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**Ancient DNA reveals that few GWAS loci have been
strongly selected during recent human history**

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1 **Abstract**

2 Genetic data from ancient humans has provided new evidence in the study of loci thought to be
3 under historic selection, and thus is a powerful tool for identifying instances of selection that might
4 be missed by methods that use present-day samples alone. Using a curated set of disease-associated
5 variants from the NHGRI-EBI GWAS Catalog, we provide an analysis to identify disease-
6 associated variants that bear signatures of selection over time. After accounting for the fact that
7 not every ancient individual contributed equally to modern genomes, a Bayesian inference method
8 was used to infer allele frequency trajectories over time and determine which disease-associated
9 loci exhibit signatures of natural selection. Of the 2,709 variants analyzed in this study, 895 show
10 at least a weak signature of selection ($|s| > 0.001$), including multiple variants that are introgressed
11 from Neanderthals. However, only nine disease-associated variants show a signature of strong
12 selection ($|s| > 0.01$). Additionally, we find that many risk-associated alleles have increased in
13 frequency during the past 10,000 years. Overall, we find that disease-associated variants from
14 GWAS are governed by nearly neutral evolution. Exceptions to this broad pattern include GWAS
15 loci that protect against asthma and variants in MHC genes. Ancient samples allow us an
16 unprecedented look at how our species has changed over time, and our results represent an
17 important early step in using this new source of data to better understand the evolution of hereditary
18 disease risks.

1 **Introduction**

2 Many studies have been conducted to understand the genetic basis of diseases and other traits.
3 Indeed, thousands of disease loci have been implicated in genome-wide association studies
4 (GWAS) across human populations (Welter et al., 2014). Due to a balance between mutation and
5 selection, alleles that are associated with Mendelian diseases tend to be rare (Weghorn et al., 2019).
6 By contrast, alleles that are associated with complex diseases often segregate at intermediate
7 frequencies (Timpson et al., 2018). GWAS loci are also enriched for derived, as opposed to
8 ancestral, alleles that increase the risks of complex polygenic diseases (Gorlova et al., 2012;
9 Lachance, 2010). There has been a great deal of interest in understanding how allele frequencies—
10 and thus, traits—have changed over time; however, until recently, only modern genomes have
11 been available. Analysis of modern human genomes has revealed that genes that confer resistance
12 to infectious diseases have been targets of recent selection (Karlsson et al., 2014), and that natural
13 selection contributes to differences in hereditary disease risks between human populations
14 (Lachance et al., 2018; Marigorta et al., 2011). Classic debates about the relative importance of
15 natural selection and genetic drift have also been rekindled (Jensen et al., 2019; Kern and Hahn,
16 2018). It has also been proposed that modern medicine has led to the relaxation of selection against
17 mildly deleterious mutations and an increase in genetic load over recent human history (Lynch,
18 2016).

19
20 During the past decade, an increasing number of ancient genomes have been sequenced, some to
21 very high read depth (Fu et al., 2014; Mathieson et al., 2015; Meyer et al., 2012; Narasimhan et
22 al., 2019; Olalde et al., 2018; Prüfer et al., 2014). High quality genome sequences of our archaic
23 hominin cousins have revealed previously unknown introgression events, and follow-up studies

1 have shown how these introgressed regions have impacted modern human health and traits
2 (Dannemann et al., 2016; Gunz et al., 2018; Simonti et al., 2016). Ancient DNA has also revealed
3 that selection on the fatty acid desaturase genes *FADS1* and *FADS2*, which are relevant to lipid
4 disorders, did not coincide with the Neolithic transition and the discovery of agriculture
5 (Mathieson and Mathieson, 2018). Application of polygenic risk scores to ancient genomes has
6 revealed that genetic disease risks have changed over the last 10,000 years (Berens et al., 2017).
7 Furthermore, ancient human genomes have revealed that many variants associated with disease
8 risk have increased in frequency during recent history (Aris-Brosou, 2019). Because ancient DNA
9 enables times series data to be analyzed, it is now possible to determine the evolutionary histories
10 of individual disease-associated loci. Large allele frequency changes during the last 10,000 years
11 are indicative of disease loci that are under natural selection, while relatively flat allele frequency
12 trajectories are indicative of disease loci that are evolving neutrally (Schraiber et al., 2016).

13
14 An open question in evolutionary medicine is whether the effects of genetic variation on disease
15 risks are decoupled from fitness effects (Rodríguez et al., 2014). Here, we use 143 ancient human
16 samples from 18 previously published studies to examine the role of selection on variants from the
17 NHGRI-EBI GWAS Catalog. Most of the ancient samples analyzed here lived during the past
18 10,000 years. First, we correct for whether ancient genomes contribute to modern human
19 populations. We then use time series data to infer allele frequency trajectories and selection
20 coefficients for a curated set of 2,709 different disease-associated variants. We also examine
21 whether protective alleles are more likely to be positively selected, and identify which diseases are
22 enriched for signatures of weak selection. Collectively, these analyses reveal that most disease-
23 associated loci are governed by nearly neutral evolution.

