

Reproductive Barriers as a Byproduct of Gene Network Evolution

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Abstract Molecular analyses of closely related taxa have increasingly revealed the importance of higher-order genetic interactions in explaining the observed pattern of reproductive isolation between populations. Indeed, both empirical and theoretical studies have linked the process of speciation to complex genetic interactions. Gene Regulatory Networks (GRNs) capture the inter-dependencies of gene expression and encode information about an individual's phenotype and development at the molecular level. As a result, GRNs can—in principle—evolve via natural selection and play a role in non-selective, evolutionary forces. Here, we develop a network-based model, termed the pathway framework, that considers GRNs as a functional representation of coding sequences. We then simulated the dynamics of GRNs using a simple model that included natural selection, genetic drift, and sexual reproduction and found that reproductive barriers can develop rapidly between allopatric populations experiencing identical selection pressure. Further, we show that alleles involved in reproductive isolation can predate the allopatric separation of populations and that the number of interacting loci involved in genetic incompatibilities, i.e., the order, is often high simply as a by-product of the networked structure of GRNs. Finally, we discuss how results from the pathway framework are consistent with observed empirical patterns for genes putatively involved in post-zygotic isolation. Taken together, this study adds support for the central role of gene networks in speciation and in evolution more broadly.

Introduction

Over the past 100 years, the role of reproductive isolation due to genetic incompatibilities has received considerable attention in both the empirical and theoretical literature on speciation (*Rieseberg et al., 1996; Coyne and Allen Orr, 1998; Marques et al., 2019; Satokangas et al., 2020*). Through this work, it is widely accepted that divergent selection on *de novo* mutations in geographically isolated populations can facilitate speciation, as originally theorized by (*Bateson, 1909; Dobzhansky, 1936; Muller, 1942*). Despite well-established examples from *Drosophila* (*Brideau et al., 2006*), *Xiphophorus* (*Wittbrodt et al., 1989; Powell et al., 2020*), *Oryza* (*Yamamoto et al., 2010*), *Arabidopsis* (*Bikard et al., 2009*), and *Mus* (*Davies et al., 2016*), the genetics and evolutionary history of incompatibilities are typically far more complex and/or less well understood than what is suggested by classical models (*Noor and Feder, 2006; Lowry et al., 2008; Presgraves, 2010; Wolf et al., 2010; Nosil and Schluter, 2011; Seehausen et al., 2014; Marques et al., 2019; Dagilis and Matute, 2020*).

Post-zygotic, genetic isolation is thought to occur due to epistatic interaction between loci, where alleles arise and fix in allopatry prior to secondary contact, e.g., the Bateson-Dobzhansky-Muller

43 (BDM) model (*Bateson, 1909; Dobzhansky, 1936; Muller, 1942*). However, many incompatibilities
44 uncovered using high-throughput molecular analyses (*Castillo and Barbash, 2017; Kuzmin et al.,*
45 *2018; Vaid and Laitinen, 2019*) and quantitative trait locus (QTL) mapping (*Moyle and Nakazato,*
46 *2008; Turner et al., 2014; Chae et al., 2014; Lowry et al., 2015; Wang et al., 2015*), do not conform
47 to the processes assumed by the BDM model. In particular, in both natural populations and
48 model organisms, studies have found that reproductive barriers often exist between allopatric
49 populations experiencing similar selection pressures and that many of the alleles underlying genetic
50 incompatibility predate the allopatric separation of populations (*Schluter, 2009; Han et al., 2017;*
51 *Guerrero and Hahn, 2017; Marques et al., 2019; Jamie and Meier, 2020*). Both the lack of divergent
52 selection and the role of standing genetic variation are clear violations of the BDM model. As a
53 result, reconciling theoretical models of how and why genetic incompatibilities arise with empirical
54 data on the molecular genetics of post-zygotic, reproductive isolation is of profound importance
55 (*Marques et al., 2019; Satokangas et al., 2020*).

56 Analytical and computational models have proposed theoretical explanations for the observed
57 patterns of complex genetic interaction underlying post-zygotic isolation. A collection of models
58 considers *de-novo* mutations at the population level and the accompanying accumulation of hybrid
59 incompatibilities. For example, *Orr (1995)* predicted that the number of incompatibilities should
60 increase faster than linearly with the number of substitutions. The study by *Orr* also suggested
61 higher prevalence of complex genetic interactions than simple pairwise incompatibilities. This so-
62 called “snowballing” effect has been further extended by incorporating protein-protein interaction
63 and RNA folding (*Livingstone et al., 2012; Kalirad and Azevedo, 2017*). Similarly, *Barton (2001)*
64 demonstrated that stabilizing selection can generate hybrid incompatibility between allopatric
65 populations using a quantitative genetics models.

