

Neutral genomic regions refine models of recent rapid human population growth

Elodie Gazave^{a,1}, Li Ma^{a,1,2}, Diana Chang^{a,1}, Alex Coventry^b, Feng Gao^a, Donna Muzny^c, Eric Boerwinkle^c, Richard A. Gibbs^c, Charles F. Sing^d, Andrew G. Clark^b, and Alon Keinan^{a,3}

Departments of ^aBiological Statistics and Computational Biology and ^bMolecular Biology and Genetics, Cornell University, Ithaca, NY 14853; ^cHuman Genome Sequencing Center, Baylor College of Medicine, Houston, TX 77030; and ^dDepartment of Human Genetics, University of Michigan, Ann Arbor, MI 48105

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Human populations have experienced dramatic growth since the Neolithic revolution. Recent studies that sequenced a very large number of individuals observed an extreme excess of rare variants and provided clear evidence of recent rapid growth in effective population size, although estimates have varied greatly among studies. All these studies were based on protein-coding genes, in which variants are also impacted by natural selection. In this study, we introduce targeted sequencing data for studying recent human history with minimal confounding by natural selection. We sequenced loci far from genes that meet a wide array of additional criteria such that mutations in these loci are putatively neutral. As population structure also skews allele frequencies, we sequenced 500 individuals of relatively homogeneous ancestry by first analyzing the population structure of 9,716 European Americans. We used very high coverage sequencing to reliably call rare variants and fit an extensive array of models of recent European demographic history to the site frequency spectrum. The best-fit model estimates ~3.4% growth per generation during the last ~140 generations, resulting in a population size increase of two orders of magnitude. This model fits the data very well, largely due to our observation that assumptions of more ancient demography can impact estimates of recent growth. This observation and results also shed light on the discrepancy in demographic estimates among recent studies.

Archaeological and historical records reveal that modern human populations have experienced dramatic growth, likely driven by the Neolithic revolution about 10,000 y ago (1, 2). Since then, the worldwide human population size has increased at a fast pace, and faster yet in the last ~2,000 y, giving rise to today's population in excess of 7 billion people (3, 4). A central question in population genetics is how such demographic events affect the effective size (N_e) of populations over time, and as a consequence, how they have shaped extant patterns of genetic variation. [Effective population size, which is typically smaller than the census size, determines the genetic properties of a population (5).] Focusing often on human populations of European descent, estimates of N_e from genetic variation have been traditionally on the order of 10,000 individuals (6–11), although higher and lower estimates have also been obtained (12–16). More recent studies based on sequencing data from a relatively small number of individuals have considered recent population growth in fitting models to the observed site frequency spectrum (SFS) and reported as much as a 0.5% increase in N_e per generation, culminating in a N_e of a few tens of thousands today (13, 14). It has been recently hypothesized that these studies could not capture the full scope of population growth because a larger sample size of individuals is needed to observe single nucleotide variants (SNVs) that arose during the recent epoch of growth (4).

With extreme recent population growth as experienced by human populations, the vast majority of SNVs are expected to be very young and rare, i.e., of very low allele frequency (4). Indeed, several recent sequencing studies with very large numbers of individuals have observed an unprecedented excess in the proportion of rare SNVs (17–19). Fitting models to the SFS, these studies have captured a clearer, more rapid recent population

growth than earlier studies (17–19). At the same time, demographic estimates varied by as much as an order of magnitude between these studies (*SI Appendix, Table S1*).