1 **Results**

2 ***Most GWAS variants do not show signatures of strong selection***

3 For each disease-associated locus, we employed a Bayesian MCMC method (Schraiber et al.,
4 2016) to infer allele frequency trajectories and selection coefficients that match time series data
5 from ancient genomes. However, inference of natural selection requires an understanding of
6 population continuity, or how much ancient individuals have contributed to modern genomes, if
7 at all. As previous studies have found differences in contribution based on lifestyle (Haak et al.,
8 2015), we grouped our ancient samples into one of three lifestyles: hunter-gatherers,
9 agriculturalists, and pastoralists. We then calculated maximum possible genetic contribution of
10 each of these groups to each variant using the method developed by Sjödin et al. (2014). Using
11 this information, we could ensure we did not include ancient individuals who might skew allele
12 frequencies in a way that did not reflect ancient demography (Figure S1).

13
14 Most GWAS loci have flat allele trajectories and selection coefficients that are close to zero. Of
15 the 2,709 variants analyzed here, we find that 895 show at least a weak signature of selection ($|s|$
16 > 0.001) and only 9 show a signature of strong selection ($|s| > 0.01$; Table 1). We also examined
17 whether protective alleles were more likely to increase in frequency during recent history than
18 risk-increasing alleles. A slight majority (52.6%) of putatively selected loci have protective alleles
19 with positive selection coefficients. However, this trend was not statistically significant (471 of
20 895 variants, binomial test, $P = 6.21 \times 10^{-2}$). We also found that derived alleles are more likely to
21 have positive selection coefficients than ancestral alleles at GWAS loci (528 of 895 variants;
22 binomial test, $P < 10^{-7}$). Taken together, our findings reveal that GWAS loci are largely governed
23 by nearly neutral evolution.

1
2 Despite most variants appearing to evolve neutrally, exceptions exist for some disease-associated
3 loci (Supplemental Table S1). For example, six of the nine variants under strong selection ($s >$
4 0.01) are associated with autoimmune diseases. One of them (rs13277113) is associated with
5 systemic lupus erythematosus (Hom et al., 2008), and has been found by the GTEx Project (v8) to
6 significantly affect expression of *BLK*, a gene involved in B cell development (Gauld and Cambier,
7 2004). Another of these variants (rs2270450) is associated with developing Hashimoto thyroiditis
8 versus Graves' disease (Oryoji et al., 2015). Curiously, this variant is significantly associated with
9 expression of *TDRD6*, a gene involved in spermiogenesis as well as autoimmune polyendocrine
10 syndrome (Akpınar et al., 2017; Bensing et al., 2007). The other four strongly selected variants
11 associated with autoimmune diseases are found within the MHC region, which is known to be
12 dense with rapidly evolving genes critical to immune function.

13

14 **Table 1. Selection coefficients inferred from ancient genomes**

Variant type	Total number of variants	$ s > 0.001$ (weak selection)	Protective allele selected	$ s > 0.01$ (strong selection)	Protective allele selected
All	2,709	895 (33.0%)	471 of 895 (52.6%)	9 (0.3%)	4 of 9 (44.4%)
MHC	148	76 (51.4%)	36 of 76 (47.4%)	4 (2.7%)	0 of 4 (0%)
Introgressed	24	8 (33.3%)	4 of 8 (50.0%)	0 (0.0%)	-

