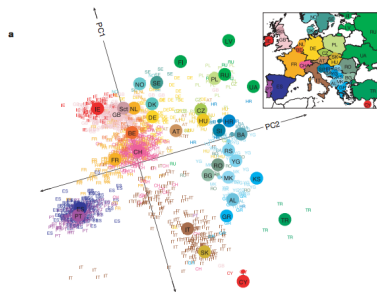
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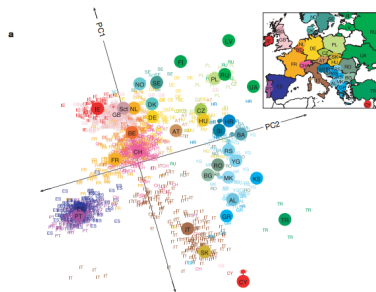
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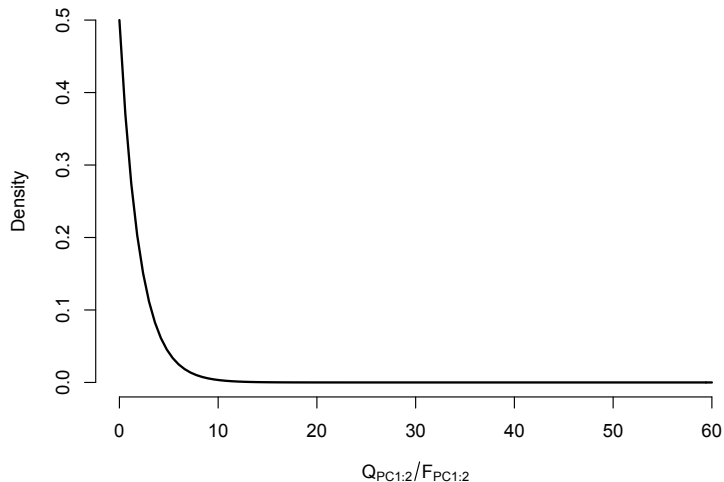
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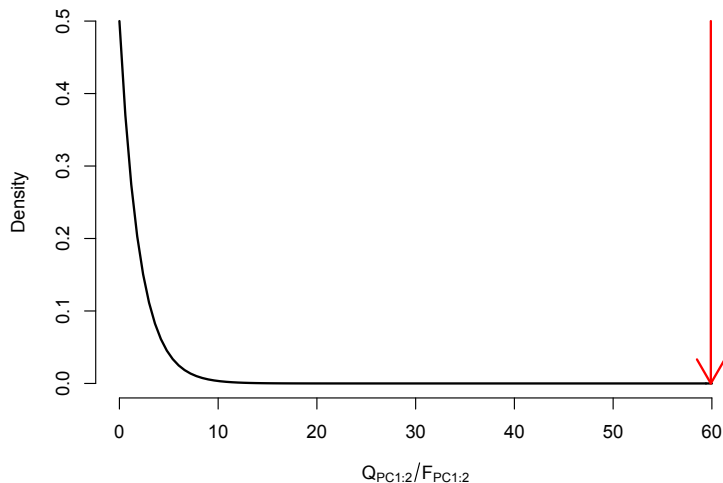
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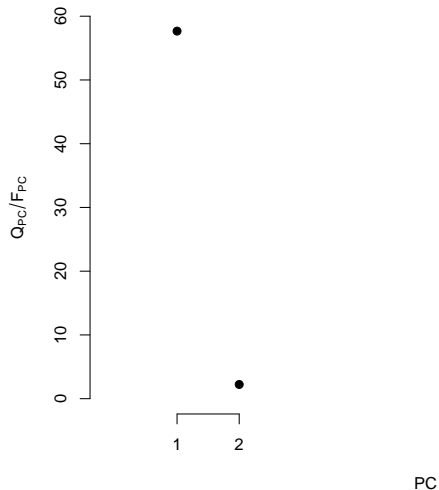
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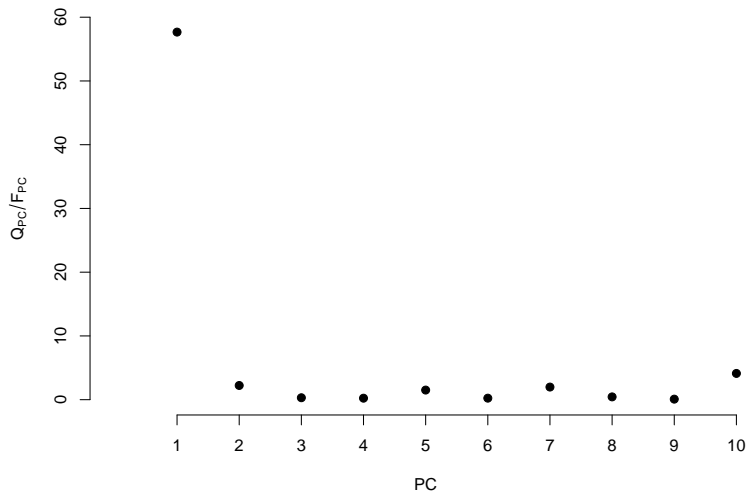
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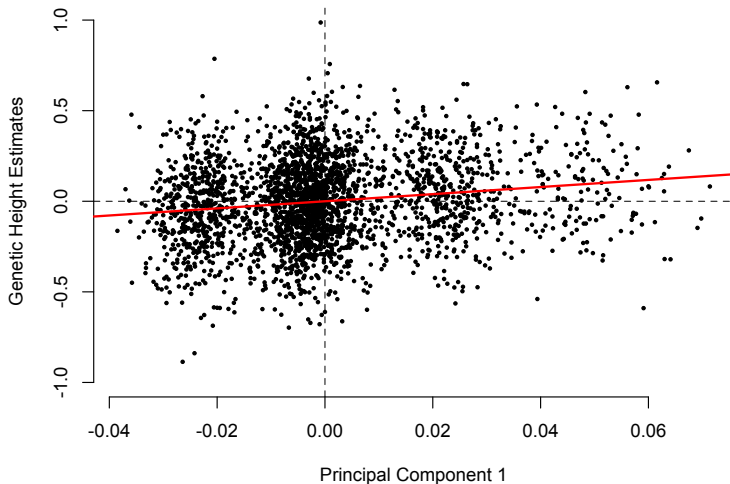
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- ▶ Significant but subtle correlation between genetic values for human height and PC1/N-S axis in Europe (but we already knew that)
- ▶  $Q_{ST}/F_{ST}$  can be formulated in terms of projections onto reduced rank factorizations of the individual-by-individual kinship matrix
  - ▶ Relationship to PCA, *structure*, factor analysis in general
    - ▶ Engelhardt and Stephens 2010
  - ▶ Every word of caution applicable to PCA/*structure* etc. applies here as well

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- ▶ Breeding designs easily be incorporated to help with estimation of genetic variance parameters

# Thanks!



**Graduate  
Research  
Fellowship  
Program**



- ▶ Coop Lab
  - ▶ Alisa
  - ▶ Gideon
  - ▶ Simon
  - ▶ Kristin
  - ▶ Chenling
  - ▶ Graham
- ▶ Annie Schmitt Lab
- ▶ Jeff Ross-Ibarra Lab
- ▶ Simon Myers