1 Contingent Convergence: The ability to detect convergent genomic

2 evolution is dependent on population size and migration

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- 21 ABSTRACT
- 22

23 Outlier scans, in which the genome is scanned for signatures of selection, have become a 24 prominent tool in studies of local adaptation, and more recently studies of genetic 25 convergence in natural populations. However, such methods have the potential to be 26 confounded by features of demographic history, such as population size and migration, 27 which are considerably varied across natural populations. In this study, we use forward-28 simulations to investigate and illustrate how several measures of genetic differentiation 29 commonly used in outlier scans (F_{ST} , D_{XY} and $\Delta \pi$) are influenced by demographic variation 30 across multiple sampling generations. In a factorial design with 16 treatments, we 31 manipulate the presence/absence of founding bottlenecks (N of founding individuals), 32 prolonged bottlenecks (proportional size of diverging population) and migration rate 33 between two populations with ancestral and diverged phenotypic optima. Our results 34 illustrate known constraints of individual measures associated with reduced population size 35 and a lack of migration; but notably we demonstrate how relationships between measures 36 are similarly dependent on these features of demography. We find that false-positive signals of convergent evolution (the same simulated outliers detected in independent treatments) 37 38 are attainable as a product of similar population size and migration treatments (particularly 39 for D_{XY}), and that outliers across different measures (for e.g. F_{ST} and D_{XY}) can occur with little 40 influence of selection. Taken together, we show how underappreciated, yet quantifiable 41 measures of demographic history can influence commonly employed methods for detecting 42 selection.

43

44 INTRODUCTION

45 Studies assessing adaptation and evolution across the genome are increasing in popularity 46 with the availability of modern sequencing technologies. These studies often centre around 47 quantifying patterns of variation in genome-wide SNPs, which can be used to highlight 48 regions or genes having experienced selection relative to the neutral backdrop of the rest of 49 the genome. These analyses, which we refer to here as outlier scans, have become a common tool in population genetics and have been useful across diverse, natural systems in 50 identifying candidate genes associated with the evolution of a range of adaptive traits 51 52 (reviewed recently by (Ahrens et al. 2018)). More recently, the method of overlapping 53 outlier scans across independent lineages has been employed to test whether the same 54 regions are involved in independent adaptation events (i.e. genetic convergent evolution) 55 (reviewed by (Fraser and Whiting 2019)). This study seeks to investigate how different 56 outlier scan methods are influenced by demographic variation in natural populations, and 57 how this may lead to overlapping false-positives.

58

59 Recent discussions have highlighted the propensity of outlier scans to yield false-positives, 60 given that outliers caused by heterogeneous genomic landscapes are commonplace 61 irrespective of selection (Ellegren and Wolf 2017). For example, background selection (BGS), 62 whereby linkage between neutral and deleterious variants reduces local diversity (Charlesworth et al. 1993; Bank et al. 2014; Burri 2017), has been invoked to offer 63 64 alternative explanations for patterns at first attributed to directional selection (Cruickshank 65 and Hahn 2014). Furthermore, the influence of neutral processes such as genetic drift (Charlesworth 2009) can similarly produce elevated genetic divergence and false-positive 66 67 signatures of selection.

68

69	The strength of these processes is dependent on demography. For example, the influence of
70	neutral processes and BGS should be more pronounced in smaller populations (low $N_{\rm e})$
71	(Charlesworth et al. 1995; Charlesworth 2009; Yeaman and Otto 2011; Cutter and Payseur
72	2013); as has been demonstrated in humans (Torres et al. 2018) and Drosophila
73	(Charlesworth 1996; Sella <i>et al.</i> 2009). This relationship, however, may not be simply linear,
74	with additional simulation evidence suggesting the effects of BGS are strongest at
75	intermediate-low N_e , and weaker at very low or high N_e (Zeng 2013).
76	
77	Lack of connectivity among populations may also elevate measures of genetic
78	differentiation, if a large global population is composed of smaller, isolated, sub-divided
79	populations that each experience the effects of reduced N_e (Charlesworth <i>et al.</i> 1997;
80	Hoban et al. 2016). In an attempt to mitigate the likelihood of false-positives, some have
81	advocated using multiple measures of population differentiation and divergence to identify
82	regions of the genome likely to be under selection (Charlesworth 1998; Cruickshank and
83	Hahn 2014). However, how these measures are correlated with each other, and with
84	selection under different demographic scenarios, has not been explored.
85	
86	A diverse array of measures of genetic differentiation and divergence have been employed
87	for outlier scans, but here we focus on two of the most common measures of relative

88 differentiation (F_{ST} and changes in nucleotide diversity [$\Delta \pi$]) and a measure of absolute

89 divergence (D_{XY}). The fixation-index F_{ST} (Weir and Cockerham 1984; Hudson *et al.* 1992),

90 which measures the relative amount of within- and between-population variance. This

- 91 measure is therefore maximised when genomic regions exhibit the lowest within- and
- 92 highest between-population variance. F_{ST} outliers at the right-tail of the distribution are

93 considered candidates for adaptation because they reflect regions with large differences in 94 allele frequency or high substitution rate (large between-population variance) and/or low 95 nucleotide variation (low within-population variance) relative to the rest of the genome. Changes in nucleotide diversity ($\Delta \pi$) are another indicator of adaptation, as selection on a 96 97 beneficial allele limits variation within a population resulting in selective sweeps (Smith and 98 Haigh 1974). Comparisons of the ratio of π between diverging populations reveal regions 99 under selection, as local π is reduced in one population in comparison to the other. Whilst 100 similar to F_{ST} , $\Delta \pi$ does not discriminate between which copy of a polymorphism is fixed, 101 such that a substitution between populations is equivalent to a common non-polymorphic 102 site. $\Delta \pi$ outliers therefore represent regions of the genome with reduced π in either 103 population relative to the rest of the genome. As a measure of absolute genetic divergence, 104 D_{XY} (Nei 1987) does not consider the relative frequencies of polymorphisms within 105 populations (Charlesworth 1998; Cruickshank and Hahn 2014). D_{XY} can be quantified as the 106 average number of pairwise differences between sequence comparisons between two 107 populations. This measure is therefore influenced by ancestral π and the substitution rate, 108 so D_{XY} outliers highlight regions that are highly variable ancestrally, or in either population 109 (large π), or exhibit many substitutions and thus increased sequence divergence.

110

Because each measure of differentiation/divergence (hereafter referred to collectively as measures of divergence) quantifies genetic variation between populations in a slightly different way, each has a unique relationship with demography. Whilst we can predict how individual measures are influenced by demography, and subsequently neutral processes, we know little about how different relationships between measures of divergence and

demography affect their combined usage. We expect then that the utility of using multiplemeasures of divergence to detect selection may vary with demography.

118

119 This complex interplay between divergence measures and demography may be further 120 exacerbated in studies that compare scans from multiple populations to identify convergent 121 genomic evolution. Here, researchers use measures of population divergence across 122 independent pairs of evolutionary replicates with outlier loci compared across results. This 123 strategy has been employed extensively across diverse taxa, including: birds (Cooper and Uy 124 2017), fish (Hohenlohe et al. 2010; Jones et al. 2012a; Fraser et al. 2015; Reid et al. 2016; Rougemont et al. 2017; Meier et al. 2018), insects (Soria-Carrasco et al. 2014; Van 125 126 Belleghem et al. 2018), mammals (Waterhouse et al. 2018), molluscs (Westram et al. 2014; 127 Ravinet et al. 2016) and plants (Roda et al. 2013; Trucchi et al. 2017). For the sake of 128 consistency, it is common to infer outlier loci within each replicate pair through a common 129 method, but if replicates differ in their demographic histories then the applicability/power 130 of that common method will also vary accordingly. This begs the question, can demographic 131 variation among replicates alone explain signals of, or lack of, convergence? 132 133 Here, we used forward-simulations to investigate the effects of different demographic 134 histories on the relationships between measures of divergence with selection. We varied 135 demography through manipulating the number of founding individuals (founding 136 bottlenecks), the population size of the diverging population (prolonged bottlenecks) and 137 the presence/absence of migration. We simulated the effects of selection on 25kb regions, 138 each with a gene designed from features taken from the guppy (*Poecilia reticulata*) genome 139 assembly, a prominent model system for studies of convergent evolution (Reznick and

140 Endler 1982; Fraser et al. 2015). Moreover, we measured genetic divergence at 12 set time 141 points through F_{ST} , D_{XY} and $\Delta \pi$ between diverging populations to examine temporal 142 relationships. Our aim was to investigate the significance of founding/prolonged bottlenecks 143 and migration between populations when employing outlier scans, and highlight 144 demographic scenarios that are susceptible to false-positives. We also aimed to test the 145 occurrence of common outliers across measures, and whether overlapping outliers are consistently good indicators of selection. We sought to answer the following questions: 1) 146 147 How do these demographic factors influence measures of divergence through time? 2) How well do measures of divergence identify regions of the genome under strong selection 148 149 through time and across demographic factors? 3) How are the different measures of 150 divergence related through time and across demographic factors? 4) Where do we detect 151 the strongest signals of convergence (i.e. overlapping outliers using single or multiple 152 measures), and are these consistent with selection?

153

154 METHODS

155 The forward-simulation software SLiM 3.0 (Haller and Messer 2019) was used to simulate 156 population divergence under contrasting demographic treatments in a fully factorial design 157 between a population with an ancestral phenotype (AP) of N = 1000 and population with a 158 diverged phenotype (DP), with a mutation rate based on the guppy genome $(4.89e^{-8})$ (Künstner et al. 2016) and scaled 100-fold over three raw mutation rates (4.89e⁻⁵, 4.89e⁻⁶, 159 4.89e⁻⁷) to ensure robustness of results across different, more realistic values of θ (4N_e μ). 160 161 These scaled mutation rates therefore represent effective population sizes of 10-, 100-, and 162 1000-times greater than the number of individuals in our simulations (N = 1000), in line with 163 estimates from other species (Charlesworth 2009). The main text reflects results for the

intermediate mutation rate 4.89e⁻⁶, with others presented in supplementary figures. SLiM
employs a classic Wright-Fisher model to simulate populations, in which a population of
diploid hermaphrodites proceeds through generations such that an individual's contribution
towards the next generation is proportional to its relative fitness.

168

169 Demographic treatments included reducing DP size (prolonged bottlenecks) relative to the 170 AP size (N = 1000) (0.01, 0.1, 0.5, 1.0), migration as a proportion of individuals exchanged 171 between populations (0.0, 0.002) and founding bottlenecks as the number of individuals 172 sampled from the burn-in population to construct DP genomes (N = 100 or 1000). For example, a demographic history with founding bottleneck = 100 individuals, DP size = 0.01, 173 174 and migration = 0.002 would represent the following scenario: 1) At generation 1, following 175 a burn-in period of 10,000 generations to reach mutation-selection balance, populations 176 split as 100 genomes are sampled from the burn-in population of 1000 to form DP, whilst AP 177 is formed by sampling all 1000 burn-in genomes; 2) At the next generation (and for the 178 remainder of the simulation), DP size reflects the prolonged bottleneck treatment, in this 179 case 10 (0.01 of 1000); 3) AP and DP experience migration in both directions for the 180 remainder of the simulation. Thus, each of our treatments can be thought of as a 181 manipulation of the following: Founding bottlenecks limit the amount of variation within the burn-in population that is available to found DP; Prolonged bottlenecks limit the size of 182 DP, reducing mutational input and moderating the strength of neutral evolution and efficacy 183 184 of selection; and migration dictates the presence of migration between AP and DP (Figure 185 1). The total N of individuals (AP + DP) within simulations varies between 1010 and 2000 186 depending on DP size parameter, however this potential expansion does not impact our 187 results (Supporting Information).

