Supporting Information for "Multiple sources of uncertainty confound inference of historical human generation times"

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Supplemental methods

Generation times needed to explain long-lasting differences between populations

Using the reported generation intervals from Wang et al. (2023) (as shown in Figure S4 in their supplemental material), we explored scenarios that could lead to the observed differences between African and non-African populations five to ten thousand generations ago, corresponding to 150-300ka. As discussed in the main text, a 5-10 year difference in generation intervals would require long-lasting structure. Admixture from an unidentified, diverged human lineage has been proposed to explain observed genetic variation in African populations (e.g., Hey et al., 2018; Durvasula and Sankaramann, 2020; Lorente-Galdos et al., 2019, but see Ragsdale et al. (2023) for alternative models that allow for ongoing gene flow between lineages). In such models, a population that was isolated for hundreds of thousands of years contributed 5–10% ancestry to West African populations (Figure 1). The remaining 90–95% ancestry is shared between present-day Eurasian and West African populations, and this ancestry would have shared historical generation times. While other models of deep population structure in Africa have been proposed, a history of strict isolation (instead of ongoing gene flow) between diverged lineages before admixture is more likely to result in a signal of differing ancestral generation times, because ancestries and their associated generation intervals would remain distinct.

In such a scenario, differences in inferred average historical generation times between West African and Eurasian populations must be due to differences in generation times between the two diverged lineages. This is because ancestry that is shared within the common branch will have been merged and average generation intervals would have likewise been shared. Using the mutation model Wang et al. (2023) inferred from Icelandic pedigree data (Jónsson et al., 2017), we modeled the Eurasian mutation spectrum from this time period using paternal and maternal generation times of 20 (18–22, from figure S4 in Wang et al.) years. The West African mutation spectrum was modeled as a mixture between this shared spectrum and the mutation spectrum from the diverged lineage, in proportions equal to the admixture proportions. This assumes (1) selection does not strongly influence mutation spectrum proportions, (2) there are no demographic effects such as severe bottlenecks that make mutation spectrum proportions unequal to admixture proportions, and (3) the rates of mutation accumulation along each lineage are similar. Additionally, age- and sex-dependent mutation rates from past populations must match the mutation model from the Icelandic trio data. It is likely that none of these assumptions perfectly hold, but these are the same assumptions in the original inference of generation time histories.

We write our mutation model as M(p, d), which takes paternal and maternal ages p and d and outputs the expected mutation spectrum. The output mutation spectrum is the relative proportions of each mutation

type (which sums to 1), and it is fit to data by minimizing the Aitchison distance between the centered log-ratio transform of both the data and expected spectra (as described in Section S3.1 in Wang et al. (2023)).

The inferred West African-ancestral paternal and maternal generation intervals were roughly 28 and 23 years (see Figure S4 in Wang et al. (2023)). Then given the admixture proportion f from the diverged lineage, we found generation times p_d and m_d in the diverged lineage such that

$$M(28, 23) = (1 - f)M(20, 20) + fM(p_d, m_d).$$

In fitting this model with f=0.1 (roughly the inferred admixture proportion from Durvasula and Sankaraman (2020)), we found $p_d \approx 92$ and $m_d \approx 48$.

If we assume average ancestral paternal and maternal ages in the Eurasian-shared lineage were each 22 years, $p_d \approx 76$ and $m_d \approx 31$. With Eurasian-ancestral intervals of 22 years and f = 0.2 (much higher than most inferences), the paternal age would still need to be over 50 years, inconsistent with average generation times in humans and great apes. More comparisons are shown in Table S1. From this, we conclude that the generation time history inferred by WANG et al. (2023) is incompatible with prevailing models of deep population structure within Africa.

	Input Parameters				Fit parameters		
f	$p_{ m EUR}$	$m_{ m EUR}$	$p_{ m AFR}$	$m_{ m AFR}$	$p_{ m d}$	$m_{ m d}$	
0.1	20	20	28	23	92.2	47.9	
0.1	20	20	30	25	111.2	67.6	
0.1	20	20	26	22	75.0	38.6	
0.2	20	20	28	23	58.0	34.4	
0.2	20	20	30	25	67.7	44.4	
0.2	20	20	26	22	48.8	29.6	
0.3	20	20	28	23	45.9	29.8	
0.3	20	20	30	25	52.4	36.4	
0.3	20	20	26	22	39.5	26.5	
0.1	22	22	28	23	75.6	30.6	
0.1	22	22	30	25	94.2	49.9	
0.1	22	22	26	22	58.4	21.4	
0.2	22	22	28	23	50.5	25.2	
0.2	22	22	30	25	60.1	36.4	
0.2	22	22	26	22	41.2	21.8	
0.3	22	22	28	23	41.4	25.2	
0.3	22	22	30	25	47.9	31.8	
0.3	22	22	26	22	35.0	21.8	

Table S1: Testing admixture proportions and generation intervals under an African archaic admixture model. In order for the generation times in the isolated branch (p_d and m_d) to be reasonably short enough for human biology, the admixture proportion would need to be $\gtrsim 0.3$ and for the inferred generation intervals in Eurasians and West Africans to be much closer than the average values shown in Figure S4 in Wang *et al.* (2023).