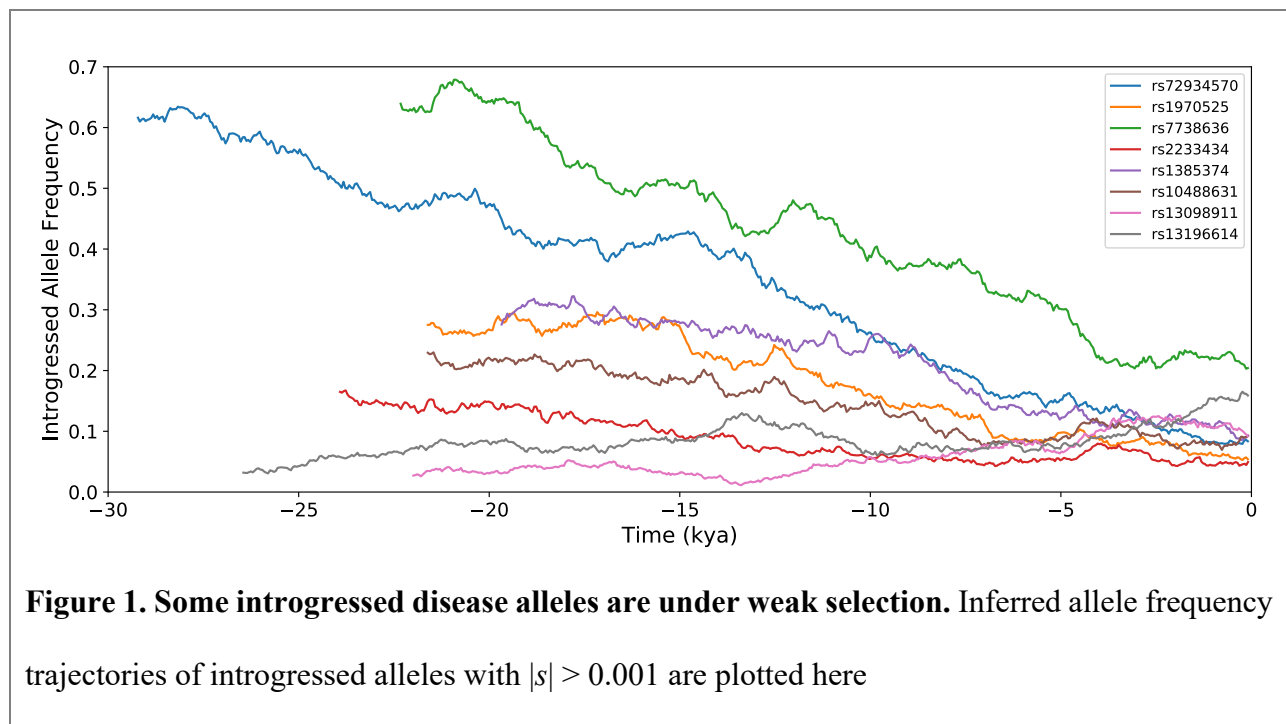
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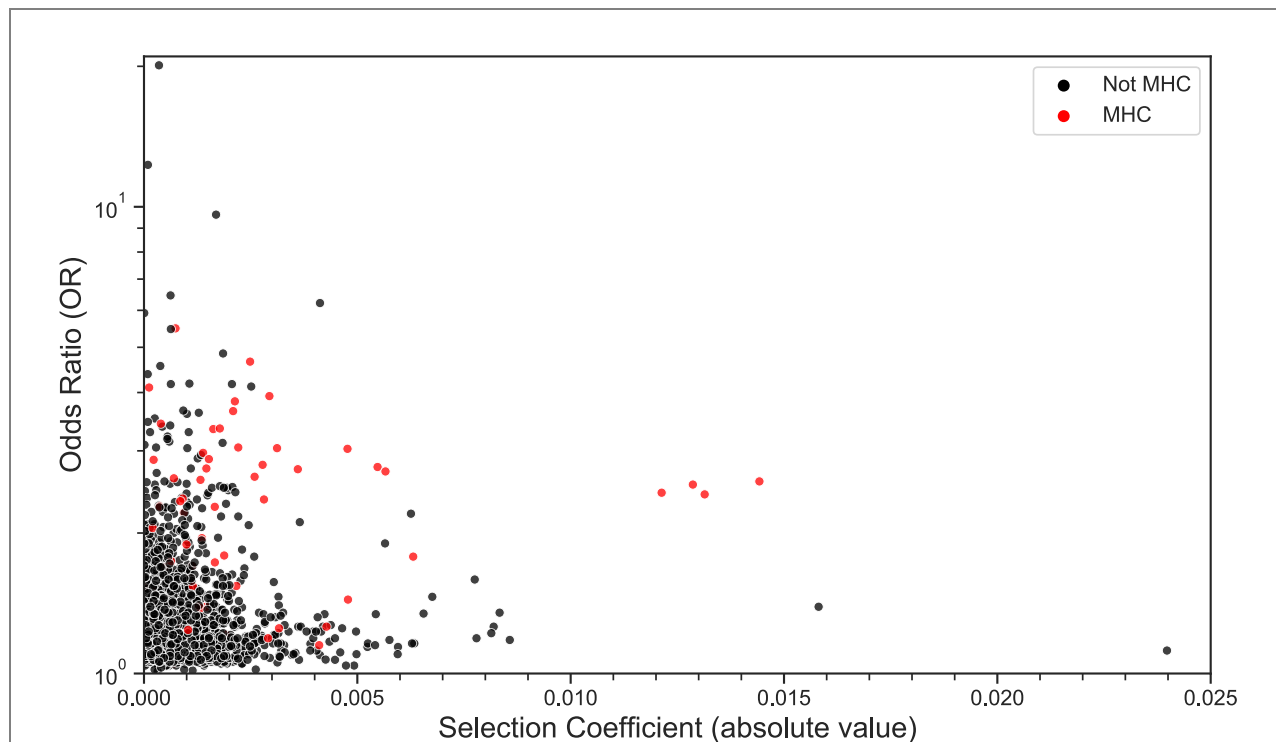
1 *Archaic introgression introduced some selected alleles at GWAS loci*