66 The substitution-based approaches, nevertheless, are often at odds with emerging data on the
67 evolutionary history of alleles involved in reproductive isolation (*Marques et al., 2019; Satokangas*
68 *et al., 2020*). In addition, many models make an implicit assumption that two allopatric lineages
69 only differ by fixed alleles, which does not capture the empirical diversity among individuals’
70 gene expression (*Kelly et al., 2017; Tyler et al., 2017; Gould et al., 2018; Mogil et al., 2018; Ryu*
71 *et al., 2019*) nor the observed importance of regulatory disruption and standing genetic variation in
72 generating reproductive isolation (*Hopkins and Rausher, 2011; Guerrero et al., 2016; Rougeux et al.,*
73 *2019; Morgan et al., 2020*). More importantly, substitutions originating from *de-novo* mutations
74 fail to explain the recent evidence that alleles underlying reproductive barriers often predate
75 speciation events and can evolve along parallel evolutionary trajectories (*Kaeuffer et al., 2012;*
76 *Sicard et al., 2015; Meier et al., 2017; Nelson and Cresko, 2018; Wang et al., 2019; Duranton et al.,*
77 *2019; Marques et al., 2019*).

78 Another class of computational approaches focuses on the regulation structure that is potentially
79 responsible for complex genetic interactions and resulting incompatibilities. Specifically, researchers
80 consider the evolution of gene regulatory networks (GRNs), which describe the inter-dependencies
81 between gene expression and encode information about both genotype and phenotype. First,
82 *Johnson and Porter (2000)* simulated a single linear regulatory pathway as a sequence of matching
83 functions for binding sites, which resulted in reduced hybrid fitness compared to non-epistatic
84 models. Next, *Palmer and Feldman (2009)* explored the developmental process where the expres-
85 sion of gene products was iteratively determined through the regulatory networks. Their model
86 demonstrated that, largely as a consequence of the diverse set of possible development pathways,
87 hybrid incompatibilities due to disrupted GRNs could evolve rapidly. More recently, *Schiffman and*
88 *Ralph (2018)* modeled gene networks as linear control systems and demonstrated that reproductive
89 isolation can be a consequence of parallel evolution of GRNs with equivalent mechanism. Lastly,
90 *Blanckaert et al. (2020)* showed the importance of higher-order interactions and cryptic epistasis
91 for the evolution of reproductive isolation in the presence of gene flow.

92 The implications from these GRN models are not mere outcomes of layering complexity onto
93 existing approaches. Instead, GRNs are a natural extension from lower-dimensional models due to

94 their close relationship with coding sequences. Ideally, and hypothetically given “omniscience” over
95 the genomes—including comprehension of every fundamental interaction between molecules—one
96 can reconstruct inter-dependencies among genes and obtain GRNs from a bottom-up approach.
97 Of course, this ambition is far from practical and even sounds like a fantasy. Yet, it shows that
98 GRNs are essentially a direct abstraction of the genome sequence. Furthermore, this abstraction is
99 central to the omnigenic perspective of complex traits (*Boyle et al., 2017*). GRNs therefore bridge
100 the gap between inheritance factors and physiological traits, whose dynamics over generations then
101 becomes a candidate for understanding the genetics of speciation due to genetic incompatibilities.
102 To investigate the role of complex genetic interactions in the speciation process, we develop
103 a network-science model for the evolution of GRNs which specifically focuses on the inherited
104 molecular pathways encoded in them. Our approach, termed the pathway framework, considers
105 GRNs as a functional representation of genotype-to-phenotype maps, where proteins are “nodes”
106 in the network and alleles of loci are “edges.” Using this framework, we show how a simple model,
107 which includes sexual reproduction, genetic drift, and natural selection, can drive a rapid increase
108 in reproductive isolation between allopatric populations from standing genetic variation under
109 identical selection pressure. Additionally, we find that genetic incompatibilities can frequently
110 involve many loci, i.e., be of higher order, simply as a by-product of GRN evolution. Finally, we
111 conclude the functional redundancy of GRNs is critical for the rapid emergence of reproductive
112 isolation during population divergence.