Historical mutation spectra

We followed the filtering choices from Wang *et al.* (2023) in retaining mutations with estimated ages. Namely, triplet mutation contexts associated with a known C→T mutation pulse in Europeans (HARRIS, 2015) and CpG sites were removed. GEVA does not provide allele ages for singletons, but we considered data

both with and without singletons from tsdate- and Relate-inferred ages. Variants with allele frequencies greater than 98% were removed to minimize the effect of ancestral-state misidentification.

Variants were binned by age in 100 epochs, divided such that a roughly equal number of variants fell within each bin, as in WANG et al. (2023). In most cases, we considered a maximum age of 10,000 generations. Mutation profile trajectories and generation time histories were smoothed using the loess_1d function from the Python loess package, with parameters frac=0.5 and degree=2.

Allele ages from GEVA

Allele age data from GEVA reported in Albers and McVean (2020) were downloaded from https://human.genome.dating/download/index. We used the median joint-estimated allele ages, "AgeMedian_Jnt". To compare to allele age data estimated from Relate and tsdate, we used allele ages estimated from the Thousand Genomes Project (TGP) data source, available from http://ftp.ensembl.org/pub/grch37/release-103/variation/gvf/homo_sapiens/.

We computed confidence intervals using a block bootstrap approach (Figure S2). For each time bin of the GEVA dataset (including all populations), we divided the autosomal genome into $\sim 5 \mathrm{Mb}$ chunks and counting dated mutation occurances within each chunk. There were 560 total chunks. To generated a bootstrap replicate, we resampled with replacement from these 560 regions. We repeated this process 560 times and took the empirical 2.5 and 97.5% interval for each mutation type within each time bin, independently.

Allele ages from Relate

Allele age data from Relate reported in SPEIDEL et al. (2019) were downloaded from https://zenodo.org/record/3234689. Relate provides allele ages separately for the 26 populations in the Thousand Genomes Project. As such, we followed the approach in Wohns et al. (2022) and computed the average upper and lower bounds of the branch the mutation maps to for each population it is present in. We then took the midpoint of those averaged upper and lower bounds as the allele age estimate.

Allele ages from tsdate

The reconstructed genealogies from Wohns et al. (2022) were downloaded from https://zenodo.org/record/5512994. Data for each chromosome arm were provided in tree sequence format, and mutation ages can be estimated from the upper and lower bounds of the genealogical edge on which it arose. We kept sites with variants that were uniquely assigned to a single branch, and we considered variants that segregate among the subset of individuals from the AFR, EAS, EUR, and SAS Thousand Genomes Project superpopulations. For such sites, allele ages were found using the function tsdate.sites_time_from_ts(ts, node_selection="arithmetic").

Distributing allele weights over branches

Instead of taking the midpoints of branches a mutation is mapped to as the allele age (in Relate and tsdate) or the reported median age from GEVA, we also accounted for uncertainty in the placement of the mutation along each branch. To do so, we assumed that mutations are distributed uniformly along each branch, so if a branch spans multiple time bins, the mutation contributes to each of those time bins relative to the proportion of the branch that overlaps with each bin. In GEVA, we similarly accounted for uncertainty in the allele age by uniformly distributing the contribution of the mutation to (potentially) multiple bins using the 95% upper and lower confidence interval bounds. Figures S15 and S16 show that this approach results in qualitatively similar mutation spectra to taking the midpoint/median allele age estimates.

Reference genomes

To determine triplet contexts for each mutation, we used the reference genomes for GRCh37 (GEVA and Relate data) and GRCH38 (tsdate data). These were downloaded from http://hgdownload.cse.ucsc.

edu/goldenPath/hg19/chromosomes/ and https://ftp.1000genomes.ebi.ac.uk/vol1/ftp/technical/reference_genome/, respectively.

Summarizing data within time bins

Within each time bin, we work with the relative proportions of observed mutations of each of the six mutation times. Percent changes (as shown in Figure 2) are the changes in proportion (multiplied by 100) of each mutation class relative to the mutation spectrum in the most recent time bin in the dataset with all populations combined. This follows the summarization approach taken by WANG et al. (2023).