2 Disentangling the effects of selection and archaic introgression can be difficult if one is analyzing
3 modern genomes (Racimo et al., 2016). However, time series data from ancient genomes can
4 sidestep many of these difficulties. Of the 2,709 disease-associated loci analyzed here, 24 contain
5 introgressed alleles from Neanderthals. Of these 24 loci, nine introgressed variants have signatures
6 of weak selection in the recent past (Figure 1). Some introgressed alleles appear to have reached
7 moderate allele frequencies prior to being negatively selected, while other introgressed alleles
8 appear to have only been positively selected during recent human history. Overall, we find that
9 disease-associated alleles that have a Neanderthal origin have similar selection coefficients to other
10 disease-associated alleles from the GWAS Catalog (Table 1). This is not wholly surprising, given
11 that purging of strongly deleterious introgressed alleles occurred shortly after admixture (Petr et
12 al., 2019), and introgressed alleles that are able to persist to the present day will have managed to
13 avoid being filtered out due to Dobzhansky-Muller incompatibilities or other hybrid fitness effects.

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Figure 2. GWAS effect sizes are generally unrelated to selection coefficients. We plotted the odds ratios (OR) of GWAS loci versus inferred selection coefficients for 1,910 disease-associated variants that were identified in a GWAS that used samples of European ancestry (MHC variants: red, non-MHC variants: black).

10 *Most selected alleles at disease loci have small effect sizes*

11 We examined whether selection coefficients are correlated with disease-related effect sizes. Given
12 that our time series dataset exclusively contains samples from Europe and effect sizes are
13 contingent on a host of factors including study population and environmental factors, this analysis
14 focused on the subset of 1,910 variants that were identified in a GWAS that used samples of
15 European ancestry (Figure 2). Overall, we find that there is no relationship between odds ratio

1 (OR) and magnitude of s for non-MHC variants ($r = -0.012$). This pattern arises because many
2 GWAS Catalog traits are largely irrelevant to fitness. For example, the variant with the highest
3 OR analyzed here (rs3825942, OR=20.1) is associated with glaucoma, a disease which normally
4 strikes long after reproductive age. Although the variants in Figure 2 are associated with a
5 heterogenous set of diseases, our results suggest that the selection coefficients are largely
6 decoupled from the effects of GWAS loci on disease risks.

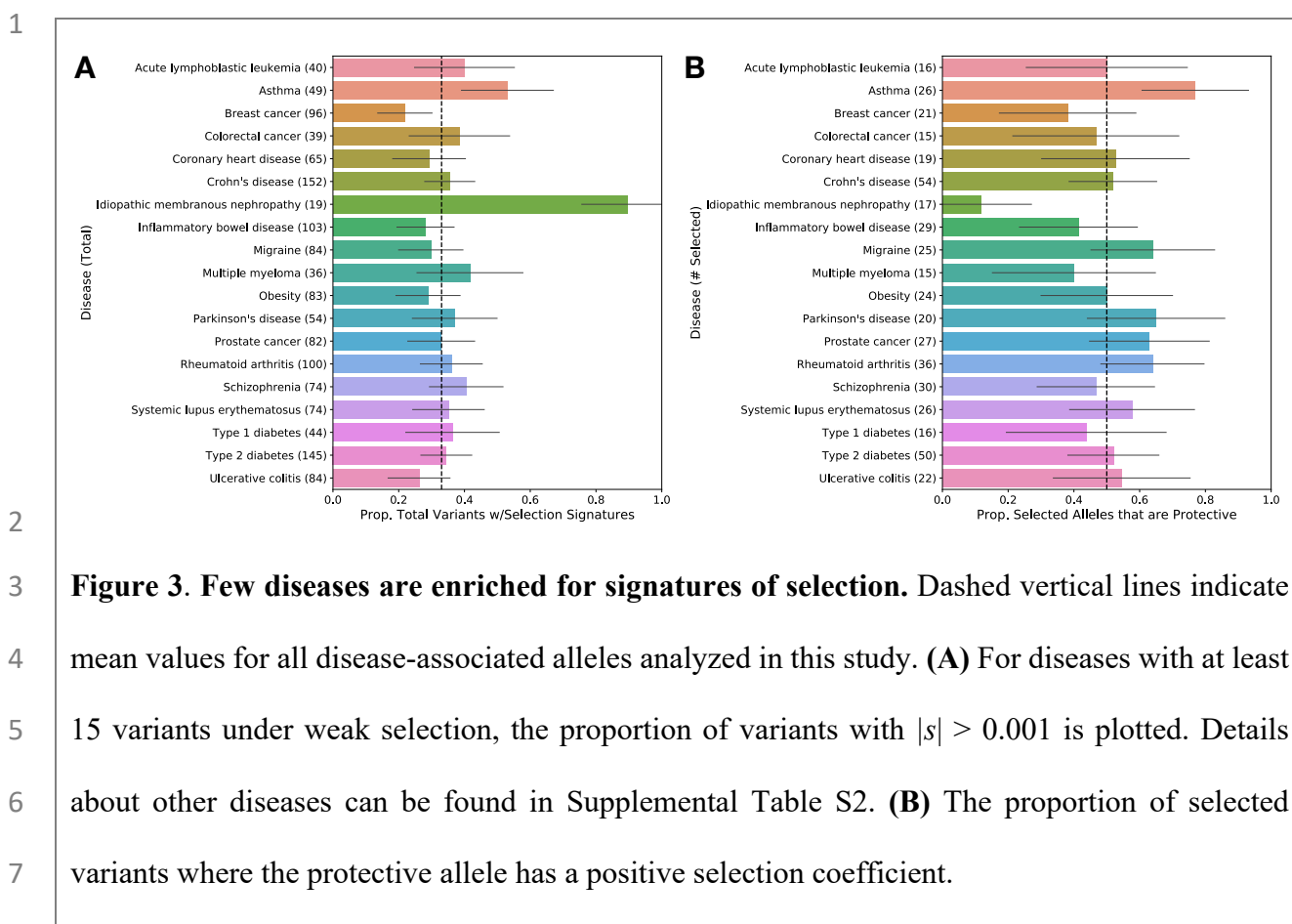
7 8 ***Variants in the MHC region show stronger signatures of selection***