113 Results

114 The Pathway Framework: Networks as a Functional Representation of Genetic In- 115 teractions

116 Gene interactions networks are conventionally built such that genes are “nodes” and interactions
117 between genes are “edges” or links, for examples see *Tong et al. (2004)*; *Schlitt and Brazma (2007)*;
118 *Langfelder and Horvath (2008)*. Here, we propose an alternative methodology—termed the *pathway*
119 *framework*—for constructing gene interaction networks. The key idea of the pathway framework is
120 to conceptualize genes, or alleles of genes, as “black boxes” that encapsulate how their expression
121 is regulated. More precisely, the pathway framework transforms alleles of genes into directed
122 edges pointing from nodes that are activator/repressor molecules, e.g., transcription factors, and
123 nodes that represent gene products, e.g., proteins. In *Figure 1* we show how: a.) a gene is activated
124 by a transcription factor and generates a protein product (top-right), b.) two genes interact via
125 a transcription factor created by one gene that activates the other (middle-right), and c.) genes
126 can interact via shared transcription factors (bottom-right). As a result of its flexibility, arbitrarily
127 complex genetic interactions can be encoded as “pathways” through a gene interaction network.

128 Importantly, while our proposed representation is closely related to conventional gene interac-
129 tion networks (and a direct mapping between the two always exists when considering interactions
130 mediated by a single class of molecules, e.g., proteins), the pathway framework is often either a
131 more compact and/or informative representation. For example, anytime a gene is regulated by a
132 protein product from another gene, the conventional framework usually includes redundancy that
133 does not appear in the pathway framework, and the pathway framework will capture information
134 not present in the conventional construction, e.g., see Box 1. Because the computational complexity
135 of network analyses often scales non-linearly with the number of edges, switching to the pathway
136 framework can facilitate a more robust exploration of model space.

137 The pathway framework further highlights how phenotypes are a product of both genetics and
138 the environment (not all nodes in the pathway framework need be gene products). Concentrating on
139 the molecular basis of physiological traits, a phenotype can be thought of as the biochemical status
140 of a universal collection of nodes in the pathway framework, e.g., gene products such as proteins or
141 environmental stimuli. Therefore, under the pathway framework, the development of a phenotype
142 can be viewed as an iterative process of chemical signals propagating through woven pathways

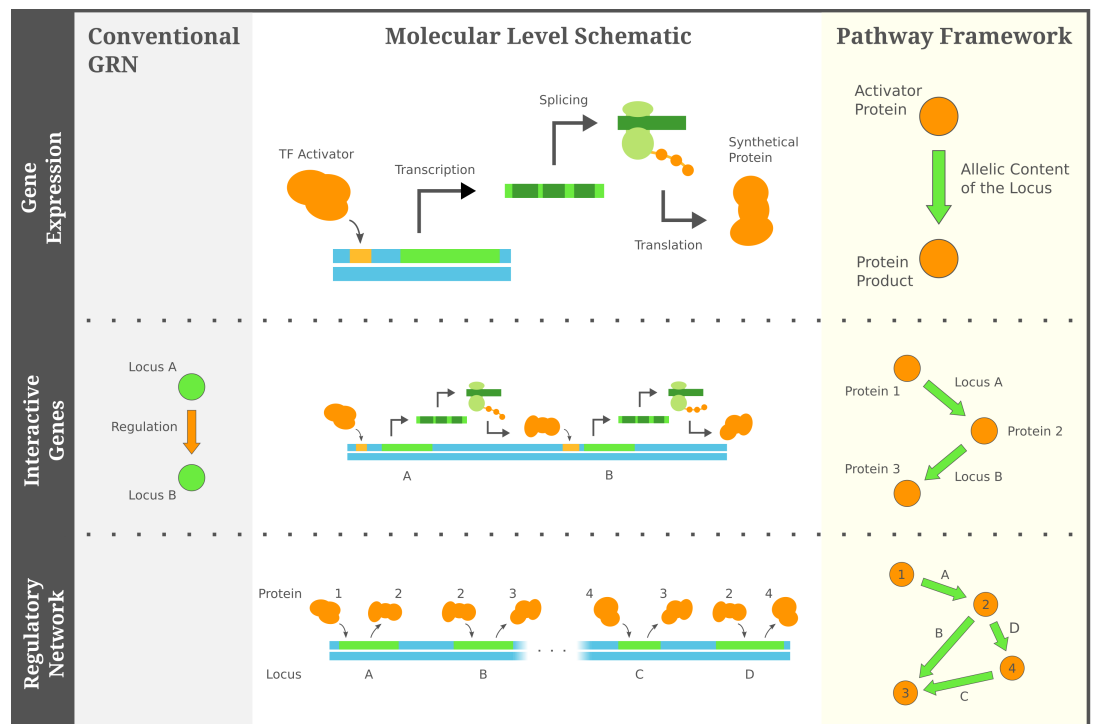


Figure 1. The pathway framework captures complex genetic interactions through consecutive regulatory pathways. In contrast to directly representing genetic interactions, the pathway framework abstracts the regulation and expression of genes as black boxes. If we consider the example of regulation by transcription factors, the pathway framework turns alleles of genes into edges between the transcription factors and the resulting protein products, and regulatory interactions between genes are encapsulated by consecutive pathways through the network.