Data availability

All analyses were performed using publicly available datasets, available from the above URLs. Python scripts to run analyses described here are available at https://github.com/apragsdale/dated-mutation-spectra/

References

- ALBERS, P. K., and G. McVean, 2020 Dating genomic variants and shared ancestry in population-scale sequencing data. PLoS Biology 18: e3000586.
- Durvasula, A., and S. Sankaraman, 2020 Recovering signals of ghost archaic introgression in african populations. Science Advances 6: eaax5097.
- HARRIS, K., 2015 Evidence for recent, population-specific evolution of the human mutation rate. Proceedings of the National Academy of Sciences 112: 3439–3444.
- HEY, J., Y. CHUNG, A. SETHURAMAN, J. LACHANCE, S. TISHKOFF, et al., 2018 Phylogeny estimation by integration over isolation with migration models. Molecular Biology and Evolution 35: 2805–2818.
- JÓNSSON, H., P. SULEM, B. KEHR, S. KRISTMUNDSDOTTIR, F. ZINK, et al., 2017 Parental influence on human germline de novo mutations in 1,548 trios from Iceland. Nature **549**: 519–522.
- LORENTE-GALDOS, B., O. LAO, G. SERRA-VIDAL, G. SANTPERE, L. F. KUDERNA, et al., 2019 Wholegenome sequence analysis of a pan african set of samples reveals archaic gene flow from an extinct basal population of modern humans into sub-saharan populations. Genome Biology 20: 1–15.
- RAGSDALE, A. P., T. D. WEAVER, E. G. ATKINSON, E. G. HOAL, M. MÖLLER, et al., 2023 A weakly structured stem for human origins in africa. Nature: 1–9.
- Speidel, L., M. Forest, S. Shi, and S. R. Myers, 2019 A method for genome-wide genealogy estimation for thousands of samples. Nature Genetics 51: 1321–1329.
- Wang, R. J., S. I. Al-Saffar, J. Rogers, and M. W. Hahn, 2023 Human generation times across the past 250,000 years. Science Advances 9: eabm7047.
- Wohns, A. W., Y. Wong, B. Jeffery, A. Akbari, S. Mallick, et al., 2022 A unified genealogy of modern and ancient genomes. Science 375: eabi8264.

Tables and figures

Dataset	$\mid A \rightarrow C$	$A{ ightarrow} G$	$A{ ightarrow}T$	$C{ ightarrow} A$	$C{ ightarrow} G$	$C{ ightarrow}T$
GEVA	0.0946	0.3600	0.0886	0.1201	0.1057	0.2310
tsdate	0.0931	0.3579	0.0899	0.1146	0.1061	0.2384
$ exttt{tsdate} (w/singletons)$	0.0989	0.3598	0.0908	0.1168	0.1062	0.2275
Relate	0.0991	0.3610	0.0863	0.1124	0.1038	0.2374
Relate $(w/singletons)$	0.1002	0.3590	0.0921	0.1164	0.1060	0.2263
Trios (phased)	0.0953	0.3649	0.0890	0.0960	0.1216	0.2332
Trios (all mutations)	0.0962	0.3638	0.0923	0.0951	0.1202	0.2324

Table S2: Mutation profiles from the past 100 generations, compared to Iceland trios. The most recent time bin for each method included the past ≈ 150 generations. When singletons were included (when using data from tsdate and Relate), the spectra of estimated recent standing variation were unchanged. Note that GEVA does not report ages for singletons. While the three methods provide similar spectra from recent mutations, the spectrum from the Iceland pedigrees differs, in particular for the C \rightarrow A and C \rightarrow G classes. These differences are up to 2% of the proportion among all mutations, which corresponds to an under- or over-count of up to $\sim 20\%$ of C \rightarrow A and C \rightarrow G mutations, respectively. This difference remains whether the spectrum is estimated from only mutations that were phased in Jónsson et al. (2017) or from all mutations (phased and unphased).

Dataset	$A \rightarrow C$	$A{\to}G$	$A{\to}T$	$C{\rightarrow} A$	$C{ ightarrow} G$	$C{\to}T$
AFR (GEVA) EAS	0.103	0.354 0.341	0.094 0.103	0.127 0.131	0.098 0.094	0.224 0.220
EUR SAS	0.111 0.102 0.095	0.355 0.355	0.093 0.090	0.125 0.123	0.102 0.099	0.222 0.238
AFR (Relate)	0.099	0.356	0.090	0.123	0.099	0.236
EAS EUR	$0.095 \\ 0.100$	$0.359 \\ 0.368$	$0.089 \\ 0.085$	$0.115 \\ 0.110$	$0.097 \\ 0.102$	$0.245 \\ 0.235$
SAS	0.100	0.344	0.090	0.110	0.102	0.246
AFR (tsdate) EAS EUR	$\begin{vmatrix} 0.092 \\ 0.098 \\ 0.091 \end{vmatrix}$	0.354 0.356 0.363	0.087 0.097 0.089	0.116 0.112 0.117	0.110 0.103 0.102	0.241 0.233 0.238
SAS	0.091	0.359	0.088	0.114	0.107	0.241

Table S3: Mutation profiles from the past 100 generations in continental population groups. For mutations that are inferred to be young, the mutation spectra are largely consistent across population groups as well as methods. As shown in Table S2 and Figure 3E, these differ from the *de novo* mutation spectrum inferred from Icelandic trios.