9 Compared to other disease-associated alleles, MHC variants show a strikingly different pattern.
10 Disease-associated variants in the MHC region on chromosome 6 have larger effects sizes than
11 disease-associated variants that are not in the MHC region (mean MHC OR: 2.11, mean non-MHC
12 OR: 1.36, t test $P = 4.12 \times 10^{-19}$). Disease-associated variants in MHC genes also show a modest
13 positive correlation between s and OR ($r = 0.167$). Variants located in the MHC region were
14 significantly more likely to show signatures of weak selection than GWAS variants found in other
15 parts of the human genome (Table 1, hypergeometric $P < 10^{-6}$). Disease-associated variants in the
16 MHC region were also significantly depleted of selection for protective alleles (hypergeometric P
17 $< 10^{-6}$). Given the highly pleiotropic nature of the immune system, it is possible that alleles that
18 increase risk for some immune diseases have been historically protective against others
19 unrepresented in the GWAS Catalog (i.e., infectious diseases).

20 21 ***Disease-specific tests for enrichment of selection signatures***

22 Although we caution against overinterpreting disease-specific results (due to genetic hitchhiking
23 and the pleiotropic nature of variants analyzed in this paper), multiple diseases were enriched for

1 signatures of weak selection. Idiopathic membranous nephropathy, an autoimmune disease that
2 severely impacts kidney function, showed the strongest signature of selection, with 17 of 19
3 variants under at least weak selection (Figure 3A; hypergeometric $P < 1.00 \times 10^{-6}$). Unsurprising
4 given the strong immune component to this disease, all but one of the variants associated with this
5 disease are found in the MHC region, which likely contributes to enrichment for selected alleles
6 that are associated with idiopathic membranous nephropathy. Curiously, alleles that protect against
7 this disease have tended to decrease in frequency during recent human history (Figure 3B;
8 hypergeometric $P = 4.76 \times 10^{-4}$). As stated above, this result could represent either genetic
9 hitchhiking or pleiotropic effects. The next strongest enrichment signal was from asthma, with 26
10 of the 49 variants associating with it being under at least weak selection (Figure 3A;
11 hypergeometric $P = 2.12 \times 10^{-3}$). We found that alleles that protect against asthma were strongly
12 enriched for being under positive selection (Figure 3B; 20 of 26 selected alleles were protective;
13 hypergeometric $P = 8.94 \times 10^{-3}$). This result was robust to the exclusion of MHC variants. A third
14 disease that showed enrichment for signatures of weak selection was acne, with 7 of its 10
15 associated variants under selection (hypergeometric $P = 1.79 \times 10^{-2}$; Supplemental Table S2).
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17 In addition, we found three diseases that were significantly depleted for signatures of weak
18 selection (Supplemental Table S2). The strongest signal was for breast cancer (Figure 3B; 21 of
19 96 variants; hypergeometric $P = 1.20 \times 10^{-2}$), followed by major depressive disorder (10 of 55
20 associated variants; hypergeometric $P = 1.27 \times 10^{-2}$), and addiction (3 of 23 variants;
21 hypergeometric $P = 2.96 \times 10^{-2}$). Taken together, these results reveal that not all diseases are
22 equally affected by selection, even when selection does not appear to be broadly acting.
23



9 Given that severity and when a disease manifests determine its fitness impact, we also examined

10 whether diseases with an early age of onset have different characteristics than diseases with a

11 late age of onset. Overall, 55.9% of alleles that are associated with increased disease risks in our

12 dataset were derived, as opposed to ancestral (binomial $P < 1.00 \times 10^{-6}$). This trend was more