Not all rare SNVs are as recent as others, and a variant's selective effect plays an important part in its frequency. Purifying (negative) selection acting on deleterious alleles is expected to give rise to an excess of rare variants, which has been demonstrated for human populations (17, 19, 20). Thus, the genetic signature left by purifying selection on the SFS confounds the signature left by recent growth (21). To minimize this confounding effect, recent studies based on protein-coding genes considered for modeling solely synonymous SNVs, which do not modify the amino acid sequence (17–19). However, synonymous mutations have been shown to be targeted by natural selection, e.g., due to their impact on translation efficiency and accuracy, splicing, and folding energy (17, 19, 22–26). Hence, to study recent human genetic history with minimal effects of selection, it is not only desirable to consider accurate sequencing data from a large number of individuals, but also to focus on genomic regions in which mutations are putatively neutral, i.e., not affected by natural selection. Another potential confounder of demographic inference is population structure. Because both

Significance

Recent rapid growth of human populations predicts that a large number of genetic variants in populations today are very rare, i.e., appear in a small number of individuals. This effect is similar to that of purifying selection, which drives deleterious alleles to become rarer. Recent studies of the genetic signature left by rapid growth were confounded by purifying selection since they focused on genes. Here, to study recent human history with minimal confounding by selection, we sequenced and examined genetic variants far from genes. These data point to the human population size growing by about 3.4% per generation over the last 3,000–4,000 y, resulting in a greater than 100-fold increase in population size over that epoch.

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¹E.G., L.M., and D.C. contributed equally to this work.

²Present address: Department of Animal and Avian Sciences, University of Maryland, College Park, MD 20742.

³To whom correspondence should be addressed. E-mail: ak735@cornell.edu.

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large-scale and fine-scale population structures exist in European populations (27–30), pooling individuals of different European ancestries can lead—when not accounted for in modeling—to biases in the observed SFS and, consequently, in estimates of recent history (*SI Appendix*).

In this study, we aim to capture recent demographic history and estimate the magnitude of the recent growth experienced by humans while limiting the confounding by natural selection and population structure. For this purpose, we selected a small set of genomic regions that are putatively neutral based on a wide array of criteria; the SFS of mutations in these regions is likely to reflect historical changes in N_e rather than selection. We sequenced these regions in a large sample of individuals that share a relatively similar genetic ancestry within Europe. Very deep sequencing coverage allowed us to reliably observe even singletons (SNVs with an allele appearing in a single copy in the sample). Based on this dataset, we explored different models of recent European demographic history. Our best-fit model estimates a growth of 3.4% per generation over the last 141 generations, which is more rapid than estimated in recent large-scale studies (17, 19). We show that differences among previous models (17, 19)—and between these models and ours—can be partially explained by a priori assumptions about more ancient demographic events.

Results

To estimate recent European demographic history with minimal confounding of natural selection, we sequenced genomic regions

that we selected such that mutations therein would be as neutral as possible. Thus, the neutral regions dataset (NR) consists of loci that are at least 100,000 bp and at least 0.1 cM away from coding or potentially coding sequences. The loci are also free of known copy number variants, segmental duplications, and loci shown to have been under recent positive selection, and have minimal amounts of conserved and repetitive elements (*Materials and Methods* and *SI Appendix*). We sequenced a final set of 15 loci that met all these criteria, spanning a total of 216,240 bp (*SI Appendix*, Table S2).

In modeling a population's recent demographic history, if the sample of individuals trace their recent ancestry to different populations, even different European populations, the number of singletons and other rare variants can be biased (*SI Appendix*, Fig. S1). To sequence the neutral regions in a sample that minimizes such population structure, we applied principal component analysis (PCA) to whole-genome genotyping data of 9,716 individuals of European ancestry from the Atherosclerosis Risk in Communities (ARIC) cohort (31). This analysis revealed extensive population structure, and we consequently sequenced 500 individuals that form a relatively homogenous cluster (Fig. 1A). Validating the choice of samples by comparing to a diverse panel of European populations from POPRES (32), these 500 individuals indeed show much less heterogeneity than the broader ARIC sample (Fig. 1B) and share a northwestern European ancestry that is similar to the POPRES UK sample (Fig. 1C).