143 built from groups of “inherited metabolisms” and external signals from the environment. As a result,
 144 the pathway framework can readily capture genetic, environment, and gene x environment effects
 145 in the same network.

160 Evolutionary Mechanisms under the Pathway Framework

161 Although in its most abstract state, the pathway framework can include nodes that are not proteins
 162 and also nodes that are not directly involved in gene regulation; here, we focus on the evolution
 163 of GRNs where all nodes are proteins directly involved in transcriptional regulation. To model and
 164 simulate the evolution of GRNs, this version of the pathway framework translates evolutionary
 165 mechanisms—such as mutation, independent assortment, recombination, and gene duplication—into
 166 graphical operations on the gene networks¹. Because mutation of a locus can potentially alter
 167 its protein product and/or the transcription factor binding region(s), we consider mutation as a
 168 rewiring process where the incoming and/or outgoing directed edges are re-directed to point from
 169 or to different nodes (**Figure 2**, top-right). Independent assortment during meiosis can be modeled
 170 via edge-mixing of parental GRNs such that an offspring acquires alleles, i.e., edges in the GRN, from
 171 both parents (**Figure 2**, bottom). Similar to mutation, recombination is an edge-rewiring process
 172 that is constrained to swapping binding sites or transcription factors at the same locus. Finally,
 173 gene duplication is equivalent to adding a parallel edge that represents the identical allelic content
 174 of a duplicated locus.

175 An individual's viability subjected to natural selection is a response to its molecular phenotypic
 176 status, which—under the pathway framework—can be modeled as a fitness function associated with

¹These graphical operations focus on edges in the GRNs, while the underlying node set is held constant because the nodes represent all *possibly existing* proteins in the organism.

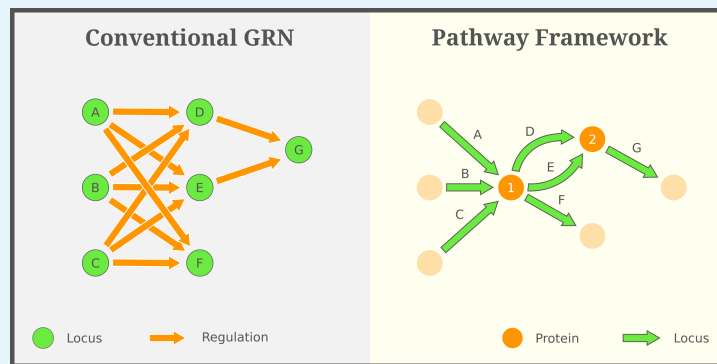
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Box 1. The pathway framework is often a more compact representation

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Because the pathway framework directly encodes the expression pattern of genes, it can contain more information than the “conventional” approach to constructing GRNs. When considering genetic interactions that are mediated by a single class of molecules, e.g., one gene being regulated by the protein product of another, the pathway framework takes advantages of this information and presents genetic interactions in a more compact format. Conversely, a conventional GRN lacks the specific regulatory context, and thus it has to present all pairs of interacting genes as individual edges, rather than summarizing these interactions by a smaller set of protein mediators. More technically, the pathway framework and a conventional GRN correspond to the first- and second-order de Bruijn graph (*De Bruijn, 1946*) respectively, where higher orders usually introduce redundant elements and additional computational complexity.

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the collective state of nodes and edges in the GRN. For example, one could study the time-varying concentration of each protein, attach a continuous dynamic or a stochastic reaction to every allele and define fitness as a function of the high-dimensional concentration vector, etc.. On the other extreme, we can consider Boolean networks, which have been shown to effectively capture many of the most relevant dynamical features of empirical regulatory systems (*Davidich and Bornholdt, 2008*). In this minimal scenario, each protein is assigned to a Boolean state (present or absent) and external environmental signals stimulate the existence of specific proteins in the organism. The logical states then cascade through the genetic pathways, where—given the presence of a gene’s transcription factor—loci activate and generates protein product(s). The phenotype of a GRN is thus the “reachability” from the environmental stimuli, whose binary survival is defined via a sharp fitness landscape over plausible collective Boolean states (*Figure 2*, top-left).

We adopt the Boolean-state assumption of GRNs because they readily shed light on the formation of hybrid incompatibilities. Hybrid incompatibilities are lethal combinations of alleles that were not prevalent or present in parental lineages, but are in hybrids. Moreover, the combination is minimal in the sense that the lack of any of its allelic elements will not lead to an inviable hybrid. In the pathway framework, suppose that binary viability only depends on a set of lethal proteins, i.e. an individual will not survive selection if any of those protein are present, a combination of alleles that includes a pathway from a environmental stimulus to a lethal protein makes the GRN inviable. If the alleles exactly comprise a simple path, which contains no cycles, they become a minimal combination and thus form an incompatibility. Additionally, The complexity of genetic interactions can be characterized by the number of alleles involved, which is called the order of hybrid incompatibility and related to the length of the simple pathway².