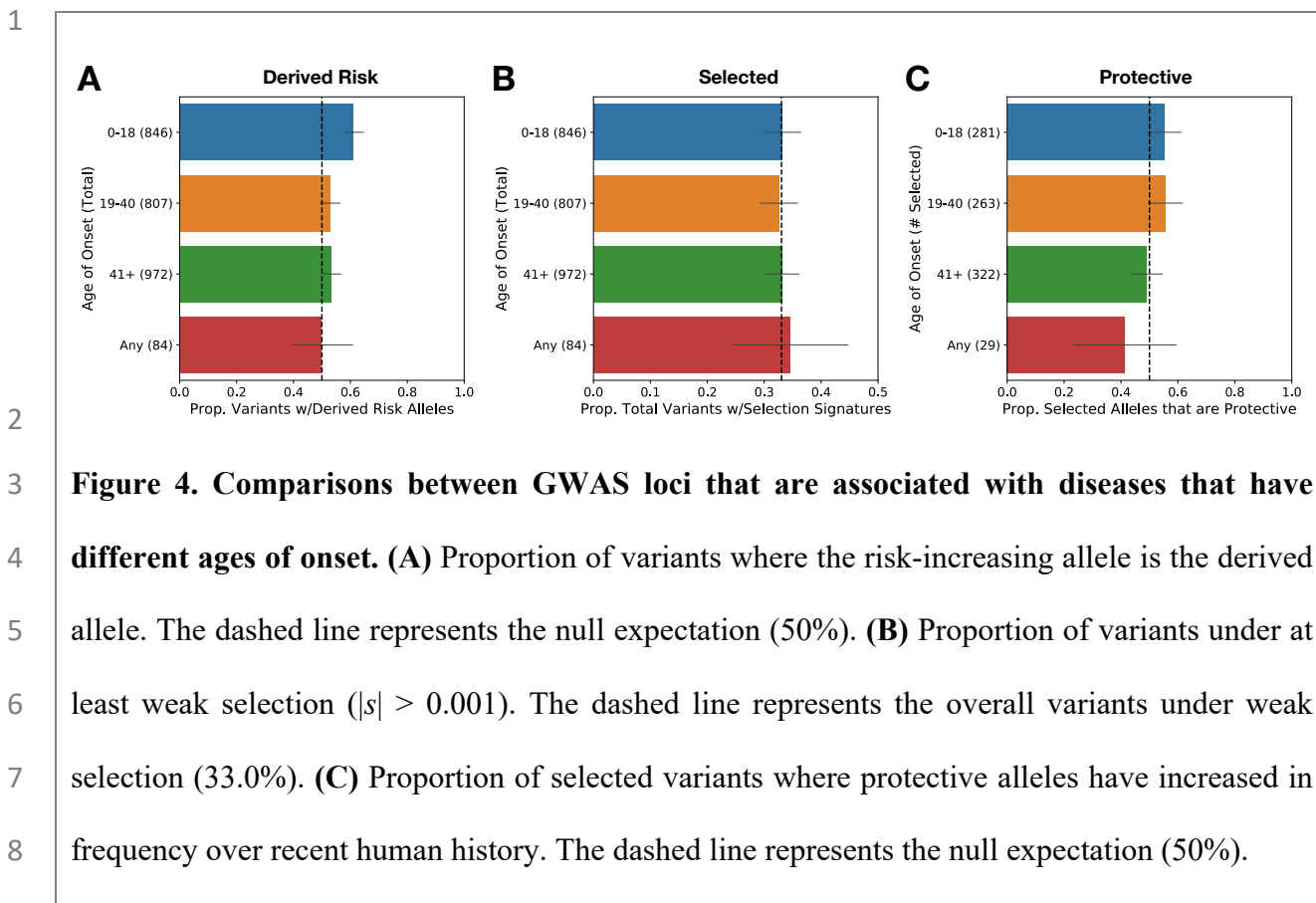
13 pronounced in diseases whose onset was before the age of 18 (hypergeometric $P = 3.50 \times 10^{-5}$;

14 Figure 4A). Despite this effect, age of onset does not seem to impact the likelihood of a variant

15 being under selection (Figure 4B). However, there is a slight bias in favor of the protective allele

16 for both the 0-18 age of onset (binomial $P = 0.047$) and the 19-40 age of onset disease variants

17 (binomial $P = 0.042$; Figure 4C).



Discussion

We find that the majority of GWAS variants do not appear to be under strong selection, and that selection coefficients (s) and odds ratios (OR) are uncorrelated. Allele frequency changes at many disease-associated loci may be due to the indirect effects of genetic hitchhiking, i.e., selection acting at closely linked loci. Because of this, our results suggest an “upper bound” for the amount of selection experienced by GWAS variants. In general, we find that our results reinforce the notion that diseases do not necessarily impact fitness. Our study also demonstrates the utility of time series data to infer the evolutionary histories of individual disease-associated loci.