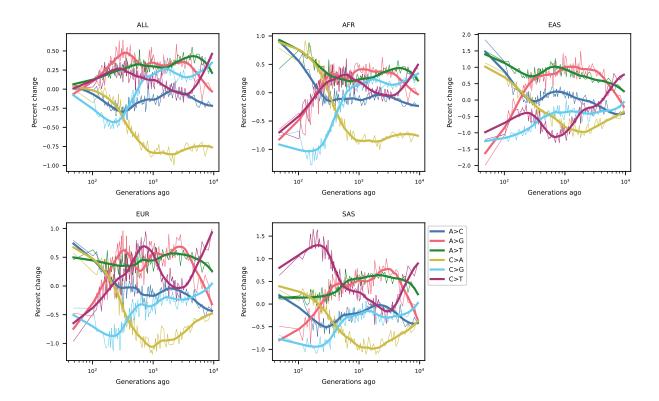
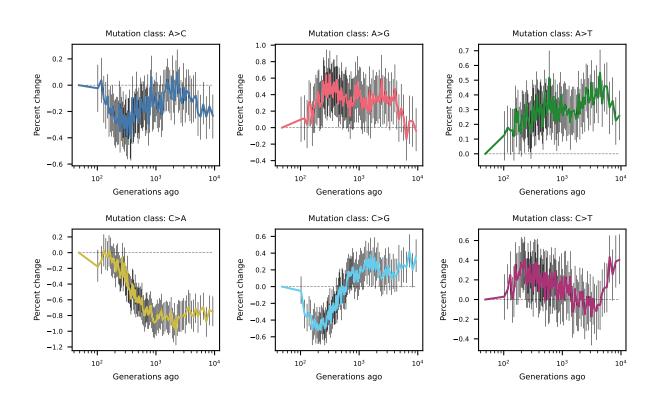


Figure S1: GEVA-inferred mutation spectrum history. Extending to 10,000 generations in the past, the mutation spectrum history from allele ages estimated by GEVA matches the spectrum history in Wang et al. (2023). In all plots showing mutation spectrum trajectories, thin lines represent the spectrum within each bin, and thick lines are the LOESS-smoothed curves fit to the underlying data.



 $\label{eq:section} \mbox{Figure S2: } \mbox{\bf Confidence intervals for $\tt GEVA-estimated mutation spectra.}$

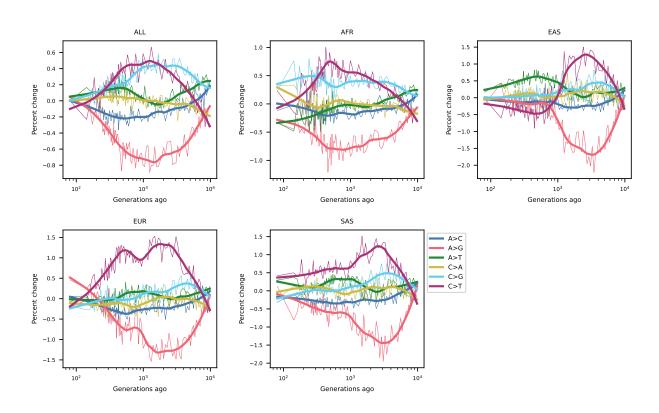


Figure S3: Relate-inferred mutation spectrum history over 10,000 generations.

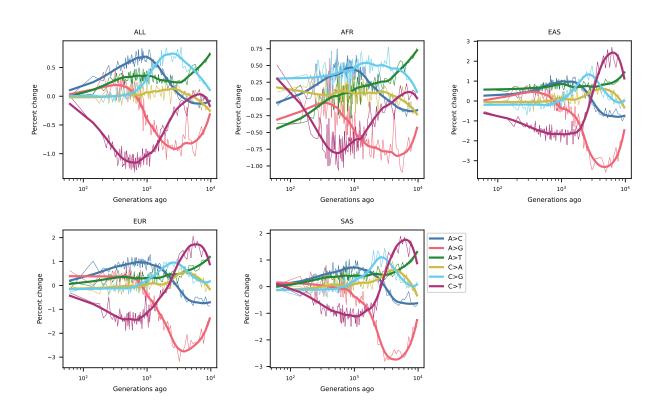


Figure S4: tsdate-inferred mutation spectrum history over 10,000 generations.