189	Combining these treatment levels in a fully factorial experimental design generated a total
190	of 16 different, independent demographic histories that all 25kb gene regions (see below
191	for architecture) experienced. This factorial design allows us to examine the relative
192	influence of founding bottlenecks, prolonged bottlenecks and migration, but our study is
193	limited to these features of demographic history and does not extend to population
194	expansions, more complex cases of migration, or demographic fluctuations through time. In
195	some cases, the influence of prolonged bottlenecks renders the effects of founding
196	bottlenecks unnecessary. However, when DP size is greater than 100, the inclusion of the
197	founding bottleneck allows us to compare populations with equivalent mutational input but
198	different standing variation.
199	
200	SLiM runs were performed independently over 25kb genomic regions with a central 'gene'
201	that functioned as a QTL and varied in length and exon content (Figure 1E); with exon
202	number, lengths, and intron lengths drawn at random from the guppy genome gene
203	annotation file (gff). In total, we simulated a dataset of 100 25kb regions (Figure 1F).
204	Recombination rate was scaled alongside mutation rate from a human-derived $r = 1e^{-8}$ to $1e^{-7}$
205	6
206	
207	Selection (S) in our model was represented as the fitness consequences incurred through
208	distance from a phenotypic optimum in a one-dimensional fitness landscape. Selection in
209	Wright-Fisher models is soft, in that low fitness individuals are not removed but have a
210	lower likelihood of contributing to the next generation. Phenotypic optima were maintained
211	over the course of simulations; thus, selection was constant throughout. This setup can be

212 considered as analogous to two environments with contrasting optimum trait values for a 213 single trait. Intensity of selection was manipulated by modifying the standard deviation (S_{σ}) 214 of the normal distribution curve from which the density distribution was calculated through 215 the "dnorm" function in SLiM. Values for S were drawn from a continuous distribution between -1.00 and 1.00 and transformed such that $S_{\sigma} = 10^{-5}$, yielding values between 0.1 216 217 and 10, with 0.1 representing the steepest fitness peak (S = 1) and 10 the shallowest (S = -1)218 (Figure 1A). Phenotypes were calculated per individual, per region, as the additive 219 phenotypic effects of exonic non-synonymous mutations, which appeared at a rate of 7/3 220 relative to synonymous mutations (assuming that most mutations in the third base of a 221 codon do not alter the amino acid). Additive genetic variance was assessed due to its 222 prevalence in complex traits in nature (Hill et al. 2008). Effect sizes for mutations with 223 phenotypic effects were drawn from a Gaussian distribution with mean = 0 and σ = 1. The 224 remaining synonymous exon mutations, and mutations in introns and outside of genes, had 225 no effect on fitness.

226

227 For each simulation, populations were seeded with 1000 individuals and allowed to proceed 228 for a burn-in period of 5*2N (10,000) generations to reach mutation-selection-migration 229 balance. During this period, burn-in populations evolved towards the ancestral phenotypic 230 optimum of 0, defined as a normal distribution with mean = 0 and σ = 1.0 (Figure 1A). Burn-231 in populations were then subjected to each demographic treatment to simulate the 232 founding of multiple populations from a shared ancestral state. During this 'divergence 233 period', AP continued to evolve around the ancestral optimum of 0, whilst DP's phenotypic 234 optimum was centred around 10, with fitness consequences defined according to S_{σ} . 235 Individuals also experienced fitness costs associated with phenotypic proximity to other

individuals within the population as a proxy for competition and to ensure a realistic amount of phenotypic variation persisted within populations. Fitness costs due to competitive proximity were scaled to a maximum value of 1 with $\sigma = 0.4$ and occurred reciprocally between local individuals with phenotypes with a difference of ≤ 1.2 (3 * 0.4).

Simulations were sampled at 100, 500, 1000, and then every 1000 generations up to 10,000 241 242 (Figure 1C). F_{ST} was calculated across the 25kb region based on the proportion of subpopulation heterozygosity (H_s) relative to total heterozygosity (H_T) (according to Hudson, 243 Slatkin and Maddison (1992)): $F_{ST} = 1 - \frac{H_S}{H_T}$. D_{XY} was calculated as the sum of nucleotide 244 differences (d_{ij}) between the i^{th} haplotype from AP and the j^{th} haplotype from DP (according 245 to Nei (1987)): $D_{XY} = \sum_{ij} AP_i DP_j d_{ij}$. Mean heterozygosity (π) for each population was 246 247 calculated as a single measure across the 25kb region. At each sampling point, each 248 measure was calculated and averaged across the preceding 20 generations. Averaging was 249 performed such that measures would not be dramatically biased by events occurring within 250 individual generations. The change in mean heterozygosity between AP and DP ($\Delta\pi$) was 251 calculated as the ratio of π_{AP} to π_{DP} , such that reduced diversity in the DP population increases the value of $\Delta \pi$: $\Delta \pi = \log_{10} \frac{\pi_{AP}}{\pi_{DP}}$. Statistics were calculated over all monomorphic 252 253 and polymorphic sites of 25kb regions. This has been designed to replicate genome scans 254 that use window-approaches, with each 25kb region analogous to an independent window. 255 In total, 100 unique 25kb regions were simulated across 16 demographic treatments across 256 three mutation rates, with results for the intermediate mutation rate presented in the main 257 text. To account for stochastic noise in the simulation, each 25kb region was iterated 20 258 times for each demographic treatment. Simulations with divergent AP and DP phenotypes

259 are referred to as "Pheno_{Div}" simulations. Additional simulations were performed in which 260 both populations shared the ancestral phenotype ("Pheno_{Null}" simulations) and in which all 261 sites were neutral with no selection imposed ("Neutral" simulations). The former of these 262 was used to assess whether patterns associated with selection were driven by phenotypic 263 divergence or variable stabilising selection within populations, whilst the latter was used to 264 disentangle effects of selection and neutral processes such as drift. A common set of 100 25kb regions were used for all simulations. Outliers for simulations were taken as upper 265 266 95% quantiles.

267

All data analysis was performed in R (3.5) (R Core Team 2016). To assess relationships 268 269 between divergence measures and selection, data were grouped by sampling generation 270 within each treatment group (N = 16) and Pearson's correlation coefficients were calculated 271 between measures of divergence and selection (S) at each sampling point for all regions (N = 272 100). Correlation coefficients were then grouped within specific treatment levels (e.g. DP 273 size = 0.5, or migration = 0.002) and averaged to give a coefficient reflecting each specific 274 treatment level. These correlation coefficients were calculated for each iteration (N = 20) 275 and averaged over to give final values.

276

To assess the effects of treatments on detecting outliers, we compared distributions and
95% cut-offs within each treatment for each measure of divergence for Pheno_{Div}, Pheno_{Null},
and Neutral simulations. We limited this analysis to early (100, 500), intermediate (3000)
and late (10,000) sampling generations. Here, data from all iterations of each 25kb region
were pooled. To calculate false positive (FPR) and false negative rates (FNR), we pooled
Neutral simulation data within treatment groups (20 iterations of 100 genes, N = 2000),

283 removed a random set of iterations (N = 100), and replaced it with an assortment of random 284 iterations of each gene (e.g. Gene 1/Iteration 2, Gene 2/Iteration 14... Gene 100/Iteration 4) 285 from Pheno_{Div} data. We calculated FPR as the proportion of data above the 95% quantile for 286 each measure of divergence/differentiation that came from neutral simulations. For single 287 measures, FPR = FNR as 5% of data in each permutation comes from Pheno_{Div}. We combined outlier sets across all combinations of F_{ST} , D_{XY} and $\Delta \pi$ and examined neutral proportions 288 289 within outlier sets to determine FPR. FNR for combined outlier sets corresponded to the 290 proportion of Pheno_{Div} data not recovered in the combined outlier sets. These permutations 291 were performed 100 times with results averaged. Proportional overlap of outlier sets was 292 also calculated and compared across demographic treatment groups to examine 293 convergence of results across treatments. Overlap was calculated within each permutation, 294 averaged over, and visualised using heatmaps with hierarchical clustering of axes. 295 296 To examine how simulated gene features influenced patterns of genetic divergence, we 297 used a linear mixed modelling (LMM) approach with gene ID and treatment group as 298 random factors. Gene features modelled as independent factors were: number of exons 299 (Exon N), gene size, the proportion of gene that is coding (selection target %), selection 300 applied to each gene (S), and the generation at which the optimum phenotype was reached 301 (Pheno Gen).

302

303 DATA AVAILABILITY

A full set of scripts including all bash, Eidos and R scripts necessary to repeat this analysis

305 can be downloaded from Github

306 (https://github.com/JimWhiting91/Contingent_Convergence_Pipeline). Supplementary

- 307 figures (S1-49) have been uploaded through the GSA figshare portal. Supplementary figures
- 308 include results for different mutation/recombination rates, Pheno_{Null} and neutral data

309 across sampling generations along with additional figures.

- 310
- 311 **RESULTS**

312 Demography modifies measures of divergence

313 Founding bottlenecks, simulated by reducing the number of possible founding genomes to a

random 10% of the ancestral population, had little measurable effect on F_{ST} , D_{XY} or $\Delta \pi$,

- 315 producing minimal variance between treatments over all sampling points (Figure 2A).
- 316

317 Prolonged bottlenecks, simulated by modifying the stable number of individuals within DP, 318 had pronounced and variable effects on all measures. F_{ST} increased with reductions in DP 319 size. This effect was generally consistent through time, although variance between 320 treatments increased gradually through time (Figure 2B). A similar effect was observed for 321 $\Delta\pi$; however, this measure was particularly susceptible to inflation under the most extreme 322 reductions in DP size, with substantially more elevated values observed between DP size 323 proportions of 0.01 and 0.1 compared with 0.1 and either 0.5 or 1.0. This pattern was 324 broadly consistent through sampling points. Such observations are unsurprising given that 325 both F_{ST} and $\Delta \pi$ increase with processes that reduce within-population genetic variance. D_{XY} 326 was generally robust to prolonged bottlenecks, but in contrast to F_{ST} and $\Delta \pi$, D_{XY} decreased 327 when DP sizes were reduced (Figure 2B).

328

The inclusion of migration reduced absolute values of all measures of divergence. For F_{ST}
 and D_{XY}, variance between migration treatments increased across the simulation, however

331 D_{XY} was generally more consistent across migration treatments. $\Delta \pi$ was also reduced in the 332 presence of migration, although the effect of migration on $\Delta \pi$ was generally consistent 333 across all generations and did not increase through time, as was the case for F_{ST} and D_{XY} . 334

Whilst F_{ST} and D_{XY} increased generally over time, $\Delta \pi$ peaked around generation 500 and declined thereafter. This peak corresponded to the median generation that DP replicates reached their optimum phenotype (median across all data = 493), suggesting this peak reflects selective sweeps. The majority of these patterns were apparent in the Pheno_{Null} (Figure S1) and neutral (Figure S2) simulations, however divergence for all measures was reduced and ultimately negligible by the removal of divergent phenotypes when migration was present.

