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Reply to : On powerful GWAS in admixed populations

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1 **Reply to Hou et al. comment; *Nature Genetics* ‘Matters Arising’**

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22 Admixed populations are sorely underrepresented in genomics research^{1,2}. To ensure that
23 medical genetic breakthroughs equitably benefit individuals of all ancestries³, there is a need for
24 the development of tools that facilitate the study of diverse and admixed populations. Our
25 manuscript⁴ proposes a novel methodology for the inclusion of admixed individuals in well-
26 calibrated genome-wide association studies (GWAS) through the incorporation of local ancestry.

1 In their comment, Hou et al. argue that alternative GWAS methods that do not include local
2 ancestry can attain improved power in circumstances where the effect sizes are equivalent
3 across ancestries. We wish to clarify that while we indeed observe a power drop due to the
4 increase in the number of parameters estimated in this edge case (addressed in the Tractor
5 manuscript in Figure 2, Extended Data Figure 3-4 and *Discussion*), in all other scenarios
6 modeled we observe a power boost. Given that minor allele frequencies and patterns of linkage
7 disequilibrium regularly differ between populations genome-wide⁵⁻⁸, as well as that differences
8 in case ascertainment, epistasis, and gene-environment interactions may differ across
9 ancestries and induce marginal effect size differences, we expect the instance of perfectly
10 identical marginal effect sizes to be the exception, not the rule, even assuming identical causal
11 effects. Tractor is therefore expected to outperform other methods at most GWAS loci.

12

13 By *marginal effect*, we mean the estimand (large-sample limit) of GWAS-style single variant
14 regression (including control for stratification). By *causal effect*, we mean the effect of allelic
15 substitution on an isogenic (and iso-environmental) background. The causal effects may of
16 course be unidentifiable from observed data; if all variation were measured and indexed with no
17 perfect LD, and there were no population stratification, then they would represent the estimand
18 or large-sample limit of the full multivariate regression. The vector of marginal effects is related
19 to the vector of causal effects by multiplication by the LD matrix.

20

21 The Tractor model parametrizes ancestry-specific *marginal* effects; hence the power loss
22 highlighted in Hou et al.'s comment pertains only to the case where these are all equal, which
23 requires not merely identical causal effects, but also identical patterns of AF and LD across
24 ancestries. Imperfect tagging will induce heterogeneity by ancestry at the tagging variant even if
25 the causal one has no allelic heterogeneity by ancestry, reducing the power of models that
26 assume no heterogeneity such as the 1 degree of freedom tests suggested by Hou et al. The

1 vast majority of GWAS loci identified are not causal⁹⁻¹¹ but rather represent tagging variants and
2 their estimated marginal effect sizes.

3

4 Tractor was specifically developed to function in diverse admixed datasets and has several
5 further advantages beyond leveraging genomic differences across ancestries to gain power.
6 Even when failing to boost power over competing methods, it produces accurate ancestry-
7 specific effect size estimates, which can be vital for efforts utilizing GWAS summary statistics,
8 such as the construction of polygenic scores for understudied populations. Tests considering
9 admixed individuals' component ancestries in aggregate do not produce ancestry-specific
10 results. Tractor additionally improves the resolution of GWAS signal, even before fine-mapping,
11 thanks to its ability to track ancestry breakpoints within admixed genomes, helping streamline
12 the interpretation of significant loci. By iterating between statistical phasing and local ancestry
13 inference, we also improve the recovery of long-range haplotypes in admixed individuals. In
14 sum, the Tractor model allows for the well-calibrated study of admixed individuals while boosting
15 power under most scenarios.

16

17 **Author Contributions**

18 E.G.A. drafted the primary text with input from A.B., A.M., B.M.N., C.M.N. and M.J.D. All authors
19 reviewed and approved the final draft.

20

21 **Competing Interests statement**

22 M.J.D. is a founder of Maze Therapeutics. B.M.N. is a member of the Deep Genomics Scientific
23 Advisory Board and serves as a consultant for the Camp4 Therapeutics Corporation, Takeda
24 Pharmaceutical and Biogen. The remaining authors declare no competing interests.

25

26 **Data and Code Availability**

1 All data referred to in this reply is available as described in the original Tractor publication⁴.

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