1 Disease phenotypes are obvious targets for natural selection, so the general lack of variants under
2 selection in this set of GWAS loci at first seems unexpected. However, a previous study estimating
3 selection coefficients from C-scores showed a remarkably similar proportion of GWAS variants
4 under weak selection (Racimo and Schraiber, 2014). Indeed, there are many reasons why we would
5 not expect many of these variants to be under strong directional selection in the timescale
6 examined. First, many of these diseases are unlikely to impact fitness, a scenario supported by our
7 result that OR and the magnitude of s are uncorrelated for most variants. Of the 178 diseases
8 considered here, 20 are late-onset (age of onset of 60 or later) and while they shorten lifespans,
9 they do so well after reproductive age. Barring strong effects from scenarios such as the
10 grandmother hypothesis (Williams, 1957) and presuming these variants substantially affect no
11 other fitness-impacting traits, this makes this group of disease variants essentially invisible to
12 selection. The fact that these diseases show no marked depletion in the proportion of variants under
13 weak selection when compared to diseases with earlier ages of onset could imply that genetic
14 hitchhiking or pleiotropy may be obscuring expected patterns of selection.

15
16 Another possibility is that selection has acted on disease traits, but the polygenic nature of the
17 disease means individual loci affecting risk might be close to neutrality. Indeed, this is expected
18 as many GWAS variants are segregating at allele frequencies that no strongly deleterious variants
19 could ever reach. Previous studies have demonstrated negative correlations between allele
20 frequency and effect size, even when study power was taken into account (Park et al., 2011). This
21 suggests that purifying selection constrains evolutionarily deleterious alleles, supporting the idea
22 that variants in the GWAS Catalog have not historically had large fitness effects. Another
23 possibility is that due to environmental changes, some of these diseases have become more

1 prevalent in recent history (so-called diseases of modernity). This would cause selection to only
2 be able to act on them recently, outside the timescale of our analyses. These scenarios do not
3 represent an exhaustive list of possibilities, nor are they mutually exclusive.

4
5 One exception to this overall pattern is that many putatively selected variants are found in the
6 highly polymorphic MHC region of the genome. Genes in this region impact resistance to
7 infectious disease, mate choice, kin recognition, reproductive success, among others (Bernatchez
8 and Landry, 2003; Piertney and Oliver, 2006). As such, they have been frequent targets of
9 recurring balancing and positive selection. When considered, these theories make it clear why
10 GWAS variants overall would be depleted of signatures of selection, apart from MHC variants. It
11 is worth noting the highly repetitive and highly polymorphic nature of this region makes
12 genotyping in the MHC region notoriously difficult, so it is possible that this has introduced bias
13 in our results (Kiyotani et al., 2017). However, there is no a priori reason why difficulty genotyping
14 would consistently result in an excess of signal for selection.

15
16 Interestingly, diseases whose onset is during pre-reproductive or reproductive age are slightly more
17 likely to have protective alleles that are positively selected. A prime example of this involves
18 variants affecting asthma, which are strongly enriched for selection overall, and positive selection
19 on protective alleles in particular. Asthma is a chronic inflammatory disorder of the airways
20 primarily affecting children whose incidence has increased substantially over recent decades
21 (Akinbami et al., 2015), which has been partially attributed to both the hygiene hypothesis as well
22 as increasing air pollution through urbanization (Bowatte et al., 2015; WHO, 2019). These factors
23 together suggest that the environmental risk for asthma has been on the rise over recent human

1 history, with commensurate increases in selective pressure resulting in the strong enrichment for
2 positive selection on protective alleles that we observed.

3

4 It is worth mentioning that the approach taken here is subject to the limitations of the GWAS data
5 to which it has been applied. While incredibly useful, GWAS are not easily conducted on certain
6 diseases that likely carry great importance to fitness, such as infectious diseases or diseases and
7 health events that result in patient death before they can be enrolled in a study (i.e., myocardial
8 infarction, stroke). Our approach here is well suited to examining the common variants typically
9 found in GWAS, but it is ill-suited to rare or family-specific variation. Additionally, the timescales
10 we can examine using this approach are defined by the density and timeline of ancient samples.
11 As many of our samples are from the last 10,000 years and the youngest is from ~1,208 years ago,
12 very recent allele frequency shifts are difficult to detect. It is possible that some variants may have
13 been under episodic selection, but our method is unable to detect selection if allele frequency
14 trajectories are U-shaped.

15

16 ***Conclusion***

17 Our study shows the utility of ancient genomic data and time series analyses in understanding the
18 effects of selection versus neutral processes on complex disease risk. These results contribute to
19 the growing body of data on how selection has shaped the human genome, as well as the
20 importance of disambiguating fitness effects from disease status. It is also worth noting that
21 incorporating information from ancient samples can help give context in situations where
22 traditional markers of selection (linkage disequilibrium, singleton density, etc.) are obscured due
23 to the history of the region. This is a particular source of trouble in regions such as haplotypes

1 introgressed from ancient hominins, whose history violates many assumptions of methods using
2 modern data alone (Vernot and Akey, 2014). As more high-quality ancient genomes are collected
3 from around the world, our understanding of evolutionary medicine will continue to grow.
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6 **Materials and Methods**