342

343 **Demography moderates the association between measures of divergence and selection**

Again, founding bottlenecks had a minimal effect on the correlations observed between
strength of selection and measures of divergence with minimal variance observed between
bottleneck treatments in all comparisons (Figure 3A).

347

Prolonged bottlenecks had substantial effects on relative (F_{ST} and $\Delta\pi$) measures and marginal effects on absolute (D_{XY}) measures of divergence (Figure 3B). F_{ST} correlations with selection became consistently weaker as DP size reduced. There was minimal difference between $\Delta\pi$ correlations with selection except for the most extreme reductions in DP size. Effects for both were generally consistent through time. For D_{XY} , correlations with selection were broadly consistent with minimal variance across DP size reductions (Figure 3B).

354

355 Expectedly, the absence of migration largely precluded the ability of measures of divergence 356 to predict strength of selection, with notable variance observed between no migration (0.0) and minimal migration (0.002) treatments emerging rapidly for all divergence measures 357 358 (Figure 3C). Both F_{ST} and D_{XY} variance between migration treatments was greatest at the 359 10,000 generations sampling point, whereas similar variance was observed between migration treatments for $\Delta \pi$ across simulations. This observation again highlights the 360 361 significance of temporal differences between measures. Interestingly, correlations between 362 $\Delta\pi$ and selection persisted, albeit weakly, in the absence of migration, which was not the case for F_{ST} and D_{XY}. Further, at larger population scaling ($\mu = 4.89e^{-5}$, $r = 1e^{-5}$) D_{XY} 363 correlations with selection were negative (although became more positive over time with 364 365 migration) (Figure S6), most likely due to a stronger influence of mutational input. In larger 366 populations, positive correlations were observed between F_{ST} and selection without 367 migration, but were weaker than with migration (Figure S6).

368

Prolonged bottlenecks had a minimal effect on how measures of divergence correlated with 369 370 selection in Pheno_{Null} data (Figure S5). Both F_{ST} and D_{XY} became negatively correlated with 371 selection over time without divergent selection, likely due to stronger selection on common 372 alleles shared between AP and DP. Negative correlations were stronger for D_{XY}, consistent with reductions in DP_{π} with stronger selection. This suggests positive associations between 373 374 selection and D_{XY} in Pheno_{Div} simulations are likely more dependent on adaptive 375 substitutions in order to overcome this effect. $\Delta\pi$ was generally positively associated with 376 selection in Pheno_{Null} simulations regardless of migration, but was slightly reduced when 377 migration was absent.

378

379 By examining the correlation coefficients of all 16 unique demographic histories, we can 380 investigate the combined effect of migration and prolonged bottlenecks and directly 381 compare effectiveness of individual measures across time (Figure 4). F_{ST} consistently outperforms D_{XY} in terms of associating with selection under most demographic treatments, 382 383 particularly when DP sizes are larger and migration is present. By 10,000 generations 384 however, the relative dominance of F_{ST} appears to subside, with the trend through time 385 suggesting a relative improvement in D_{XY} in treatments with migration (Figure 4). $\Delta \pi$ is 386 similarly more informative than D_{XY} across sampling generations under most demographic 387 treatments. Interestingly at sampling generation 10,000, reductions in prolonged 388 bottlenecks produce the biggest bias towards $\Delta \pi$ (Figure 4). The resilience of $\Delta \pi$ under no-389 migration treatments is also apparent in F_{ST} - $\Delta\pi$ comparisons, such that at 3,000 390 generations $\Delta \pi$ is more informative than F_{ST} in the absence of migration. Consistent with its 391 rapid response to sweeps around 500 generation, $\Delta \pi$ slightly outperforms F_{ST} under most 392 demographic scenarios in early generations. By 10,000 generations, however, F_{ST} performs 393 as well as $\Delta \pi$ without migration and outperforms $\Delta \pi$ with migration. 394 395 Demography moderates the shape and tail end of divergence distributions By comparing distributions across simulations with divergent (Pheno_{Div}) and stabilising 396 397 (Pheno_{Null}) selection with neutral runs, we can examine the effect of demographic 398 treatments on the ability of each measure of divergence to discriminate between them

- 399 (Figure S11-13; Figure 5). There are few differences between distributions of F_{ST} for the
- 400 three simulation types when migration is absent between AP and DP replicates, highlighting
- 401 an increased likelihood of false-positives. The exceptions occur in early sampling points at
- 402 100 and 500 generations (Figure S12) when sweeps are most common. With migration,

403 Pheno_{Null} F_{ST} is marginally elevated compared with neutral F_{ST} , but distributions are broadly 404 similar. Pheno_{Div} F_{ST} distributions however become more positive and flattened, according to 405 variable selection, with the majority of Pheno_{Div} F_{ST} above the 95% quantiles of Pheno_{Div} and 406 neutral F_{ST} by 10,000 generations (Figure 5).

407

408 Similar patterns were observed for D_{XY} distributions (Figure S14-17), with little to 409 discriminate between in treatments without migration. However, without migration, neutral 410 D_{XY} was generally reduced relative to Pheno_{Null} and Pheno_{Div} D_{XY} at earlier sampling points. 411 With migration, like F_{ST}, Pheno_{Div} D_{XY} was readily distinguishable from Pheno_{Null} and neutral 412 distributions, but Pheno_{Null} D_{XY} was also generally more positive than neutral D_{XY}. These 413 patterns also emerged more slowly than for F_{ST} . In contrast, Pheno_{Div} $\Delta\pi$ (Figure S18-21) was 414 elevated according to DP size, such that at 500 generations the majority of 25kb regions 415 under divergent selection exhibited $\Delta \pi$ above neutral and Pheno_{Null} 95% cut-offs for all 416 treatments with DP size ≥ 0.5 .

417

418 We quantified false-positive rates (FPR) by permuting over merged data comprised of 419 randomly sampled 5% Pheno_{Div} regions and 95% neutral regions and observing the upper 420 5% quantile (Table S1). By 100 generations, F_{ST} FPR ranged between 0.06 and 0.91, and was 421 lower with increased DP size and lower in treatments without migration (Table S1). By 500 422 generations (Table 2), FPR rates were lower with migration and higher without, but only for treatments with DP sizes of 0.5 and 1.0. F_{ST} FPR remained high (> 0.81) for all treatments 423 424 with smaller DP sizes. By 3,000 generations, migration was the most important demographic 425 factor for F_{ST} FPR. With migration, FPR ranged from 0.15 – 0.61, and decreased with 426 increasing DP size. Without migration, FPR were high (0.88 - 0.97), close to the random

427 proportion of neutral (0.95) data. By the end of simulations, F_{ST} FPR was as low as 0.13, and 428 was no greater than 0.27 with migration and DP size \geq 0.1. Without migration, FPR was > 429 0.94.

430

431Initial D_{XY} FPR were generally high irrespective of demographic treatment, ranging between4320.78 and 0.93. FPR were largely similar after 500 generations, but by 3,000 generations433there was a distinction between treatments with $(0.07 \le FPR \le 0.71)$ and without $(0.85 \le$ 434FPR ≤ 0.88) migration. Interestingly, here FPR rates were lower $(0.07 \le FPR \le 0.24)$ when DP435were smaller (size = 0.01, 0.1) rather than larger $(0.47 \le FPR \le 0.71)$. This pattern was also436observed at the end of simulations, with FPR lower without migration $(0.01 \le FPR \le 0.34)$ 437and lowest with DP size = 0.1.

438

 Δ π FPR rates were generally higher across all sampling generations, with FPR not falling below 0.28. There was a clear distinction based on DP size in earlier (100 and 500) sampling points, with FPR lower with larger DP size. However, at later sampling generations (3,000 and 10,000), FPR were generally high (≥ 0.68) regardless of treatment.

443

Taken together, there are clear effects of DP size and migration on distributions of genetic variation and upper quantiles of interest. DP size appears initially most important in the first few hundred generations for F_{ST} and $\Delta \pi$, but these effects are later swamped by the effect of migration for F_{ST} and are simply eroded for $\Delta \pi$. D_{XY} exhibits similar patterns to F_{ST} , but these develop after many more generations, and whilst gene flow increases the informativeness of D_{XY} for detecting divergent selection, as it does for F_{ST} , D_{XY} and F_{ST}

450 experience opposing effects of increases to DP size.

452	Demography moderates relationships between measures of divergence
453	Given $F_{ST},$ D_{XY} and $\Delta\pi$ are all measures of population genetic divergence, there is an
454	assumption that positive correlations should exist between them. We employed the same
455	analysis as above for correlations with selection, but instead examined correlations between
456	individual measures. Founding bottlenecks had minimal effects on the correlations observed
457	between all measures of divergence (Figure 6A).
458	
459	Positive correlations between F_{ST} and D_{XY} emerged rapidly irrespective of DP size, but
460	smaller DP sizes generally increased the correlation (Figure 6B), with variance between
461	treatments generally decreasing over time. Similarly, F_{ST} and $\Delta\pi$ were generally positively
462	correlated, however reductions in DP size reduced correlation coefficients. By 4,000
463	generations, F_{ST} - $\Delta\pi$ correlations for DP sizes ≥ 0.1 stabilised around 0.4, but correlations
464	under extreme prolonged bottlenecks continued to decline to a low of 0.19 (Figure 6B). D_{XY} -
465	$\Delta\pi$ correlations were generally weaker than other comparisons across the course of
466	simulations, but were minimally affected by prolonged bottlenecks.
467	
468	Migration induced substantial variance between correlations of divergence measures, with
469	effects dependent on sampling point (Figure 6C). In the absence of migration, F_{ST} and D_{XY}
470	were more strongly correlated for the first 4,000 generations than in treatments with
471	migration. However, from here until 10,000 generations this pattern reversed and F_{ST} - D_{XY}
472	correlations increased with migration and deteriorated in allopatry. F_{ST} - $\Delta\pi$ correlations

473 were strong initially, but a lack of migration weakened the correlation over time until

474 measures were uncorrelated by around 4,000 generations. In contrast, in the presence of 475 migration, positive correlations between F_{ST} and $\Delta\pi$ were strong and relatively stable ($R^2 =$ 476 0.75 – 0.61 over the whole simulation period). Interestingly, without migration, D_{XY} and $\Delta\pi$ 477 were largely uncorrelated, but migration induced a positive correlation between D_{XY} and $\Delta\pi$ 478 that emerged after 2,000 generations and continued to increase through time.

479

Contextualised by our previous demonstrations of associations with selection, these results 480 481 highlight that selection can induce positive correlations between measures. By 10,000 482 generations, all pairwise comparisons of divergence measures become positively correlated 483 with migration, which we know is when variation is most strongly associated with selection. 484 Crucially however, this relationship only emerges after several thousand generations, before 485 which we observe positive correlations in migration-absent treatments when associations 486 with selection are weak for all measures (F_{ST} - D_{XY} in particular). Extreme reductions in DP size also increase positive correlations between F_{ST} and D_{XY} despite poor associations with 487 488 selection in these treatments. These results highlight that positive correlations between 489 statistics are also achievable in the absence of divergent selection. It is also interesting to note the decay of correlations with $\Delta \pi$ and both F_{ST} and D_{XY} in the absence of migration. 490 491 These observations are most likely driven by the substitution rate. Substitutions that are not linked to selection (drift with ineffective selection) likely drive increased F_{ST} and D_{XY} but not 492 493 Δπ.