²Since for $n \geq 1$, $n + 1$ alleles form an n th-order incompatibility, the order of genetic interaction is then the path length minus one.

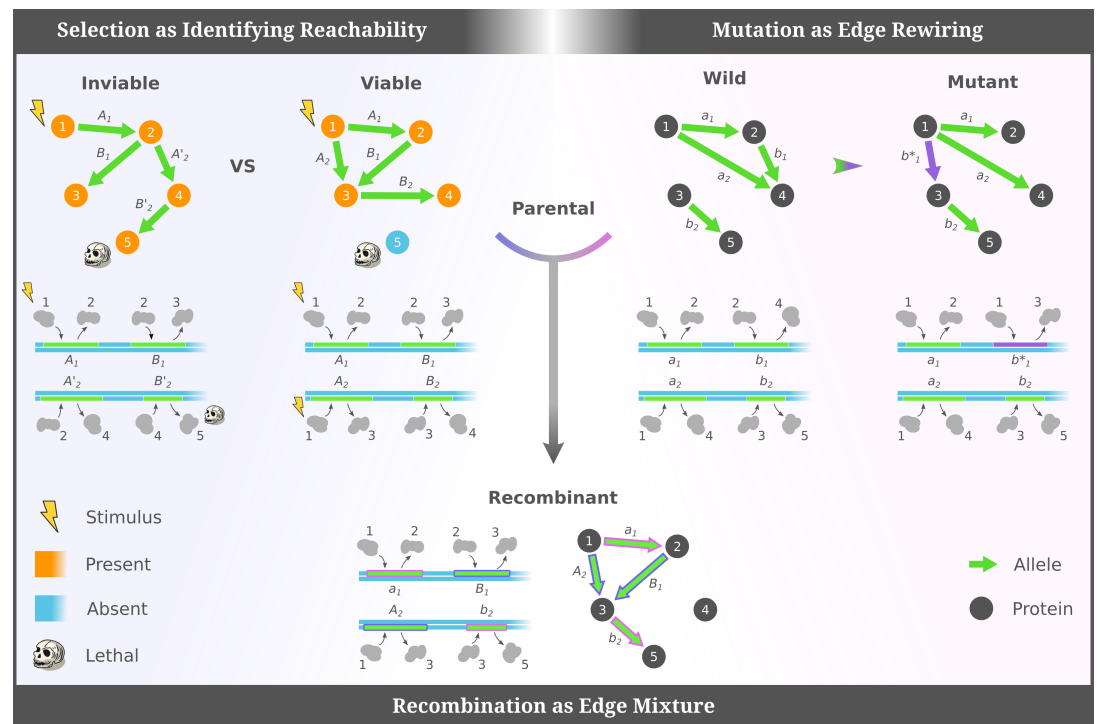


Figure 2. How the pathway framework turns evolutionary mechanisms into graphical operations on the GRNs. Since the pathway framework directly models the functionality of alleles of genes as edges, mutation, meiosis, and recombination can be modeled as edge-rewiring and edge-mixing, while a minimal selection scenario of binary fitness can be modeled as identifying “reachability” in a GRN.

199 Simulating the Evolution of GRNs

200 Briefly, we consider a Wright-Fisher model of evolution with natural selection, i.e., constant popula-
 201 tion size, no mutation, no migration, non-overlapping generations, and random mating. Selection
 202 occurs during the haploid stage of the life-cycle, where individuals that survive selection fuse
 203 randomly, i.e., create diploids, and undergo meiosis to generate the subsequent generation. Popu-
 204 lations are seeded such that each individual has a randomly generated GRN and evolve until a
 205 single GRN fixes in the population. Simulations are further detailed in the *Methods*.

206 **Figure 3a** shows the proportion of individuals in the population that survive natural selection.
 207 Initially, due to the variation of randomly seeded GRNs, the fraction of viable individuals differed
 208 substantially between simulations with different initial conditions. However, as the gene networks
 209 evolved, the population’s viability increased and quickly reached a state where every individual
 210 survived selection (dashed line). During this 100% survival stage, natural selection was no longer
 211 effective and the population evolved to fixation via genetic drift. Not surprisingly, our results
 212 demonstrate that GRNs can rapidly evolve from a heterogeneous population with low average
 213 viability to “match” an imposed selective regime or environment.