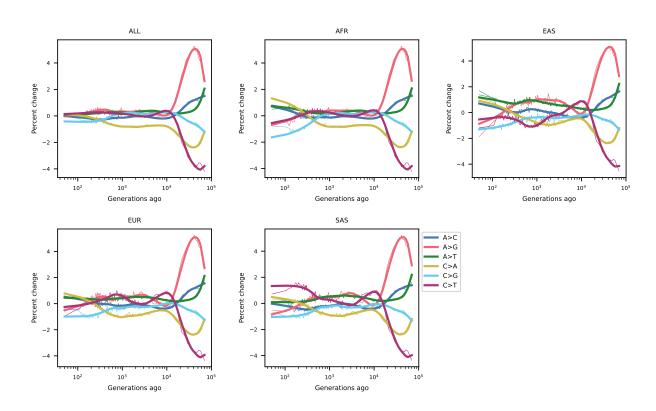


Figure S5: GEVA-inferred mutation spectrum history, extending to 80,000 generations.

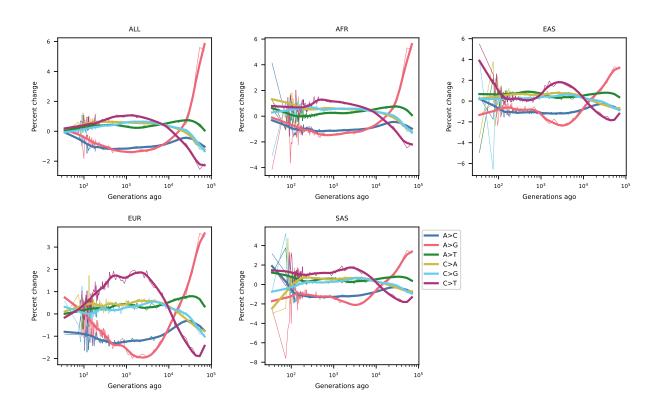


Figure S6: Relate-inferred mutation spectrum history, extending to 80,000 generations.

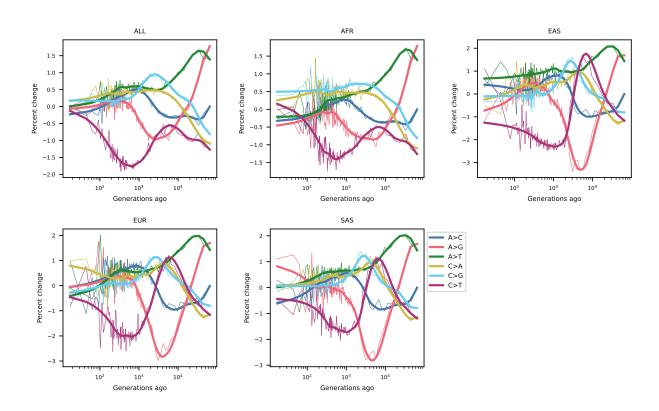


Figure S7: tsdate-inferred mutation spectrum history, extending to 80,000 generations.

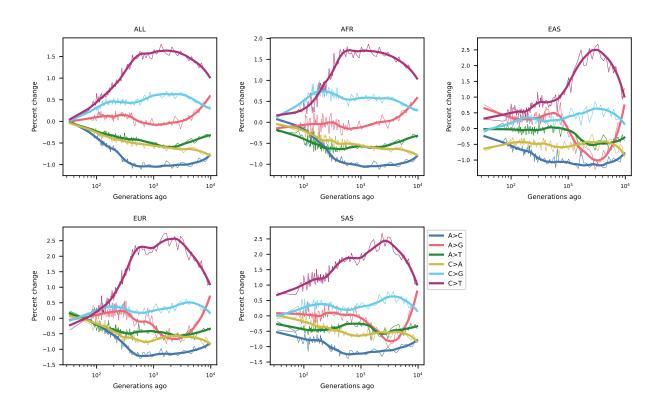


Figure S8: Relate-inferred mutation spectrum history, including singletons. The inclusion of singletons has only a small effect on the mutation spectrum from recent time periods, but a larger effect in older time bins. Compare to Figure S3.

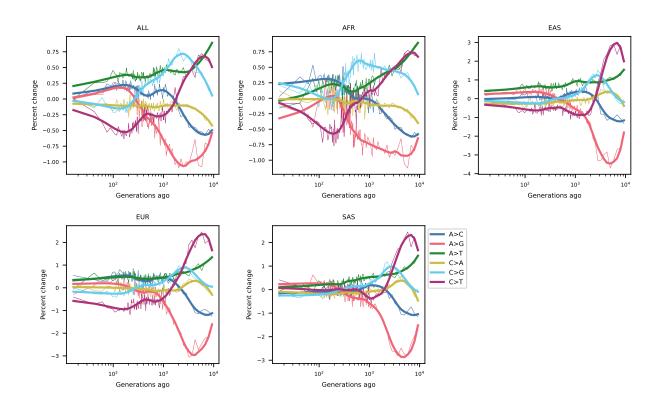


Figure S9: tsdate-inferred mutation spectrum history, including singletons. The inclusion of singletons using tsdate does not have as strong of an effect on the mutation spectrum history as doing so in Relate (Figure S8), though still results in some qualitative differences from the spectrum history without singletons (Figure S4).