494

In Pheno_{Null} simulations, F_{ST} and D_{XY} were positively correlated in all treatments, but stronger
 associations linked with demographic treatments with effective selection did not emerge

497 (Figure S22). This was also true for neutral simulations (Figure S23), but F_{ST} - D_{XY} correlations 498 were slightly larger than for Pheno_{Div} and Pheno_{Null} when selection was ineffective, reaching a maximum of $R^2 = 0.81$ without migration (Figure S23C). This demonstrates that the 499 500 positive correlations in Pheno_{Div} simulations are driven in part by divergently adaptive allele 501 frequency shifts and substitutions when selection is effective, but these correlations can 502 also emerge under stabilising selection or neutrality. Specifically, strong positive correlations 503 with $\Delta \pi$ were dependent on divergent selection, and $F_{ST} - \Delta \pi$ correlations became negative 504 over time in treatments without migration under neutrality. $D_{XY} - \Delta \pi$ correlations became 505 negative in Pheno_{Null} data with migration and were unassociated without. Thus, these 506 results highlight that the relationships between measures of divergence are highly 507 dependent on migration, population size, time, and selection experienced over a genomic 508 region.

509

almost all divergent regions.

510 We then examined FPR and false negative rates (FNR) when combining outliers across F_{ST}, 511 D_{XY} and $\Delta\pi$ (Table S1; summaries from 500 and 10,000 generations in Table 2). Combined F_{ST} - D_{XY} outliers exhibited FPR rates that were highly variable (0.00 - 0.95) and similar to or 512 513 slightly lower than F_{ST} alone at generations 100 and 500, suggesting some improvement in 514 reducing FPR. During this period, FNRs were also high (≥ 0.78), suggesting most regions with 515 divergent selection could not be detected on a neutral backdrop. Combined F_{ST} - D_{XY} outlier 516 sets performed well at generations 3,000 and 10,000 for treatments with migration, in some 517 cases dropping to 0 although FNR were highly variable ($0.26 \le FNR \le 1.00$). High FPR ($0.84 \le$ 518 FPR \leq 0.99) and high FNR (0.93 \leq FPNR \leq 1.00) were observed without migration, 519 highlighting most common outliers between F_{ST} and D_{XY} to be neutral, and a failure to detect 520

521

522 Combined F_{ST} - $\Delta\pi$ outliers tended to outperform F_{ST} and $\Delta\pi$ outliers according to FPR with 523 DP sizes of 0.5 or 1.0 and in earlier (100 and 500) sampling generations. Here, FPR dropped 524 to a low of 0 but FNR were reasonable through this time (\geq 0.35). Beyond this (sampling 525 generations 3,000 and 10,000), FPR again dropped to 0, however these were generally 526 alongside high FNR of up to 1.0 without migration, highlighting a failure to detect any 527 common outliers at all. A good example of improvement over singular measures was 528 observed at generation 500, with a founding bottleneck, equal sized populations, and 529 migration. Here, an average of ~66% of divergent regions were detected with an average 530 FPR of 0. This is compared with: singular F_{ST} , where FPR/FNR = 0.18; and singular $\Delta \pi$ where 531 FPR/FNR = 0.29. By 10,000 generations, combined outlier sets of F_{ST} - $\Delta\pi$ performed poorer 532 than singular F_{ST} with migration present, but generally returned low numbers of false 533 positives when migration was absent, unlike F_{ST} - D_{XY}.

534

535 Combined D_{XY} - $\Delta \pi$ outliers performed poorly across all treatments and all sampling 536 generations, with FNR failing to fall below 0.71. There were, however, some benefits in 537 terms of low FPR for treatments with larger DP sizes (0.5 and 1.0) across all sampling points, 538 suggesting high confidence in outliers (although most divergent regions are missed). This 539 discordance between D_{xy} and $\Delta\pi$ and large FNR also limited the combined usage of all three 540 measures together, with similarly high FNR largely precluding their combined usage. All 541 three statistics did exhibit low FPR with larger DP populations at 100, and 500 generations 542 despite migration. However, at later sampling generations performance of all three 543 combined outlier sets was poor (high FPR/FNR) if migration was absent.

545 These results therefore highlight that combining measures can help reduce FPR, but usually 546 at the cost of increased FNR (expectedly), and only under certain demographies. Our 547 observation that high FPR are prevalent among combined outlier sets from statistics, 548 particularly in the absence of migration, suggests their usage must be dependent on a 549 knowledge of disparity in population size and connectivity of populations. These findings 550 also highlight that the strong correlations that emerge between measures of divergence 551 under scenarios with ineffective selection or even under neutrality do extend to the tail-552 ends of distributions.

553

554 Demography drives signals of convergence irrespective of selection

555 Clusters of overlapping outliers developed steadily over time (Figure S26-28). By sampling 556 generation 10,000, significant proportions of overlapping outliers were recovered across 557 different demographic treatment groups (Figure 7). For F_{ST} and D_{XY}, clustering of treatments 558 was driven by the presence/absence of migration, with the highest proportions of 559 convergent outliers observed between treatments with migration.

560

561 Interestingly, for D_{XY} reasonable proportions of convergent outliers were also recovered 562 across no migration treatments, and the same was true of F_{ST} by 3,000 generations (Figure 563 S28), and for both measures at 10,000 generations in 'smaller' populations with reduced scaling ($\mu = 4.89e^{-7}$, $r = 1e^{-7}$; Figure S37). This is despite these treatment groups lacking 564 565 effective selection. Importantly, there was little overlap between migration and nomigration clusters, suggesting different convergent outliers within each. Combining outliers 566 from F_{ST} and D_{XY} reduced overlap among no-migration treatments, but did not remove 567 568 overlapping outliers altogether.

570	There were minimal convergent outliers observed for $\Delta\pi$ outliers, however combining $\Delta\pi$
571	with F_{ST} and D_{XY} did appear somewhat effective in removing convergent outliers found
572	between no-migration treatments. However, for both combination of $\Delta\pi$ with F_{ST} and D_{XY}
573	the highest proportional overlap was observed for treatments with the smallest DP size.
574	
575	Interestingly, the clustering of F_{ST} - D_{XY} outliers in the presence of migration was greatly
576	reduced when divergent selection was removed in both Pheno $_{Null}$ (Figure S29-32) and
577	neutral data (Figure S33-36), but clusters of outliers in the absence of migration were still
578	apparent.
579	
580	Because migration was the dominant factor in clustering of treatments with convergent
581	outlier overlap, we sought to investigate what features of simulated genes drove variance in
582	measures of divergence with treatments separated by migration factor using linear mixed
583	models at the final sampling generation. With migration between AP and DP, selection had
584	by far the strongest effect on F_{ST} (Table 3) in the expected positive direction. We also
585	observed a weaker positive association with selection target (% coding) of gene (Table 3),
586	and weaker negative associations with Pheno Gen (generation DP optimum reached) (Table
587	3). These fixed effects explained 48.96% of variance in F_{ST} with migration.
588	
589	Conversely, fixed effects explained minimal variance (1.10%) of F_{ST} in treatments without
590	migration. These fixed effects were significant, but had weak positive associations with
591	selection, exon N and selection target %, and a weak negative association with Pheno Gen.
592	

593	D_{XY} was similarly most strongly positively associated with selection in treatments with
594	migration (Table 3), but the strength of this effect relative to the other model effects was
595	not as large as observed for F_{ST} . D_{XY} was also negatively associated with Pheno Gen (Table
596	3), as was F_{ST} , but negatively associated with Exon N (Table 3). This model however
597	explained less variance of D_{XY} with migration (9.53%) than F_{ST} with migration. In treatments
598	without migration, selection target % was strongly negatively associated with D_{XY} (Table 3),
599	and this fixed effect explained 30.70% of D_{XY} variance without migration.

600

601 Selection was the most important fixed effect for $\Delta \pi$ regardless of migration (Table 3),

602 however both models explained minimal variance (8.27% with migration, 0.59% without 603 migration). This is consistent with the previous demonstration of the erosion of $\Delta\pi$ over

time (Figure 1).

605

Removing divergent selection (i.e. in Pheno_Null simulations) modified models for F_{ST} and D_{XY} 606 607 for treatments with migration. Selection and selection target remained the most important 608 model effects, but had more similar sized effects, and ultimately variance explained 609 dropped from 48.96% to 3.60%. Conversely, the model for Pheno_{Null} D_{XY} with migration 610 increased variance explained from 9.53% to 13.10% compared with Pheno_{Div} D_{XY}. Selection 611 target had a strongly significant negative association alongside strength of selection in this 612 model. $\Delta\pi$ models were largely unchanged. Together, these results confirm that divergent 613 selection, and not stabilising selection within DP, drive F_{ST} and D_{XY} variation in Pheno_{Div} 614 simulations.

615

616 **DISCUSSION**

617 Summary of results

Here, we show that features of demography can have dramatic effects on how measures of population divergence identify regions of the genome under selection. Effects are also strongly time-dependent. Using simulated populations, we have demonstrated the relative influences of founding bottlenecks, prolonged bottlenecks, and migration on three commonly used measures of genetic divergence (F_{ST} , D_{XY} , $\Delta\pi$), whilst demonstrating the relative usefulness of each measure for informing on selection when population sizes and connectivity vary.

625

We find that founding bottlenecks have little effect on population divergence measures, 626 627 potentially either because populations quickly recover (before first sampling after 100 628 generations), or founding bottlenecks of 10% (100 individuals) were not extreme enough. 629 Prolonged bottlenecks (reductions in DP size) however, artificially inflate F_{ST} and $\Delta \pi$ but 630 reduce D_{XY} , and can erase the relationship of F_{ST} and D_{XY} with selection under the most 631 extreme reductions in population size. Relative measures are, in part, driven by intra-632 population changes in allele frequency, which become exaggerated in smaller populations 633 as a product of drift (Charlesworth 2009; Ellegren and Galtier 2016). As a consequence, we 634 observe inflated measures of relative divergence as allele frequencies drift in smaller DP 635 replicates.

636

637 In contrast, D_{XY} increases with larger DP size, as a product of the relationship between the 638 number of segregating sites and the population-level mutation rate ($4N_e\mu$) (Hartl *et al.* 639 1997). D_{XY} is a measure of sequence divergence and is averaged across all sites (although 640 similar statistics limit averaging to segregating sites only), which results in higher D_{XY} as

641 segregating sites are introduced into either population at a rate of 4N_eµ. This relationship 642 with the number of segregating sites can be observed by examining the positive 643 relationships between D_{XY} and DP_{π} (Figure S38). Overall, the relationship between D_{XY} and 644 selection is less affected by prolonged bottlenecks than F_{ST} and $\Delta \pi$, likely due to the lack of 645 allele frequency relevance. Consider for example, two SNPs with minor allele frequencies of 646 0/0.5 (SNP 1) and 0.5/0.5 (SNP 2) in AP/DP. Each locus contributes equally towards D_{xy} (SNP $1 = [0 \times 0.5] + [1 \times 0.5] = 0.5$; SNP $2 = [0.5 \times 0.5] + [0.5 \times 0.5] = 0.5$), whereas the reduction of 647 648 within-population variance observed for SNP 1 inflates F_{ST} and $\Delta \pi$. However, we also see 649 evidence of D_{XY} FPR increasing with increased DP size (Table 2), suggesting this relationship 650 with increased acquisition of segregating sites may conflict with increased efficacy of 651 selection.