214 In addition to achieving 100% survival, populations always fixed a single GRN. **Figure 3b** plots
 215 the number of structurally-distinct GRNs in each generation. The decreasing trend demonstrates
 216 that, although various GRNs have equal survival probability, it becomes more and more likely that
 217 individuals shared a common GRN. Moreover, the populations always fixed a single GRN (dotted
 218 line) after a sufficiently long period of time. This phenomenon can be intuitively explained by
 219 the mechanism of sexual reproduction. In our model, parents with identical GRNs would lead to
 220 offspring of the same GRN, since any two corresponding groups of segregated alleles retrieved the
 221 parental gene network. Thus once there was a majority GRN in the population, it would have a
 222 higher chance of retaining its genetic configuration in the next generation, as compared to being

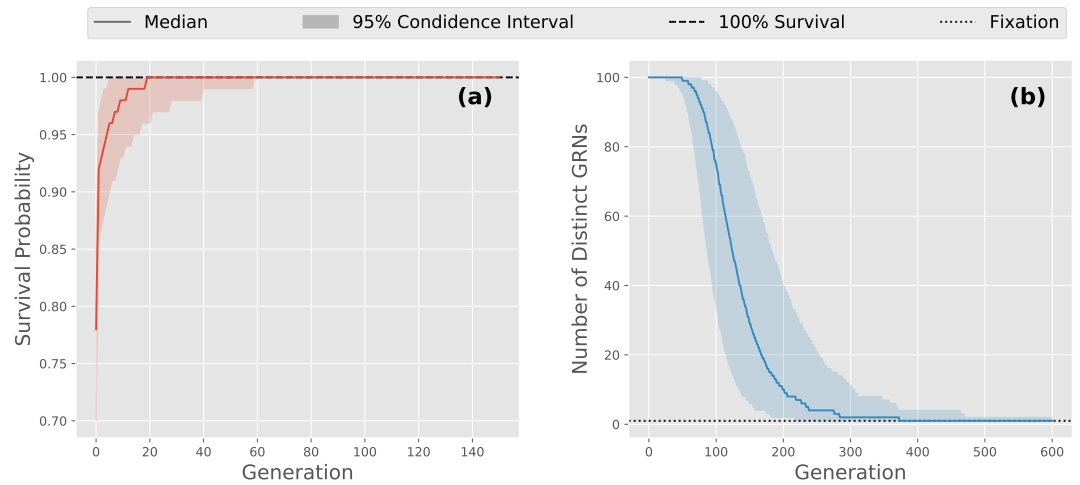


Figure 3. Populations adapt to the environment and then fix a single GRN. Here, we show for every generation of GRN evolution, across multiple allopatric populations with different initial conditions: **(a)** the survival probability of an individual and **(b)** the number distinct GRNs in each population, where two individuals' GRNs were deemed effectively identical if they were isomorphic. The average viability of each population increased over time and rapidly achieved 100% survival, which indicates that evolution of GRNs drove adaptation toward the imposed environment. We also observe decreased variation of GRNs as they evolved, with individuals in the same allopatric population, i.e., simulation run, eventually fixing for the same GRN.

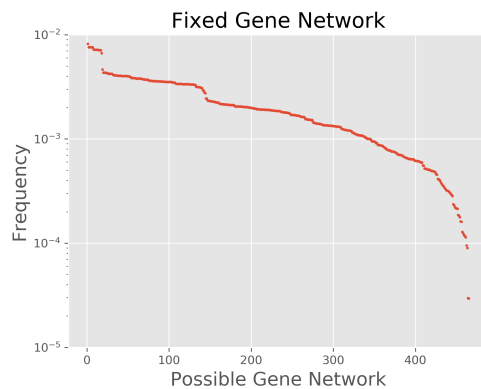


Figure 4. Fixation of parallel lineages resulted in a wide range of GRN structures. We simulated isolated populations from the same initial conditions until they reached fixation. In this case Setup 2 in Methods was applied in order to tractably enumerate all plausible GRN, and the ancestral populations were chosen such that the fixation was unbiased by the initial allele frequencies. The 10^7 acquired GRNs were categorized into 465 viable structures and the fixation frequency of each structure was plotted in a descending order. The distribution shows that isolated lineages fixed alternative gene networks, some among which were more favorable under our model of GRN evolution.

223 replaced by meiotically shuffled variants.