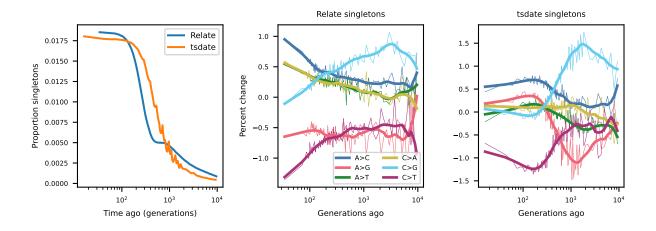


Figure S10: Mutation profiles of singletons from Relate and tsdate Left: Singletons make up over half of all dated mutations from Relate and tsdate, though most are estimated to be young mutations, as expected. Center and right: the mutation spectrum histories for only singletons, anchored by the observed mutation spectrum in the youngest time bin for *non*-singletons. Changes in the singleton mutation profiles deviate from zero at the same order of magnitude as deviations seen in the full dataset, though their inclusion does not make the inferred mutation spectra to match that estimated from pedigrees (Table S2).

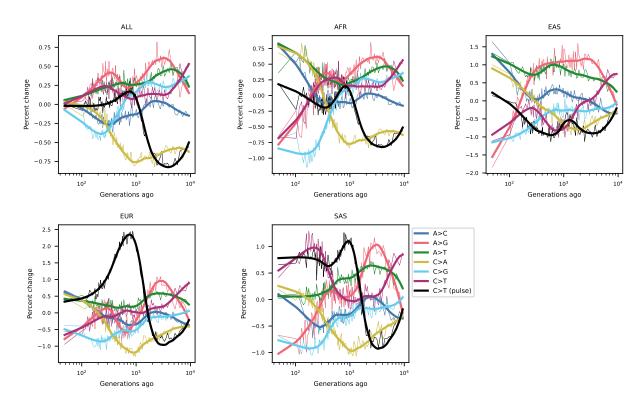


Figure S11: GEVA-inferred mutation spectrum history, including European pulse-associated $C \rightarrow T$ contexts. GEVA captures the known pulse of $C \rightarrow T$ mutations among certain triplet contexts, in European populations (HARRIS, 2015).

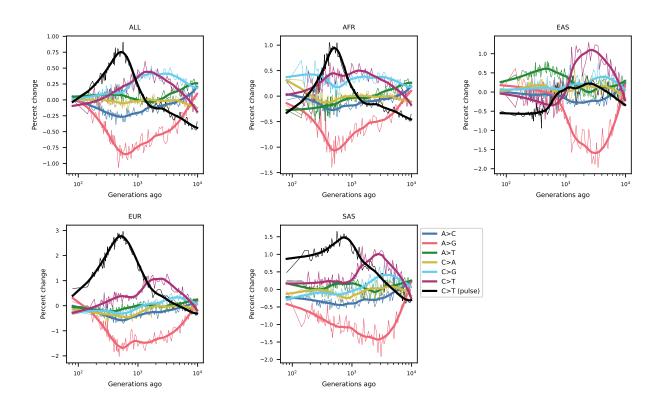


Figure S12: Relate-inferred mutation spectrum history, including European pulse-associated $C \rightarrow T$ contexts. Relate recovers the known pulse of $C \rightarrow T$ mutations in European populations, and also finds the same signal in South Asian and African populations. South Asians and Europeans have more recent shared ancestry, on average, while the signal in African populations could be due to some European-related ancestry found in some of the AFR-labeled populations in the 1KGP (ASW, ACB, and LWK). Note that the scales differ between panels.

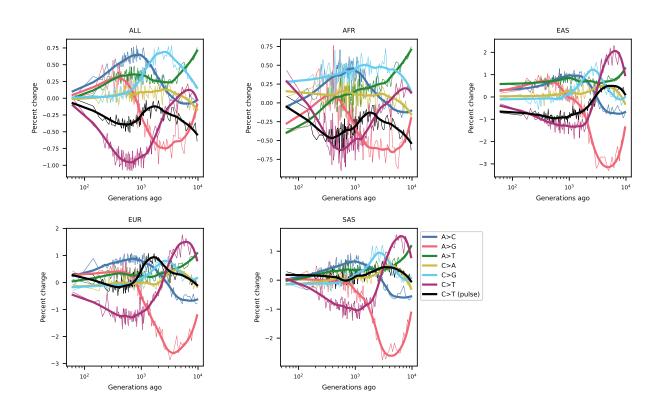


Figure S13: tsdate-inferred mutation spectrum history, including European pulse-associated $C \rightarrow T$ contexts. tsdate does not pick out the European-related pulse in certain $C \rightarrow T$ triplet mutation classes.