652

653 Migration, even at the relatively modest rate of 0.2% employed here, substantially reduced 654 absolute values for all measures of divergence. However, whilst absolute values were 655 reduced, their informativeness of selection coefficients increased dramatically (both in 656 terms of their overall relationship with selection and in identifying outliers). Such a result is 657 expected given the role of gene flow in homogenising neutral loci (reducing measures of 658 divergence), whilst retaining population divergence around adaptive loci (increasing 659 informativeness). The well-known 'genomic islands of divergence' model is often invoked to 660 explain this pattern of heterogenous genomic divergence in studies of speciation-with-gene-661 flow (Turner et al. 2005; Nosil et al. 2009).

662

663 Migration also exhibited interesting temporal patterns that are useful for discussing the 664 discrepancies observed between $\Delta \pi$ and both F_{ST} and D_{XY} . Of the measures considered here,

665 $\Delta\pi$ uniquely disregards SNP substitutions in its calculation, as fixed substitutions have no 666 influence on intra-population heterozygosity beyond reducing the heterozygosity of 667 proximate SNPs in the aftermath of a hard sweep. This characteristic explains why $\Delta \pi$ responds to selection more rapidly than F_{ST} and D_{xy} and is influenced by migration in a 668 669 constant manner across time. In addition, the inability of $\Delta \pi$ to account for adaptive 670 substitutions is likely why the informativeness of $\Delta\pi$ peaked at around 500 generations 671 (approximate median for sweeps), decayed, and then stabilised. In contrast, the 672 contributions of adaptive substitutions to F_{ST} and D_{xy} over time increases their predictive power. This characteristic of $\Delta \pi$, however, also makes it unable to differentiate between 673 674 divergent and stabilising selection. This temporal observation has important implications for 675 studies of rapid adaptation on the scale of 10s to 100s of generations, in which our 676 simulations suggest $\Delta \pi$ may be the most informative measure of divergence, whilst D_{xy} is 677 initially uninformative for several thousand generations.

678

679 Examining the effects of bottlenecks and migration on the associations between measures 680 of divergence themselves is a novel element to this study. The relative weaknesses of 681 individual measures of divergences has prompted a recent movement within the literature 682 to employ multiple measures of divergence to avoid false-positives (for e.g. Tine et al. 2014; 683 Malinsky et al. 2015; Hämälä and Savolainen 2019). Our results provide some support for 684 this strategy, with reductions in FPR in treatments with gene flow generally, and low FPR 685 when combining either F_{ST} or D_{XY} with $\Delta \pi$ (albeit at a reasonably high FNR). However, we 686 also find large numbers of overlapping outliers across combined F_{ST} - D_{XY} with a large FPR 687 across treatments without migration. Further, these false-positives persisted in Pheno_{Null} 688 and neutral data, whereas clusters of treatments with overlapping outliers (Figure 7) and

with low FPR were restricted to simulations with divergent phenotypes. It is clear then that
 combining outlier sets of F_{ST} and D_{XY} only improves analyses under certain demographic
 histories, in particular when populations are connected by migration.

692

693 Cruickshank and Hahn (2014) suggested that a disagreement between F_{ST} and D_{XY} outliers in 694 genomic-islands-of-divergence tests highlights a particular susceptibility of F_{ST} to BGS 695 (although see (Matthey-Doret and Whitlock 2019)). Our results are in line with the notion 696 that D_{XY} may be more resistant to false positives due to BGS, given that reductions in DP size 697 resulted in minimal variance in D_{XY} (assuming reductions in population size are analogous to 698 different rates of BGS across the genome exhibit reduced N_e). However, BGS was not 699 specifically manipulated in these simulations, and results are difficult to disentangle with 700 variation in efficacy of removing deleterious mutations. Further, this minimal variance may 701 be explained by the opposing forces of selection efficacy and acquisition of segregating sites 702 discussed previously. We also found that a greater proportion of variance could be 703 explained by the size of selection target for D_{XY} (30.7%) in the absence of migration than for 704 F_{ST} (1.1%). We found that F_{ST} and D_{XY} are positively correlated under several demographic 705 scenarios, but this strong association only reflects selection when gene flow is present and 706 only after several thousand generations, consistent with previous simulation work (Ravinet 707 et al. 2017). When migration is absent, and selection ineffective, F_{ST} and D_{XY} are also 708 positively correlated; but this relationship decays over time (Figure 6C), with empirical 709 evidence (see below) suggesting a negative relationship is likely to emerge without gene 710 flow. No-migration treatments are consistent with Isolation-By-Distance demographic 711 histories and, similarly, comparisons between reproductively-isolated populations or 712 species. Indeed, negative correlations between F_{ST} and D_{XY} within and between clades of

713 birds (Irwin et al. 2016; Vijay et al. 2017), within a radiation event of monkeyflowers 714 (Stankowski et al. 2019) and between speciating orca populations (Foote et al. 2016) 715 support a declining relationship between these measures over long periods of time in 716 isolation. In agreement, we find that without migration F_{ST} and D_{XY} exhibit opposite 717 associations with the proportion of regions made up of coding elements. Mechanistically, a 718 larger selection target increases the rate of deleterious mutation, reducing local π directly 719 through loss of polymorphic deleterious sites, or indirectly through the loss of linked neutral 720 variants under a BGS model. Reductions in local π increase F_{ST} and decrease D_{XY}. Over time, 721 associations between F_{ST} and D_{XY} should stabilise, given π is generally well-conserved in 722 stable populations even across long time periods (Romiguier et al. 2014; Dutoit et al. 2017; 723 Van Doren et al. 2017).

724

725 By comparing our results to a second dataset that lacked divergent selection (Pheno_{Null}), we 726 found consistent support that positive associations between D_{XY} and selection are strongly 727 dependent on the inclusion of a divergent phenotype. Positive associations with F_{ST} are 728 attainable only in the absence of migration, and are weakly negative without, and $\Delta\pi$ 729 patterns are primarily driven by variable stabilising selection and made weaker by the 730 inclusion of phenotypic divergence. These comparisons are useful in highlighting the relative 731 roles of adaptive allele frequency changes and substitutions in driving patterns of genetic 732 differentiation. It is also of interest to note that overlapping outliers are readily attainable 733 (most strongly for D_{XY}) across no-migration treatments in Pheno_{Null} (Figure S32) and neutral 734 simulations (Figure S36), but not for treatments with migration. This confirms that 735 overlapping outliers in no-migration treatments occur due to common non-divergent 736 processes within genomic regions, whereas overlapping outliers in treatments with

migration are driven by the effects of divergent selection. The discrepancies between our
Pheno_{Div} and other simulated datasets highlight the necessity in quantifying phenotypic
differences or environmental selection pressure when interpreting patterns of variation
across the genome.

741

742 Detecting genetic convergence

743 In addition to understanding how outlier detection in individual pairs were affected by 744 bottlenecks and migration, we wanted to explore how studies looking at overlapping 745 outliers in multiple pairs (i.e. detecting genetic convergence) were affected by these aspects 746 of demography. Our simulation design, in which an ancestral burn-in population is used to 747 found 16 independent AP-DP pairs is analogous to replicated ecotype population pairs in 748 model systems, such as various ecotype pairs of the three-spined stickleback, Gasterosteus 749 aculeatus (Hohenlohe et al. 2010; Jones et al. 2012a); high/low predation Trinidadian 750 guppies, Poecilia reticulata (Fraser et al. 2015); crab/wave ecotype periwinkles, Littorina 751 saxitilis (Westram et al. 2014; Ravinet et al. 2016; Kess et al. 2018), and alpine/montane 752 ecotypes of Heliosperma pusillum (Trucchi et al. 2017). We found overlapping outliers 753 between demographic treatments and thus, that signals of convergent outliers are 754 attainable for singularly used F_{ST} and D_{XY} , and combined outlier sets for $F_{ST} - \Delta \pi$, $D_{XY} - \Delta \pi$ 755 and F_{ST} - D_{XY}. Clustering of outliers was predominantly driven by the presence or absence of 756 migration (with minimal overlap between clusters) (Figure 7).

757

The overlap of quantile-based outliers between demographic treatments without migrationand ineffective selection may be explained in part probabilistically. With migration

760 restricted, AP and DP exhibit significantly elevated measures of divergence, as seen in Figure

1. This increase results in a normal distribution of F_{ST} and D_{XY} across neutral simulations
without migration. In contrast, with migration, drift is limited and random recombination
influences gene flow and subsequently variation in divergence. Distributions of divergence
with migration under neutrality are therefore are heavily right tail-skewed (Figure S39).
Spread of data increases with longer right tails, and density of data in each overlapping
distribution is limited to the median and lower quantiles.

767

We also expect some effect of different amounts of starting variation among genome
regions following burn-ins. With gene flow restricted, this variation may promote overlap
under neutral conditions given all demographic treatments are founded from a common
burn-in. However, this feature of our simulations is analogous to the conserved landscapes
of variation observed in natural genomes (Burri 2017; Vijay *et al.* 2017; Stankowski *et al.*2019).

774

Empirically, the influence of migration on outlier overlap has been observed in replicate pairs of parasitic and non-parasitic lampreys. As we show here, when comparing outliers from disconnected and connected parasitic/non-parasitic pairs, Rougemont et al. (2017) recover greater numbers of overlapping outliers among comparisons of disconnected pairs than connected pairs. Overlapping outliers among connected pairs are however better correlated, which the authors suggest reflects selection.

781

782 Limitations of simulations

In our analyses, we grouped genomic regions within 16 unique demographic treatments,
assuming the effects of reductions in population size and migration are equivalent for all

785 regions. This may be unrepresentative of genomes sampled from the wild, in which gene 786 flow and effective population size can vary across genomic regions through structural 787 variation, variable recombination rate and BGS (Gossmann et al. 2011). A prominent 788 example of such a mechanism is the well-characterised consequence of reduced gene flow 789 within inversions that carry locally adapted alleles. Assuming inversion variants are fixed 790 between populations, gene flow across the locus is limited by the prevention of 791 recombinant haplotypes and resistance to introgression (Kirkpatrick and Barton 2006; 792 Ravinet et al. 2017). Recent genome scan studies have highlighted convergent outliers 793 within inversions (Jones et al. 2012b; Nishikawa et al. 2015; Morales et al. 2019), confirming 794 theoretical models regarding their role in shielding adaptive haplotypes from introgression 795 during the adaptation process. Our simulations suggest that genes with reduced migration, 796 and reduced Ne as a consequence, will have inflated measures of divergence and 797 differentiation relative to other genomic regions. Therefore, we predict this may have led to 798 their over-representation in genome scan outliers, and increased potential to overlap across 799 replicate populations. Thus, caution should be taken regarding the adaptive significance of 800 these outliers relative to absolutely lower values of genetic divergence attained from 801 regions outside of chromosomal rearrangements.

802

By choosing to use a factorial design here, we have increased our understanding of the
interplay between specific features of demographic history and multiple measures of
population divergence. However, computational limitations constrained absolute
population sizes to a maximum of 1,000 individuals and generations to a maximum of
10,000 (with 10,000 generation burn-in). To mitigate these constraints, we repeated the
analysis over multiple mutation rates (and scaled recombination rate) to illustrate patterns

809 over 100-fold variation of θ . In general, most trends were consistent, suggesting that results 810 should be consistent across taxa of variable effective population size. However, certain 811 patterns were exaggerated or dampened with increased or decreased mutation rate 812 respectively. For instance, the overlap of outliers between no-migration treatments was 813 exaggerated at our smallest level of population scaling (Figure S37), suggesting false-positive 814 signals of convergence may be more likely with reduced Ne. Further, patterns associated with D_{XY} and selection vary according to population size, appearing delayed in smaller 815 816 populations (Figure S7) and swamped by mutational input in larger populations (Figure S6). 817 This latter effect can induce negative associations between selection and D_{XY} with effective 818 selection, as selection reduces local genetic variation that would otherwise increase D_{XY}. It is 819 well-documented that both N_e (Frankham 1995) and mutation rate (μ) (Hodgkinson and 820 Eyre-Walker 2011) are highly variable across taxa, which suggests that applying knowledge 821 of the relationships between measures of population differentiation will vary in nature.