Sequencing was carried out with Illumina HiSeq; 100-bp paired-end for a median average coverage depth of 295X per individual

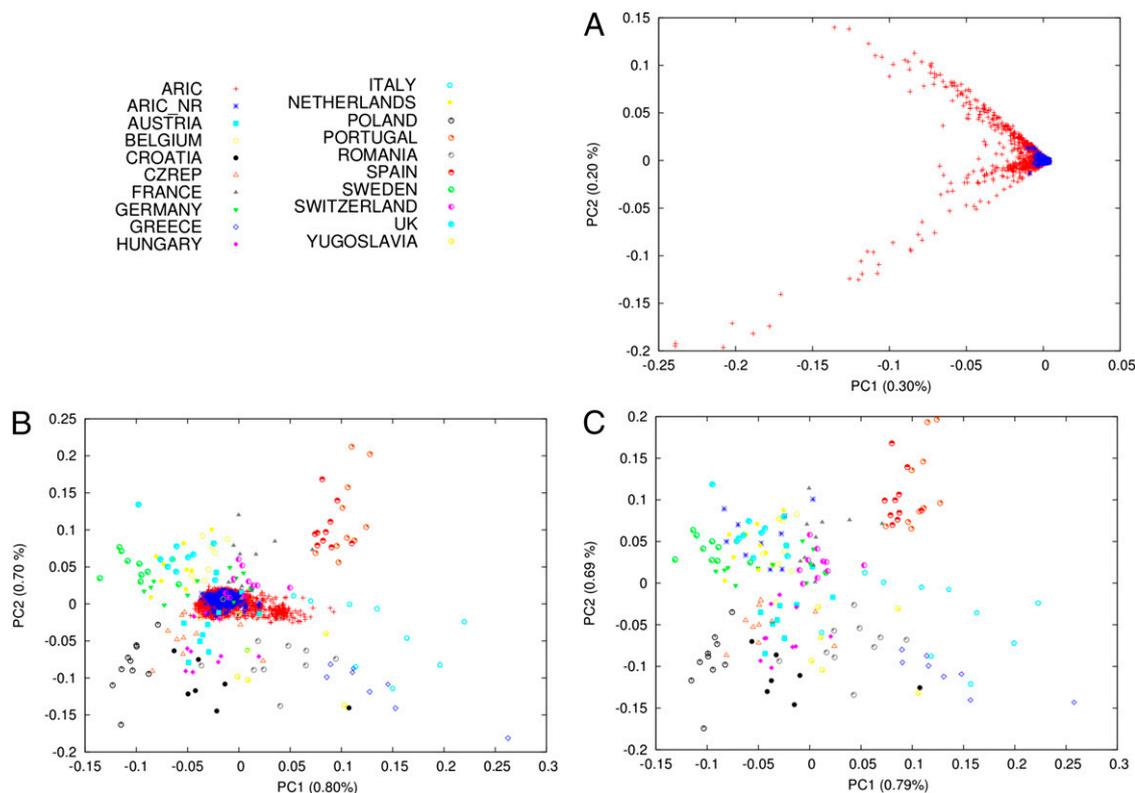


Fig. 1. Genetic ancestry of the NR sequenced individuals. (A) PCA of all individuals of European ancestry from the ARIC cohort, with the exception of outlier individuals (*SI Appendix*). Principal components 1 and 2 are plotted and reveal extensive population structure. Individuals chosen for sequencing in the present study are denoted in blue. (B) PCA of individuals from the POPRES cohort, with the individuals from A subsequently projected onto the resulting principal components (*SI Appendix*). Principal component 1 (x axis) appears to capture southern vs. northern European ancestry, whereas principal component 2 (y axis) captures western vs. eastern European ancestry, in line with the results of Novembre et al. (27). The full set of individuals from ARIC (ARIC) show greater variability, mostly across the first principal component, than the set of individuals sequenced in this study (ARIC_NR). (C) Same as B, except that the PCA includes 10 randomly chosen individuals from the present study rather than projecting all of them as in B. These 10 individuals cluster with individuals from the POPRES UK and related populations, which is also the case for other random sets of 10 individuals.