224 Lastly, to better understand how parallel lineages evolve, we consider a scenario where mul-
225 tiple allopatric populations are seeded with the *same* initial conditions. Similarly, each allopatric
226 population rapidly achieved 100% survival and then fixed a single GRN. However, across allopatric
227 populations seeded from the same initial conditions, many different GRNs fixed. **Figure 4** presents
228 the distribution of fixed GRNs for a smaller-scale simulation (Setup 2 in Methods). We see that the
229 fixed GRNs were diverse and non-uniformly distributed. Despite being under identical selection
230 forces and having the same initial condition, lineages evolving from a common ancestral population
231 fixed alternative GRNs. This result demonstrates that a broad range of GRNs can survive the given
232 selection pressure. Furthermore, none of the viable GRN structures had a zero fixation probability,
233 indicating a thorough exploration of evolution in the space of possible GRNs. That so many different
234 GRNs fixed suggests that evolution was less governed by a definite trajectory, but instead it occurs
235 via an uncertain realization among all the possibilities constrained by the ancestral population and
236 the selection pressure.

237 **Reproductive Barriers Arose Rapidly as Gene Networks Evolved**

238 If the survival probability and fitness of GRNs were identical, the distribution of fixed networks
239 should be uniform over all viable conformations. Because we observe a strongly non-uniform
240 distribution (see **Figure 4**), some other form of selection, i.e., as opposed to simply viability selection,
241 is likely operating on the GRNs. We note that during random mating, even between two parents
242 with viable GRNs, some of their shuffled offspring can be inviable. Coupled with the observation
243 that different allopatric populations, i.e., simulation runs, fix alternative GRNs from the same initial
244 conditions, we hypothesized that some degree of reproductive isolation may exist between these
245 fixed populations.

246 To test for the presence of reproductive isolation, we performed a “hybridization” experiment
247 between parallel lineages that had reached fixation. Starting with lineages branched from a
248 common ancestral population, two fixed lineages were randomly selected and interbred. Hybrids
249 were generated and the reproductive isolation metric (RI) between the parental populations was
250 computed (see **Methods**). By repeating this procedure, we obtained a distribution of reproductive
251 isolation, as demonstrated in **Figure 5a** inset. Despite a large fraction of crosses resulting in nearly
252 zero RI, we discovered pairs of lineages with positive reproductive isolation metric. Specifically,
253 the RI distribution displays several regions of positive reproductive isolation such that a high
254 percentage of hybrid offspring are inviable. Thus, we conclude that reproductive barriers between
255 fixed lineages, derived from the same initial population and experiencing identical selection, exist.

256 Given noticeable reproductive barriers between fixed lineages, we further studied when those
257 barriers first manifested during GRN evolution. Note that because our simulations did not contain
258 mutation, incompatibilities arise because of shuffling during meiosis. Here, instead of waiting until
259 GRN fixation, we instead evolve lineages for T generations and then cross them to generate hybrids
260 as described above. By varying T , a series of reproductive isolation distributions were acquired.
261 **Figure 5a** collects and displays them in a heat map. A vertical slice represents a RI distribution as
262 in the inset panel, but crosses were made after T generations rather than waiting for lineages to
263 reach fixation. We see that the regions of high incompatibility noted in **Figure 5a** inset becomes
264 bands in the heat map, which allows us to trace the emergence of reproductive barriers.

265 Initially the reproductive isolation distribution was relatively symmetric around zero. However,
266 As GRNs evolved, the range of RI broadened and its extreme value in the positive tail increased.
267 The trend towards higher levels of RI decelerated after 100 generations; it then stabilized and
268 formed a band structure, where crosses cluster around certain levels of reproductive isolation.
269 **Figure 5a** hence reflects that reproductive barriers existed at low levels as soon as the lineages
270 started evolving independently and peaked at a time prior to GRN fixation. By assumption, the
271 alleles underlying RI were present in the ancestral population, but we further conclude that RI
272 peaked well before fixation of GRNs.

273 Next, for incompatible hybrids generated in our crossing experiment, we determine how complex
274 the underlying mechanism of RI was. Specifically, **Figure 5b** shows how frequently an inviable hybrid
275 resulted from an incompatibility of a certain order. We see that hybrid incompatibilities spanned a
276 broad range of interaction orders. Importantly, the simple two-allele interaction was only slightly
277 more common than incompatibilities resulting from three or four interacting alleles and interactions
278 above fourth order made up almost 3% percent of all incompatibilities. However, we note that the
279 frequencies of incompatibility order varied depending on the ancestral population.