822

823 In addition, temporal variation within our simulations is confounded by the time at which 824 there was a major shift in the DP population phenotype (Figure S40), and by extension when 825 selective sweeps occur. This variation in timing is random with respect to adaptive 826 mutations arising de novo, but is also influenced by demographic treatment. For example, 827 treatments that experience founding bottlenecks are less likely to evolve using variation in 828 the founder, increasing dependence on *de novo* mutations for adaptation. Additionally, 829 variation in our DP size parameter modifies the per population number of new mutations 830 per generation. This is also true for features of simulated genes, such as size of selection 831 target. Predictable temporal variation in the time at which adaptation is likely to occur is a

probable source of variance between measures of divergence and is particularly clear for
Δπ, but this was controlled for in later modelling analyses as a fixed effect.

834

835 A further consideration for these simulations concerns the architecture of the phenotype. 836 Results reported here pertain to mutation effect sizes drawn from a distribution centred at 837 0 with σ = 1. This produces mutations of typically large effect, but was selected on the basis 838 of phenotypic optima being reasonably distant, with a difference of 10. Thus, 99% of 839 mutations in simulations produce phenotypic differences of less than a third the divergence 840 distance of AP and DP phenotypes. There are numerous factors that influence the 841 distribution of mutation effect sizes in nature, including: selection, mutation, drift, gene 842 flow, extent of pleiotropy and distance to phenotypic optima (Dittmar et al. 2016), with no 843 single expectation for natural systems as a result. The relatively large distance between 844 optima in our simulations, as well as the rapid change in optima implemented in simulations 845 (Collins and De Meaux 2009), likely gives increased importance to mutations of large effect. 846 The interactions between mutation effect size and the results presented here are beyond 847 the scope of the current study, but we did investigate the effect of reducing μ_{σ} of mutation 848 effect distributions to 0.1 (Supporting Information; Figures S40-45). Briefly, we see 849 reductions in the strength of correlations and associations with selection with decreasing 850 phenotypic effects of mutation, consistent with the notion of softer sweeps on small-effect 851 loci. We also see increased variance in the amount of time taken for simulations to reach 852 the Pheno_{Div} optimum, which agrees with the probable importance of large effect loci in our 853 standard dataset. We, however, retain strong positive associations between measures such 854 as F_{ST} and D_{XY}, as we see in neutral simulations, as well as overlapping outliers linked to 855 selection at the tail ends of Pheno_{Div} distributions. Running the simulations in this way

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856 suggests that many of the patterns described here may be robust to scenarios with reduced857 mutation effect sizes.

858

859	It is also important when translating these results to genomic data to consider how
860	correlations between measures of divergence depend on the selection type used in
861	simulations. For example, F_{ST} and D_{XY} are strongly positively correlated under neutrality
862	without migration, but under the same demographic scenarios we observe a decay in the
863	relationship between F_{ST} and D_{XY} when divergent selection is involved. Genomes of natural
864	populations will include regions that are neutral or nearly neutral, under stabilising selection
865	around a common phenotypic optimum, or divergent between populations. Thus, the
866	patterns described here may not apply to all genomic regions pooled together.

867

868 Concluding remarks

869 We have used forward-in-time simulations to perform a factorial experiment in which we 870 explored the relationships between three measures of genetic divergence, selection, and 871 features of demographic history that are commonly variable in natural populations. In agreement with previous theoretical work, we found the reliance of measures of genetic 872 873 divergence to identify loci under selection are dependent on population size and migration, 874 and variable through time, with a notable lag in D_{XY}. Furthermore, we provided novel 875 comparisons between measures of genetic divergence that call into question the use of 876 multiple measures to rule out false-positives. We also demonstrated that signals of 877 convergent evolution across independent replicates can be driven by similar features of 878 demographic history with minimal influences of selection, specifically, across replicate 879 populations pairs that lack migration. Therefore, we strongly advise those using overlapping

38

880 outlier scans to carefully consider the demographic context of their system to avoid false-881 positives. In particular, the presence or absence of migration between diverging populations is a key factor determining the informativeness of genetic variation for selection, and 882 883 importantly shapes our expectations of outlier overlap among replicate population pairs. It 884 is tempting to assume that replication in study design or analysis in the form of taking 885 multiple measures of genetic divergence can reduce the risk of attaining false-positives. We 886 hope to emphasise in this study that this is not always the case, as false-positives (i.e. 887 genome scan outliers that are not associated with regions under divergent selection) can be 888 driven by non-random genomic or common demographic features that cannot be bypassed 889 through replication. Moreover, many of the patterns we observe are variable through time, 890 such that the relevant pitfalls of analyses will depend on the age of the populations being 891 considered. It should thus also be important to estimate population splits, as a young 892 replicate pair and older replicate pair with similar demographic histories should be expected 893 to exhibit potentially different patterns of genetic variation.

894

895 Recent simulation work by Quilodrán et al. (2019), has also emphasised the influence of 896 genomic features and demography, and includes simulation software for estimating the 897 distribution of genetic variation over user-defined chromosomes. Such an approach is 898 particularly useful for systems with chromosome-level genome assemblies in order to gain a 899 sense for how features such as recombination, gene density, and selection targets may 900 produce false-positives under certain demographies. The software employed here, SLiM 901 (Haller and Messer 2019), may also be used to this end, and the scripts accompanying this 902 study will facilitate similar analyses over system-specific genome regions. Further, recent 903 work on genomic landscapes of linked selection (Stankowski et al. 2019) has highlighted that

39

much of the total variance of genetic divergence such as F_{ST}, D_{XY}, and π can be explained by
the major principal component (PC1) over numerous pairwise comparisons. These
population comparisons need not reflect divergent phenotypes, as PC1 reflects genomic
features associated with diversity landscapes. Adopting this approach may be useful for
systems lacking a chromosome-level genome assembly by estimating SNPs or regions with
non-random elevated measures of divergence associated with genome features. Such SNPs
or regions may be particularly prone to false-positives under certain demographic histories.

911

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- 920

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- 1089 1090

1091 FIGURE LEGENDS

1092

Figure 1: Experimental design for simulations. A) Examples of selection treatments
 experienced by genes from across the range, illustrated as the relationship between relative
 fitness of an individual and its phenotype. Each facet represents a different fitness
 landscape modified through editing the standard deviation of the normal distribution of
 fitness consequences in DP (blue, dashed). Facet labels constitute *S*, which were

- 1098 transformed as 10^{-S} to give fitness function standard deviations (S_{σ}) The x-axes represent
- 1099 phenotype as calculated through non-synonymous mutations and the y-axes represent
- 1100 relative fitness of individuals. The ancestral phenotype of AP (red, solid) is the same in all
- 1101 treatments (mean = 0, σ = 1), whilst DPs have a diverged phenotypic optimum (mean = 10, σ 1102 = S_{σ}). **B**) Distribution of *S* values applied to genes (1 per gene) **C**) Demographic
- 1103 representation of treatment factors. **D)** Representation of simulation timeline for
- 1104 treatments, illustrating that all treatments share an ancestral burn-in population before 1105 splitting into 16 replicated "AP" (solid) and "DP" (dotted) population pairs. Red, dashed lines
- 1106 denote sampling generations at which F_{ST} , D_{XY} and $\Delta\pi$ are calculated and averaged across
- 1107 the preceding 20 generations. The purpose of this averaging was to achieve a general sense
- 1108 of population differentiation at sampling points, such that values represent stable patterns
- 1109 rather than stochastic generation to generation variation. **E)** Examples of two simulated
- 25kb regions, showing central genes that function as QTL, and illustrating how regions vary
 in gene length, exon N and selection target (%). F) Representation of 100 simulated 25kb
- regions dataset per iteration (N = 20) per treatment group (N = 16).
- 1113
- Figure 2: Effects of demographic treatments on measures of genetic divergence across allsampling generations. Point colour and shape denote treatment groups for founding
- 1116 bottlenecks (A), prolonged bottlenecks (B) and migration (C). Each point represents values
- 1117 of divergence averaged across all genes within individual treatments groups, averaged
- 1118 within treatment levels, and averaged over 20 iterations.
- 1119

- **Figure 3:** Effects of demographic treatments on the relationship between selection and measures of genetic divergence across all sampling generations. Point colour and shape denote treatment groups for founding bottlenecks (**A**), prolonged bottlenecks (**B**) and migration (**C**). Each point represents correlation coefficients calculated across all genes within individual treatments groups, averaged within treatment levels, and averaged over 20 iterations.
- 1126

1127 Figure 4: Pairwise comparisons between the correlation coefficients of selection with F_{ST} , D_{XY} and $\Delta \pi$ 1128 across four sampling points. Each data point represents a unique demographic treatment with 1129 points coloured according to DP population size and shaped according to migration level. Correlation 1130 1 refers to the first measure listed in the comparison and Correlation 2 to the second. The y=x line is 1131 plotted within each facet to illustrate biases towards one measure. Points below the line are biased 1132 towards Correlation 1, whilst points above the line are biased towards Correlation 2. Each point 1133 represents correlation coefficients calculated across all genes within individual treatments groups 1134 and averaged over 20 iterations.

1135

Figure 5: Distributions of F_{ST} under each of the 16 unique demographic treatments under three
selection regimes: Pheno_{Div} (divergent selection), Pheno_{Null} (stabilising selection) and Neutral, after
10,000 generations. Upper 5% quantiles are highlighted for each distribution, with linetype
corresponding to selection: Solid = Divergent, Dashed = Stabilising, Dotted = Neutral. Each

- distribution represents data pooled from 20 iterations of 100 25kb regions (N = 2000).
- 1141

Figure 6: Effects of demographic treatments on the relationship between measures of genetic
 divergence across all sampling generations. Point colour and shape denote treatment groups for
 founding bottlenecks (A), prolonged bottlenecks (B) and migration (C). Each point represents
 correlation coefficients calculated across all genes within individual treatments groups, averaged
 within treatment levels, and averaged over 20 iterations.

1147

Figure 7: The proportional overlap of outliers above the 95% quantile, averaged across 100

downsampled datasets consisting of 95% Neutral and 5% Pheno_{Div} data for each of the 16
 demographic treatments after 10,000 generations. Axis orderings were determined through

1150 hierarchical clustering. Heatmaps are shown for single measures of F_{ST} , D_{XY} and $\Delta\pi$ in the first

1152 column, and combined measures in the second column. Heatmaps are coloured according to a

- 1153 common scale of 0 to 1. Treatments are labelled with founding bottleneck (Bot), DP population size
- 1154 (Pop2), and migration (Mig) values.