7 *GWAS variant and ancient DNA curation*

8 Data was downloaded and curated as described in (Berens et al., 2017). Briefly, variants were
9 downloaded from the GWAS catalog (accessed 28 September 2016) and associations with benign
10 phenotypes removed. Specific variant associations were removed from consideration if two
11 variants associated the same disease and were within 100 kb of each other, with a preference for
12 maintaining the variant-phenotype association with the lower p-value. The risk allele for each
13 variant was classified as derived or ancestral based on data from the 1000 Genomes Project (Auton
14 et al., 2015). We used genomic data from 143 ancient individuals from 18 studies (see (Berens et
15 al., 2017) for further details on the curation of this data). As time series data requires a continuous
16 population, non-European ancient human samples (e.g., Mota and Anzick) and archaic hominin
17 Neanderthal and Denisovan samples were not included from the larger set described in Berens et
18 al (2017).
19

20 *Age of onset determination and phenotype collapsing*

21 When available, we used the disease information collated by Google from multiple data sources
22 (for more information, see: <https://support.google.com/websearch/answer/2364942>). Onset was
23 broken down into seven age ranges: 0-2, 3-5, 6-13, 14-18, 19-40, 41-60, and 60+. For each disease,

1 we used the age range determined by the highest frequency of ages affected. When multiple age
2 ranges were equally likely, we used the youngest age range. For the diseases that Google did not
3 have this information, we used either age of onset data or the age of study participants from the
4 studies contributing to the GWAS Catalog (Welter et al., 2014). For phenotypes that lacked an age
5 of onset (allergic reactions, injuries, etc.), we used the category “Any.” In addition, we collapsed
6 similar phenotypes into an umbrella phenotype (Supplemental Table S2). For example, all
7 symptoms associated with type II diabetes were collapsed into the type II diabetes umbrella
8 category.

9

10 ***Population continuity and contributions to modern genomes***

11 We used a method developed by Sjödin et al (2014). Ancient individuals were assigned into three
12 groups based on lifestyle: agriculturalists, hunter-gatherers, and pastoralists. For each variant, we
13 used this program to determine the maximum possible genetic contribution of individuals from
14 each lifestyle to modern EUR individuals. Maximum contribution was calculated by decile using
15 a uniform prior and scaled admixture time of 0.01 (5000 years ago, given a generation time of 25
16 years and N_e of 10,000). This method was shown to be robust to a difference in the time of
17 admixture compared to the age of the sample as well as variation in sample age. Consistent with
18 previous findings (Sjödin et al., 2014), similar results were observed when using the Griffiths
19 distribution, which incorporates ancestral and derived state information.

20

21 ***Allele frequency trajectory and selection inference***

22 We used a method developed by Schraiber et al (2016). For variants where the maximum
23 contribution of individuals of a particular lifestyle was less than 100%, we down-sampled the

1 individuals from that lifestyle by enforcing a chance of inclusion equal to the maximum
2 contribution of that lifestyle. Individuals were then binned by age (>9500, 9500-8000, 8000-6500,
3 6500-5000, 5000-3500, and <3500 years ago). Each time point was determined by calculating the
4 median age of all individuals included in the bin. Time was then scaled by generation time (25
5 years) and N_0 (10,000). The program was then run twice for each variant, once using a
6 demographic model of constant population size, and the other including the out of Africa
7 bottleneck and subsequent exponential growth - parameters used from Gravel et al (2011). Growth
8 was modelled as a step-wise exponential increase in population size every 2500 years until a
9 population size of 20,000 was reached, after which population size was held constant through to
10 present day. Variants were only included for analysis if at least 20 ancient individuals total
11 contributed over at least two time points (determined after individuals were down-sampled). In
12 instances of individual down-sampling, the same individuals were used for each variant for both
13 constant and exponential runs. The final selection coefficient (s) was determined by averaging the
14 s_1 (selection on heterozygote) and $\frac{1}{2} s_2$ (selection on homozygote) values generated by this method.
15 Due to overestimation of s when the derived allele frequency started very high in ancient
16 populations, we repolarized the test to treat an ancestral allele as if it was derived when the derived
17 allele frequency at the first time point was greater than or equal to 75%.

18

19 ***Introgressed and MHC variant identification***

20 We determined the introgression status of variants using the haplotypes and variants identified in
21 a study of Neanderthal and Denisovan introgression across modern Eurasian and Melanesian
22 groups (Vernot et al., 2016). Coordinates defined by the Genome Reference Consortium were used

1 to specify the MHC region (hg38 chr6:28,510,020-33,480,577). When necessary, we used liftOver
2 to convert data from hg38 to hg19 or vice versa (Hinrichs et al., 2006).

3

4 ***Binomial and hypergeometric enrichment***

5 We used the numpy module in python to generate binomial and hypergeometric distributions. In
6 all cases, we simulated 1,000,000 draws. Unless otherwise stated in the text, hypergeometric
7 distributions were generated based on the results from the overall set of 2,709 GWAS variants
8 with selection information.

9

10

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14

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