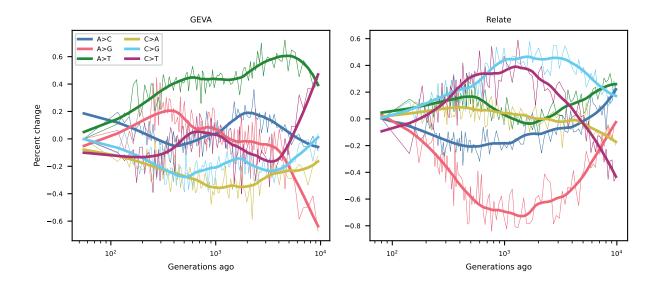


Figure S14: Mutation spectrum histories from mutations that were dated by both GEVA and Relate. Using only mutations that were dated by both GEVA and Relate, we find that the qualitative differences in mutation spectrum histories from each method remain. Thus, mutations dated by only one of the two methods are unlikely to be driving the differences in mutation spectra between methods.

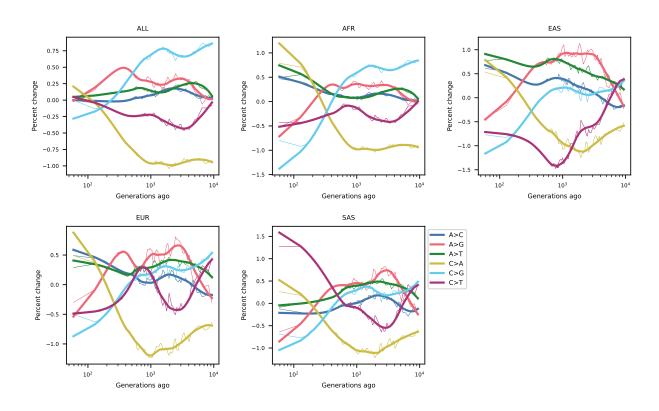


Figure S15: GEVA-inferred mutation spectrum history, assuming a uniform distribution of ages within the 95% confidence interval. Compare to Figure S1, which uses the median age estimate from GEVA.

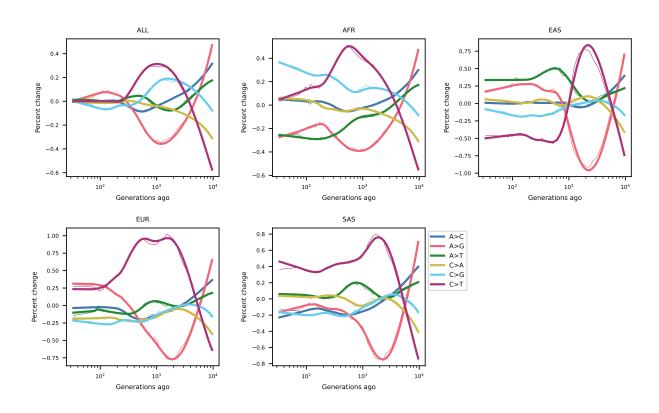
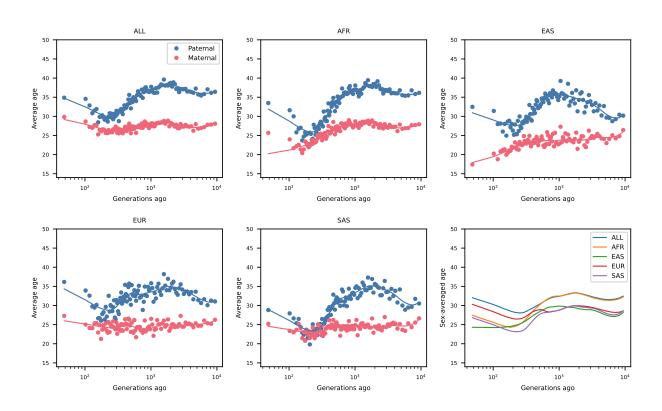
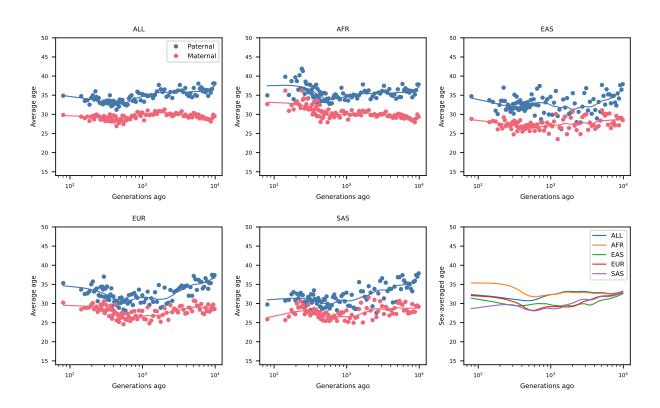


Figure S16: Relate-inferred mutation spectrum history, assuming a uniform distribution of ages along a branch. Compare to Figure S3, which uses branch midpoints to assign allele ages.