TABLE 1: SIMULATION PARA	METERS
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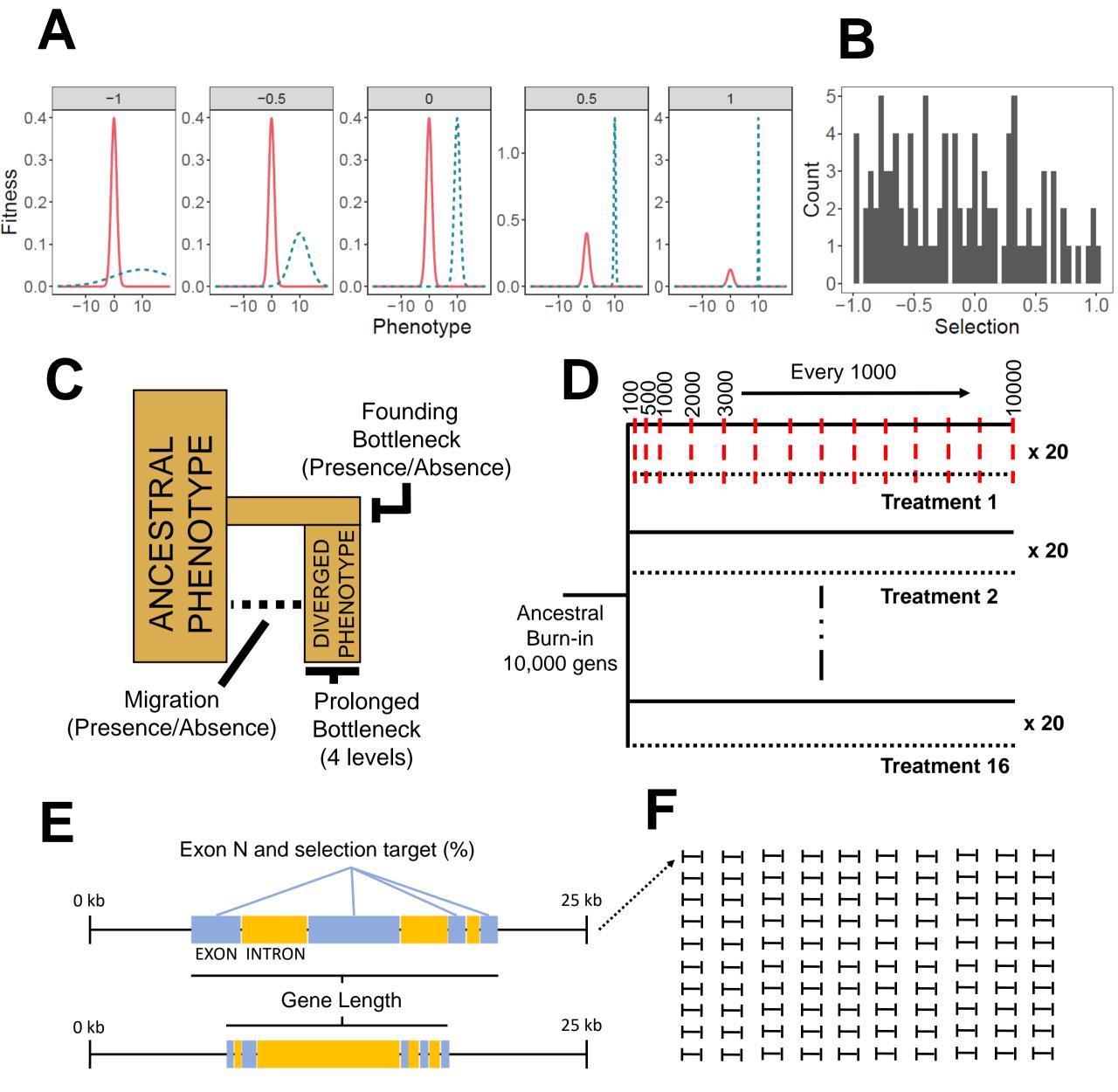
Variable	Value	Description
AP	0	Ancestral phenotypic optimum
$AP-S_{\sigma}$	1	AP Selection (σ of fitness around phenotypic optimum, after transforming)
AP _N	1000	AP population size
DP	10	Diverged phenotypic optimum
$DP\text{-}S_{\sigma}$	0.1-10.00	DP Selection (σ of fitness around phenotypic optimum, after transforming)
DP _N	(10, 100, 500, 1000)	DP population size
BN	(100, 1000)	Founding bottleneck (N burn-in genomes sampled to populate DP)
т	(0, 0.002)	Migration (Percentage gene flow in both directions)
μ	4.89e ⁻⁶ (4.89e ⁻⁵ , 4.89e ⁻⁷)	Mutation rate (bp ⁻¹) (additional rates for higher/lower scaling)
μ_{σ}	1.00	Mutation effect size (σ of distribution of effect sizes)
r	1.00e ⁻⁶ (1.00e ⁻⁵ , 1.00e ⁻⁷)	Recombination rate (bp ⁻¹) (additional rates for higher/lower scaling)
C _{max}	1.00	Maximum fitness cost through competition
Cσ	0.40	Local phenotypic competition (σ of fitness reductions between individuals)
C _{Dist}	1.20	Maximum phenotypic distance between competitive individuals

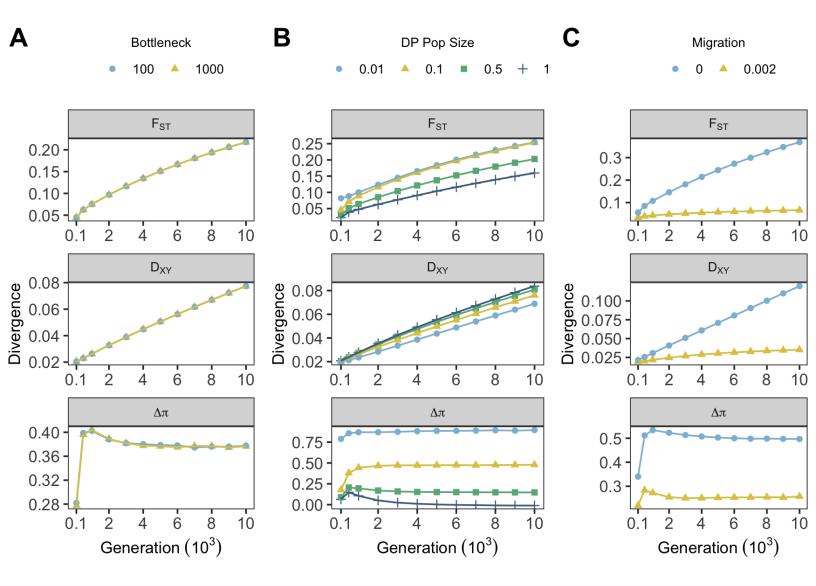
TABLE 2: FALSE POSITIVE (FPR) AND FALSE NEGATIVE RATES (FNR) CALCULATED ACROSS ALL MEASURES OF DIVERGENCE AND THEIR COMBINED USE. ESTIMATES WERE CALCULATED BY COMBINING 5% OF DATA UNDER DIVERGENT SELECTION WITH 95% NEUTRAL DATA AND TAKING UPPER 5% CUT-OFFS. FOR SINGLE MEASURES, OUTLIER N IS ALWAYS 100 (5% OF 2,000) AND FNR = FPR.

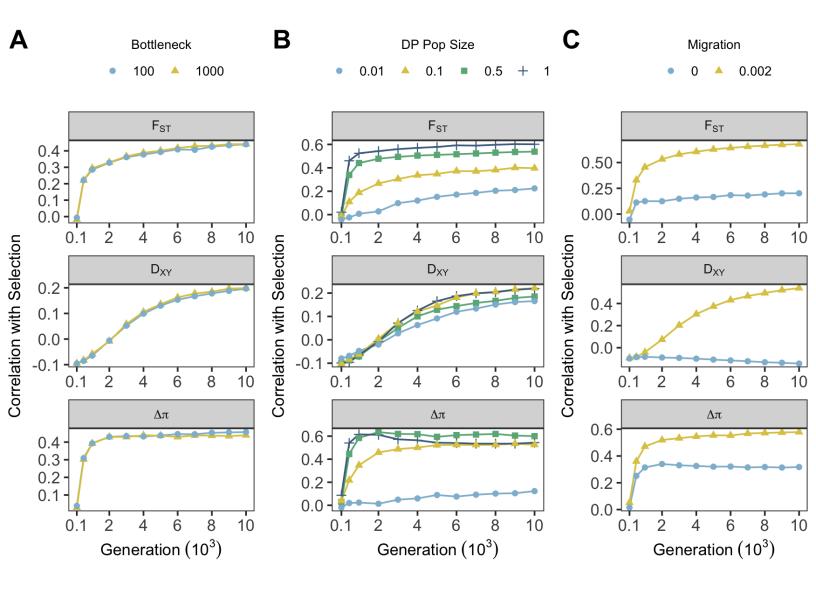
	Demograp	hic															
Gen	Treatments		Single Measures			Combined Measures											
		DP	F _{ST}	D _{XY}	Δπ	F _{ST} & D _X Outlier	Y		F _{ST} & Δτ Outlier	T		D _{XY} & Δτ Outlier	T		All 3 Outlier		
	Migration	Size	FPR	FPR	FPR	Ν	FPR	FNR	Ν	FPR	FNR	Ν	FPR	FNR	Ν	FPR	FNR
500	0	0.01	0.87	0.87	0.99	62.21	0.87	0.92	9.64	0.98	1.00	26.21	0.98	1.00	9.64	0.98	1.00
500		0.1	0.91	0.86	0.99	54.79	0.89	0.94	14.77	0.98	1.00	13.63	0.99	1.00	7.89	0.98	1.00
500		0.5	0.50	0.81	0.47	31.56	0.49	0.84	41.54	0.19	0.66	12.11	0.37	0.92	10.01	0.24	0.92
500		1	0.28	0.80	0.28	26.84	0.28	0.81	59.81	0.04	0.43	14.99	0.00	0.85	14.75	0.00	0.85
500	0.002	0.01	0.93	0.76	0.98	60.15	0.92	0.95	19.57	0.97	0.99	17.07	0.96	0.99	15.21	0.96	0.99
500		0.1	0.85	0.81	0.96	14.83	0.78	0.97	29.09	0.89	0.97	1.48	0.72	0.99	1.48	0.72	0.99
500		0.5	0.35	0.90	0.47	10.56	0.37	0.93	58.81	0.17	0.51	5.20	0.21	0.96	5.20	0.21	0.96
500		1	0.18	0.90	0.30	11.37	0.29	0.92	66.35	0.02	0.35	6.61	0.12	0.94	5.67	0.00	0.94
10000	0	0.01	0.95	0.89	0.97	27.86	0.96	0.99	0.00	0.00	1.00	7.57	0.96	1.00	0.00	0.00	1.00
10000		0.1	0.98	0.89	1.00	31.29	0.99	1.00	0.73	0.73	1.00	1.53	0.98	1.00	0.00	0.00	1.00
10000		0.5	0.98	0.88	0.98	31.21	0.99	1.00	7.60	0.99	1.00	4.98	0.95	1.00	3.79	0.99	1.00
10000		1	0.94	0.88	0.95	31.47	0.95	0.98	5.25	0.82	0.99	5.15	0.87	0.99	2.80	0.89	1.00
10000	0.002	0.01	0.53	0.17	0.79	56.84	0.21	0.55	34.41	0.44	0.81	22.76	0.17	0.81	22.56	0.17	0.81
10000		0.1	0.27	0.04	0.89	72.06	0.00	0.28	24.08	0.54	0.89	11.12	0.00	0.89	11.12	0.00	0.89
10000		0.5	0.17	0.17	0.70	74.68	0.02	0.27	32.26	0.09	0.70	28.57	0.00	0.71	28.57	0.00	0.71
10000		1	0.14	0.34	0.78	67.03	0.07	0.37	25.33	0.11	0.78	20.70	0.05	0.80	20.70	0.05	0.80