(after filtering of duplicated reads; *SI Appendix, Fig. S2*). We used UnifiedGenotyper (GATK) for variant detection and genotype calling (33, 34), and after applying strict filters to its calls, we obtained 1,834 high quality SNVs (*SI Appendix*). Of these variants, 62.5% have not been reported in dbSNP 135 (novel SNVs). The Ti/Tv (transition/transversion) ratio showed no indication of biases, for both all SNVs (Ti/Tv = 2.22) and for novel SNVs alone (Ti/Tv = 2.29). None of the called SNVs presented significant departure from Hardy–Weinberg equilibrium. We further validated the quality of variant and genotype calling by comparing to those from whole-genome sequencing of the Cohorts for Heart and Aging Research in Genetic Epidemiology (CHARGE-S) project, which overlaps with a few individuals from our NR dataset (35). This validation supports the high quality of the NR dataset due to the very high sequencing coverage (*SI Appendix*). High-quality genotypes for at least 450 individuals were obtained for 95% of SNVs, which are used for presentation of the SFS throughout while probabilistically subsampling 900 random chromosomes for each SNV (*SI Appendix*). We used the full set of SNVs for demographic modeling, where our approach accounts for missing data (*Materials and Methods*).

We compared the SFS from the NR dataset to that from the Exome Sequencing Project (ESP), which is of equivalent deep sequencing (*SI Appendix, Fig. S3*). We randomly subsampled the latter to 900 chromosomes and stratified by functional annotation. The more likely to be functional an annotation is, the more the ESP SFS deviates from that of the neutral regions: the highest agreement is observed for intronic and intergenic annotations from the ESP data, although these are still significantly different from the NR ($P < 10^{-3}$ for a goodness of fit test; *SI Appendix, Table S3 and Fig. S4*). Agreement is much worse between synonymous SNVs and the NR data ($P = 5.4 \times 10^{-19}$) and worst for missense, splice, and nonsense SNVs ($P < 10^{-30}$ for each; *SI Appendix, Table S3 and Fig. S4*). This lack of agreement is due to a higher proportion of very rare variants in the ESP data (*SI Appendix, Fig. S4*), which is consistent with purifying selection playing a larger role in maintaining alleles at lower frequencies in and around genes. We further examined the NR SNVs in comparison with synonymous SNVs via genomic evolutionary rate profiling (GERP) scores (36), showing our data to be much more narrowly distributed around a score of 0, which corresponds to the absence of functional constraint (*SI Appendix, Fig. S5*). These low GERP scores might simply reflect the NR regions being chosen to minimize conserved elements, but applying the same conservation criteria to synonymous SNVs leads to similar

results (*SI Appendix, Fig. S5*). This set of results combined support our unique choice of regions and the relatively neutral nature of SNVs in these regions, as well as further validate our SNV and genotype calling pipeline.

Although the SFS of the NR dataset has a lower proportion of singletons compared with sites under purifying selection, it still exhibits a marked enrichment in this proportion (Fig. 2) compared with the expectation for a population that has remained at constant size throughout history (38.4% vs. 13.6%). This enrichment is consistent with the impact of recent population growth on the distribution of allele frequencies (4, 17–19). However, the SFS predicted by recently published demographic models of European populations that include recent exponential population growth (17, 19) do not closely match the SFS of the NR data (*SI Appendix, Fig. S6*). These models predict a higher proportion of rare variants and a smaller proportion of common variants than we observed, which is consistent with these models being based on synonymous SNVs with increased effect of purifying selection (17, 19). Hence, we next estimated the magnitude and duration of population growth by fitting the SFS of the NR to several different models of recent history.

The first demographic model that we fit to the SFS consists of a recent exponential population growth with two free parameters: the time growth started and the extant N_e , with the growth assumed to continue into the present. More ancient demographic events, before the epoch of growth, including two population bottlenecks, were assumed to follow the model and estimates of ref. 9 (*SI Appendix, Table S1*). The resulting model (model I) estimates the extant population size and, as a consequence, the growth rate, with very large uncertainty, as evident from the 95% CIs (Table 1), and the model does not fit the data very accurately (Fig. 2).