 $\label{eq:sigma} \mbox{Figure S17: GEVA-inferred generation time histories.}$



 $\label{eq:sigma} \mbox{Figure S18: Relate-inferred generation time histories.}$

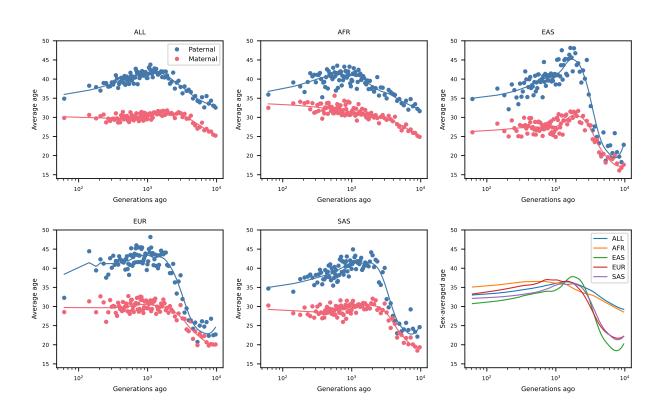


Figure S19: tsdate-inferred generation time histories.

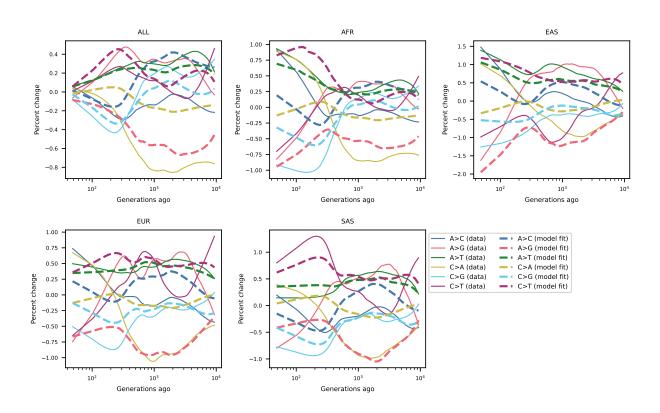
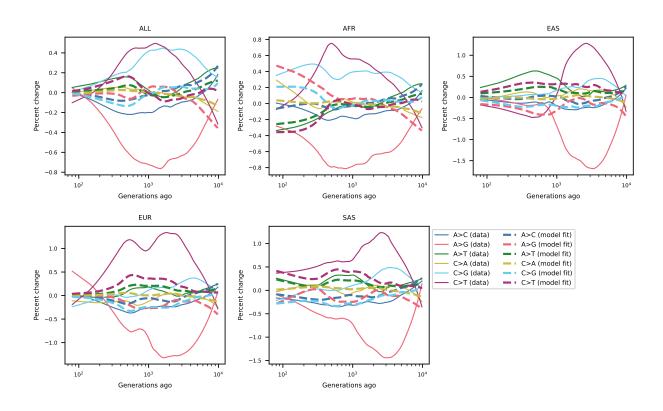
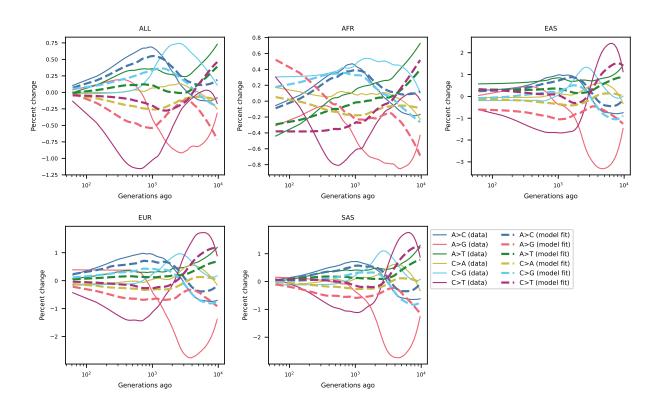


Figure S20: Model prediction of mutation spectrum history from GEVA-inferred generation times.



 $\label{eq:solution} \mbox{Figure S21: Model prediction of mutation spectrum history from $\tt Relate-inferred generation times.}$



 $\label{eq:solution} \mbox{Figure S22: Model prediction of mutation spectrum history from tsdate-inferred generation times.}$