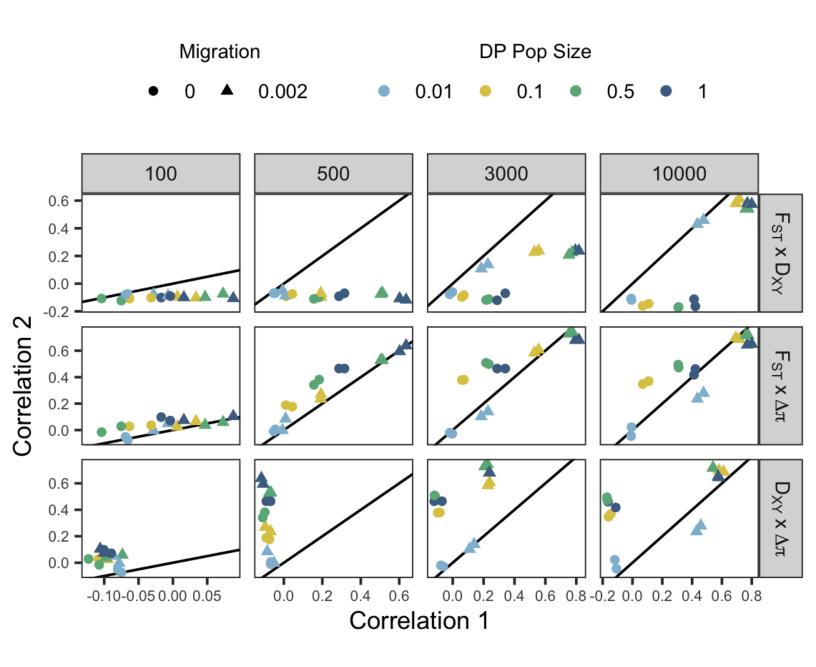
		Var.	L (0()						
Maaaaaa	Minnetien	explained (%)					-14		-
Measure	Migration	Fixed	Total	Fixed Effect	Estimate	Std. Error	df	t	Р
F _{ST}	0.002	48.96	69.12	Selection	0.044	0.002	98	27.27	<2.00E-16
				Selection Target	0.009	0.001	103	9.32	2.47E-15
				Pheno Gen	-0.002	0.000	14530	-7.55	4.60E-14
F _{ST}	0	1.10	96.84	Selection	0.005	0.001	96	4.32	3.78E-05
				Pheno Gen	0.000	0.000	14480	-2.58	0.010*
				Exon N	0.005	0.002	96	2.51	0.014*
				Selection Target	0.004	0.002	97	2.46	0.015*
D_{XY}	0.002	9.53	84.25	Selection	0.007	0.000	98	16.97	<2.00E-16
				Pheno Gen	-0.001	0.000	14560	-10.49	<2.00E-16
				Exon N	-0.001	0.000	101	-4.15	6.89E-05
D _{XY}	0	30.70	53.94	Selection Target	-0.003	0.000	98	-11.57	<2.00E-16
Δπ	0.002	8.27	76.20	Selection	0.184	0.006	99	29.82	<2.00E-16
				Selection Target	0.018	0.004	120	4.71	6.84E-06
				Pheno Gen	0.006	0.002	14250	2.92	0.004
Δπ	0	0.59	95.84	Selection	0.066	0.004	99	16.14	<2.00E-16
				Exon N	-0.018	0.003	111	-6.15	1.24E-08
				Pheno Gen	-0.004	0.001	13900	-3.33	8.67E-04

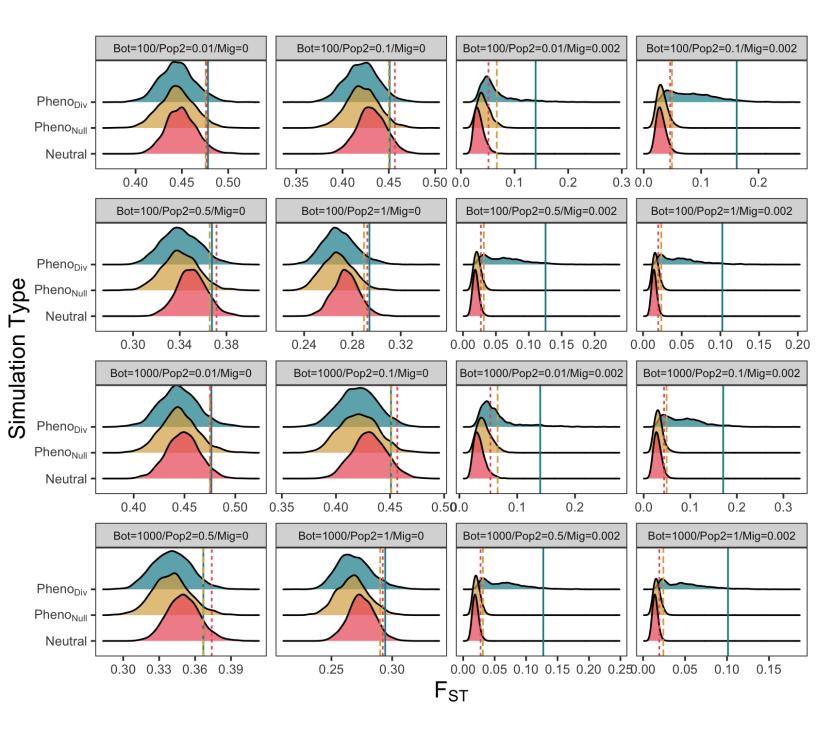
TABLE 3: LMM RESULTS FOR MODELS OF MEASURES OF DIVERGENCE EXPLAINED BY FEATURES OF SIMULATED REGIONS. FOR ALL MODELS, RANDOM VARIABLES INCLUDED GENE ID AND DEMOGRAPHIC TREATMENT.

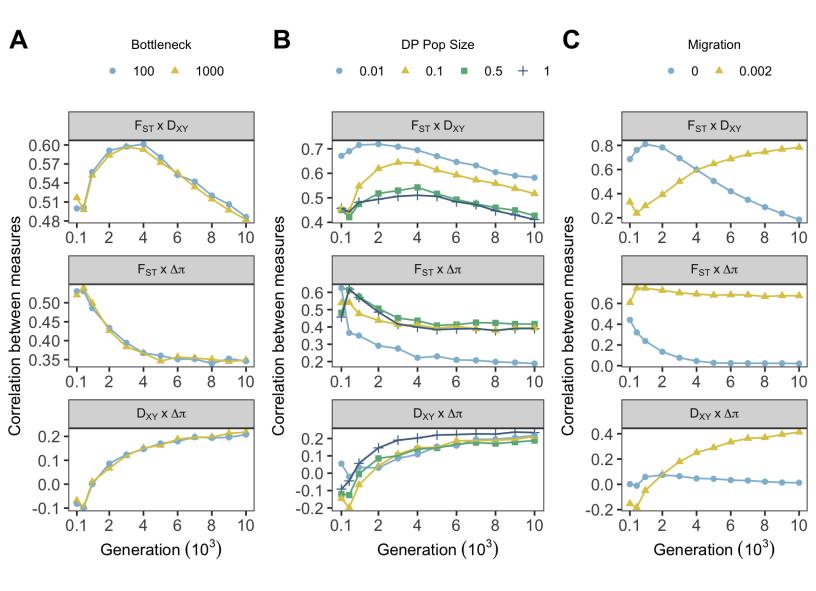












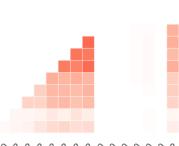
$F_{ST} + D_{XY}$

1

Bot=100/Pop2=0.1/Mig=0 Bot=100/Pop2=0.5/Mig=0 Bot=100/Pop2=0.01/Mig=0 Bot=1000/Pop2=0.01/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=1000/Pop2=0.5/Mig=0 Bot=1000/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.01/Mig=0.002 Bot=100/Pop2=0.01/Mig=0.002



 $F_{ST} + \Delta \pi$



Bot=1000/Pop2=0.1/Mig=0 Bot=100/Pop2=0.5/Mig=0 Bot=100/Pop2=0.5/Mig=0 Bot=100/Pop2=0.1/Mig=0 Bot=100/Pop2=0.01/Mig=0 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=1000/Pop2=0.5/Mig=0.002 Bot=1000/Pop2=0.1/Mig=0.002 Bot=100/Pop2=0.1/Mig=0.002 Bot=100/Pop2=0.1/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=1/Mig=0

Bot=1000/Pop2=0.1/Mig=0.002

Bot=1000/Pop2=0.5/Mig=0.002

Bot=100/Pop2=0.1/Mig=0.002

Bot=1000/Pop2=1/Mig=0.002

Bot=1000/Pop2=1/Mig=0

Bot=100/Pop2=0.1/Mig=0

Bot=1000/Pop2=0.1/Mig=0

Bot=1000/Pop2=0.5/Mig=0

Bot=100/Pop2=0.5/Mig=0

Bot=100/Pop2=1/Mig=0

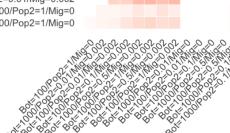
Bot=100/Pop2=0.01/Mig=0

Bot=1000/Pop2=0.01/Mig=0

Bot=100/Pop2=0.01/Mig=0.002

Bot=1000/Pop2=0.01/Mig=0.002

Bot=100/Pop2=1/Mig=0.002



$D_{XY} + \Delta \pi$

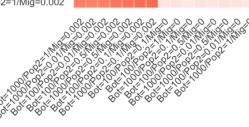


Bot=1000/Pop2=0.01/Mig=0 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=1000/Pop2=1/Mig=0.002 Bot=1000/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.1/Mig=0.002 Bot=1000/Pop2=0.01/Mig=0.002 Bot=1000/Pop2=0.01/Mig=0 Bot=1000/Pop2=0.5/Mig=0 Bot=1000/Pop2=0.5/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=1000/Pop2=0.1/Mig=0

$\mathsf{D}_{\mathsf{X}\mathsf{Y}}$

 F_{ST}

Bot=100/Pop2=0.01/Mig=0 Bot=1000/Pop2=0.5/Mig=0 Bot=1000/Pop2=0.01/Mig=0 Bot=1000/Pop2=0.5/Mig=0 Bot=1000/Pop2=0.1/Mig=0 Bot=100/Pop2=0.1/Mig=0.002 Bot=1000/Pop2=0.1/Mig=0.002 Bot=1000/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.01/Mig=0.002 Bot=1000/Pop2=0.01/Mig=0.002 Bot=1000/Pop2=1/Mig=0.002 Bot=1000/Pop2=1/Mig=0.002



Bot=1000/Pop2=0.01/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=1/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.5/Mig=0.002 Bot=100/Pop2=0.1/Mig=0 Bot=100/Pop2=0.1/Mig=0 Bot=100/Pop2=0.5/Mig=0 Bot=100/Pop2=0.5/Mig=0 Bot=100/Pop2=0.1/Mig=0 Bot=100/Pop2=0.01/Mig=0 Bot=100/Pop2=0.01/Mig=0 Bot=100/Pop2=0.01/Mig=0