Model I, similar to other recent models of population growth (17–19), assumed more ancient demography as fixed, with the intention of obtaining better resolution for estimating the two parameters of recent history. However, different recent models of population growth have assumed different models of ancient demography (*SI Appendix, Table S1*): Tennesen et al. (19) assumed what had been estimated previously by Gravel et al. (14), Nelson et al. (17), and Coventry et al. (18), what has been estimated by Schaffner et al. (15), and here what has been estimated by Keinan et al. (9). To test how sensitive model I is to the details of assumed ancient history, we repeated fitting model I while assuming each of the above ancient demographic models. Our results point to large differences among the three resulting models, with some parameters for recent demography being as

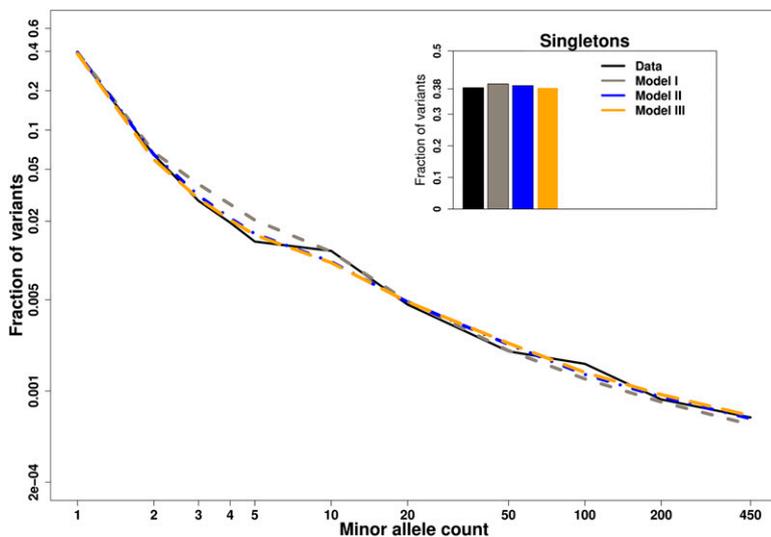


Fig. 2. SFS of the NR dataset and demographic models. *x* axis represents, in log scale, a partition of the number of copies of the minor allele with each number indicating the upper bound of a bin. (Minor allele counts of 1–5 are not binned.) *y* axis presents, in log scale, the proportion of SNVs that fall into each bin. (*Inset*) Fraction of variants that are singletons (*y* axis is presented in linear scale). Data, empirical SFS of NR; model I, a two-parameter model with one epoch of growth, where the duration of growth and final N_e were estimated; model II, an extension of Model I with a third parameter corresponding to N_e before the growth epoch; model III, a model with two separate epochs of growth (Table 1). For clarity, model IV is not presented because its SFS is very similar to that of model III.

Table 1. Four models of recent demographic history and population growth

Model	Number of free parameters	Ne before growth	Duration of earlier growth (generations)	Ne after earlier growth	Duration of recent growth (generations)	Ne after recent growth (millions)	Growth rate during recent growth	Log likelihood
Model I	2	10,000	NA	NA	112.8 (92.9, 136.8)	5.2 (0.8, 300)	5.54% (3.2, 11.1)	-3,595.141
Model II*	3	5,633 (4,400, 7,100)	NA	NA	140.8 (116.8, 164.7)	0.654 (0.3, 2.87)	3.38% (2.4, 5.1)	-3,583.975
Model III	3	5,633	267.3	5,362 (3,614, 7,955)	132.7 (101.8, 165.5)	0.73 (0.3, 5.7)	3.70% (2.6, 6.4)	-3,584.178
Model IV	4	5,633	200 (200, 600)	5,000 (3,000, 15,000)	140 (80, 160)	0.5 (0.3, 50)	3.84% (0.36, 4.44)	-3,583.501

The table describes the recent history estimated by four models, as well as the goodness of fit of each (log likelihood). Bold values denote the maximum likelihood estimates (and 95% CIs) of the free parameters estimated by each model. Italicized values are assumed as fixed in the model, and regular font denotes parameters that are a direct function of estimated parameters. All four models assume the model of ancient demographic history as estimated in ref. 9, which includes two population bottlenecks (Fig. 3). Results based on other models of ancient demographic history are provided in *SI Appendix*.

*This model is considered as the best-fit model because none of the models with additional parameters provide a significantly improved fit.

much as an order of magnitude different (*SI Appendix, Table S4*). We stress that both data and methodology underlying these inferences are identical and hence conclude that the assumption of ancient demography has a major effect on estimating the timing and magnitude of recent population growth, which explains some of the differences among the recently published models (17–19).

To alleviate some of the sensitivity to ancient demography assumptions, we fit model II that extends model I by adding an additional parameter for the effective population size just before exponential growth. This three-parameter model fits the NR data significantly better than model I ($P = 2.3 \times 10^{-6}$; Fig. 2). It estimates the ancestral N_e before the growth to be 5,633 (CI of 4,400–7,100), markedly lower than the fixed value of 10,000 in model I (Table 1). It estimates growth starting 141 (117–165) generations ago, which is a little earlier than in model I, with a less rapid growth rate of 3.4% (2.4–5.1%) per generation, which culminates in an extant N_e of 0.65 (0.3–2.87) million individuals (Table 1 and Figs. 3 and 4).

To test whether this improved model II can explain the differences between different assumed ancient demographic histories, we repeated fitting its three parameters to the NR similarly to above with model I. When ancient demography is assumed from Gravel et al. (14), this model fits the data significantly better ($P = 2.9 \times 10^{-7}$) than the equivalent of model I with the same ancient demography. Parameter estimates become practically identical to those of the above model II based on Keinan et al. (9) (Fig. 4 and *SI Appendix, Tables S4 and S5 and Fig. S7*). Model II based on Schaffner et al. (15) does not fit the data better than the respective model I ($P = 0.52$) and provides the poorest fit of all three models. One notable difference in the model of Schaffner et al. (15) is that the timing of the second European population bottleneck is assumed as fixed at over twofold that estimated in the other two models (9, 14). The extant N_e is almost identical for all these three models based on

model II, with best-fit estimates varying between 0.47 and 0.77 million individuals (Fig. 4 and *SI Appendix, Table S5*). We conclude that by modeling the epoch before growth, the improved model II is much less sensitive to assumptions about more ancient demography, and it goes a long way in closing the gap between different published models of recent growth (17, 19) and between these and model I.

Archeological and historical records suggest that the growth of the human census population size has accelerated over time (3, 4). Our models thus far considered a single epoch of exponential growth, estimated to have started ~3,500 y ago (assuming 25 y per generation). Hence, we considered several additional models in which growth can span two separate epochs with a different growth rate in each: model III with three parameters, model IV with four parameters, and all other possible four-parameter models (Table 1). None of these more detailed models fit the data better than model II ($P > 0.86$; Table 1 and Fig. 2). They all estimate the second, more recent epoch of growth to be practically identical to the one estimated in model II and the earlier epoch of growth to be equivalent to an epoch of constant population size (Table 1 and *SI Appendix, Fig. S8*).

We investigated whether low statistical power due to a limited amount of data could explain the lack of an acceleration of growth. We simulated a scenario that is identical to model II, except for the addition of an earlier epoch of milder growth, and estimated how often model III provides a significantly better fit than model II (*SI Appendix*). Our modeling has a nonnegligible statistical power of capturing two separate epochs of growth (*SI Appendix, Fig. S9*). Power is 86% when the earlier growth rate is about half that of the more recent epoch. It decreases for milder growth during the first epoch—being as low as 25% for a growth rate of only 0.3% per generation—as well as when growth during the earlier epoch becomes similar to the recent rate (*SI Appendix, Fig. S9*). Overall, power is >60% for detecting two distinct epochs of growth as long as the growth rate during the earlier epoch is in the range of 0.6–1.8% (compared with 3.4% in the recent epoch), which is consistent with archaeological data (*SI Appendix*).

Discussion

Recent studies have provided clear evidence that human populations have experienced recent explosive population growth, although detailed estimates of growth varied greatly (17–19). These were in the context of medical genetic studies, hence based on the sequencing of protein-coding genes. Here we generated a dataset with the sole purpose of accurately capturing rare putatively neutral variants for studying recent human history and population growth. As such, our NR data consists of several characteristics. First, because both demography and natural selection shape the distribution of allele frequencies, loci for the NR data were carefully chosen to minimize the influence of natural selection. Second, because population structure also affects the distribution of allele frequencies, the data consist of



Fig. 3. Schematic representation of the best fit model. N_e is shown in log scale during the last 5,000 generations, with the last 620 generations as estimated by model II (Table 1), and the preceding period following ref. 9.

Choice of Target Putatively Neutral Regions. To minimize the effect of selection, we considered genomic regions located at least 100,000 bp and 0.1 cM from any coding or potentially coding loci. We excluded genomic sequences containing segmental duplications and known copy number variants (SI Appendix), as well as regions under recent positive selection (45). Among contiguous genomic regions of at least 100 kb that satisfy these criteria, we then ranked targets for sequencing by their content of conserved and repetitive elements and removed CpG islands. The resulting NR dataset spans a total of 216,240 bp across 15 regions, each between 5,340 to 20,000 bp long (SI Appendix, Table 2). These and additional criteria for selecting regions are implemented in the Neutral Regions Explorer web-server at <http://nre.cb.bscb.cornell.edu> (46).

Sequencing, Mapping, and Variant Calling. Illumina HiSeq. 2000 with 100-bp paired-end reads was used for sequencing. Reads were mapped to hg18 human reference genome using Burrows-Wheeler Aligner (BWA) (47) (SI Appendix). For each individual, aligned reads were subjected to duplicate removal using Picard v.1.66 (<http://picard.sourceforge.net>). Subsequent SNV calling, quality control filtering, and genotype calling were performed with the Genome Analysis ToolKit, GATK-1.5–31 (33, 34), as detailed in SI Appendix. Analyses are based on 493 individuals that were successfully sequenced.

Demographic Inference. To obtain estimates of recent demographic history, we calculated the likelihood of the observed SFS conditioned on several demographic models. To reduce parameter space, we fixed ancient history as estimated by previous studies (9, 14, 15) and only estimated parameters of more recent history. These models have either a single epoch of recent

growth or an additional, earlier epoch of growth. Models include different combinations of the following parameters: the time recent growth started, final N_e after recent growth, N_e before growth, start time of earlier growth, and N_e after earlier growth (Table 1). We tested whether a model provides a better fit than another using Vuong's test (48). For each model, we estimated the SFS at different grid points using ms (49), with each grid point being a particular combination of parameter values. We then calculated the composite likelihood of the model following the approach of ref. 9, as the probability of the observed minor allele (the less common of the two alleles) counts of all SNVs while accounting for missing data (SI Appendix). We profiled the likelihood surface using for each parameter 7–16 predefined grid points that span a range of plausible values. We increased the number of grid points for each parameter 10-fold by fitting a smooth spline function for the proportion of SNVs of each allele count as a function of all parameters, which improved accuracy (SI Appendix, Fig. S10), with only a minor increase in computational burden. Two-sided 95% CIs for each parameter was estimated following a $\chi^2(1)$ distribution that accounts for variation across SNVs (SI Appendix).

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