280 The pattern of complex genetic interactions provides insights on the distribution of reproductive
281 isolation. Based on the independent assortment mechanism in our model—and assuming that
282 multiple incompatibilities rarely occurred between two parental GRNs—we conclude that hybrid
283 incompatibilities quite often involved higher order interactions, which did not arise as a result
284 of selection, but simply were an expected consequence of GRNs being high order (**Appendix 1**).
285 Further, the discrete characteristic of hybrid incompatibilities led to a higher likelihood at certain
286 RI levels. The band structure in **Figure 5a** agrees with this prediction (**Appendix 1**), which suggests

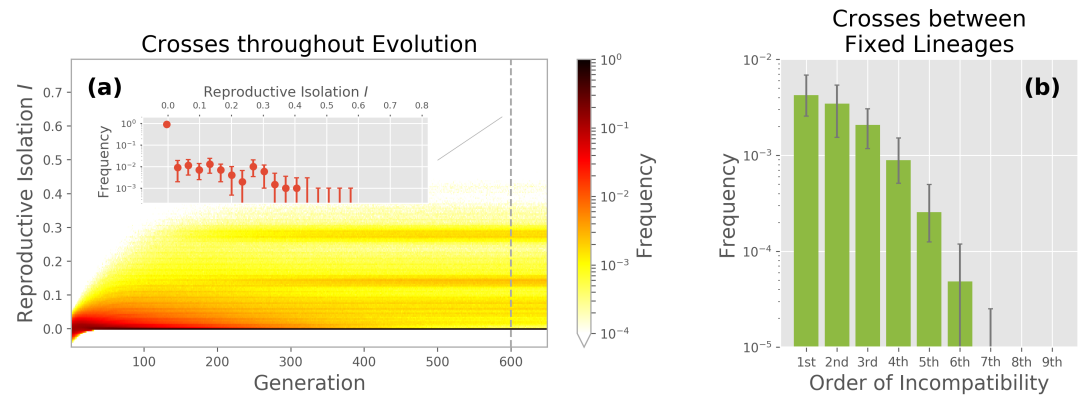


Figure 5. Reproductive barriers arose rapidly between allopatric populations. (a, Inset) Distribution of reproductive isolation between pairs of fixed lineages. A non-negligible fraction of crosses led to positive reproductive isolation, which reflects the occurrence of inviable hybrids and indicates reproductive barriers between fixed lineages. **(a)** We crossed allopatric populations at every generation during GRN evolution and stacked the RI distributions into a heat map. A vertical slice in this heat map represents the RI distribution at a given time, similar to the inset, but where the color shows the mean frequency for each bin. The growing level of positive RI indicates that reproductive barriers arose at the early stage of evolution. **(b)** Frequency that incompatibilities with various order were observed among hybrids between fixed lineages. We see that the order of incompatibilities included a broad range and that the simple pairwise interaction did not significantly dominate over more complex incompatibilities. Moreover, hybrid incompatibilities are consistent with the clustered level of RI and hence sheds light on the observed RI distribution (*Appendix 1*). In both the inset and panel (b), the plots show the statistic of the distribution among multiple groups of allopatric populations, specifically the median frequency and the 95% confidence interval.

287 that reproductive barriers are strongly influenced by the concealed hybrid incompatibilities and are
288 coupled with the genetic interaction pattern shown in *Figure 5b*.

289 **Early Divergence between Lineages was Critical for Reproductive Barriers to Emerge**

290 To further study the emergence of reproductive barriers in our model, we investigated the relative
291 importance of various evolutionary forces in generating the observed patterns of RI. In particular,
292 were the barriers attributed to selection pressure, random genetic drift, or both? We designed
293 two “control scenarios” that were based upon the previously simulated model, but contained
294 modifications to remove the effects of either selection or drift. Comparing the strength and pattern
295 of RI resulting from the two control scenarios, i.e., the removal of drift or selection, to the original
296 GRN dynamics, which contain both evolutionary forces, provides an assessment of the removed
297 component’s role in shaping the observed pattern of RI.

298 Removing the effect of natural selection is straightforward to simulate. In this control scenario,
299 populations simply evolve in a selectively neutral environment where all GRNs are viable. Thus, all
300 individuals survived and genetic drift became the only remaining evolutionary force. Of course,
301 this neutrality concurrently made the RI metric ill-defined. We avoided this issue in the crossing
302 experiments to calculate RI by placing the parental populations under the same non-neutral
303 environment in the original model, so the hybrids would be generated from survivors subjected to
304 selection pressure. The reproductive isolation metric could then be computed with respect to the
305 non-neutral environment. Placing the parental population through a round of viability selection
306 just prior to hybridization ensures comparability between the model and the “no selection” control
307 scenario since the survivability of hybrids was evaluated under the same environment and was not
308 biased by the otherwise inviable parents.

309 *Figure 6a* shows the contrast of barriers observed in the original GRN evolution model (red) and
310 in the scenario with no selection (blue). We traced a measure of reproductive isolation over time,
311 defined as the 99th percentile of the RI distribution, which is a sufficient indicator of reproductive

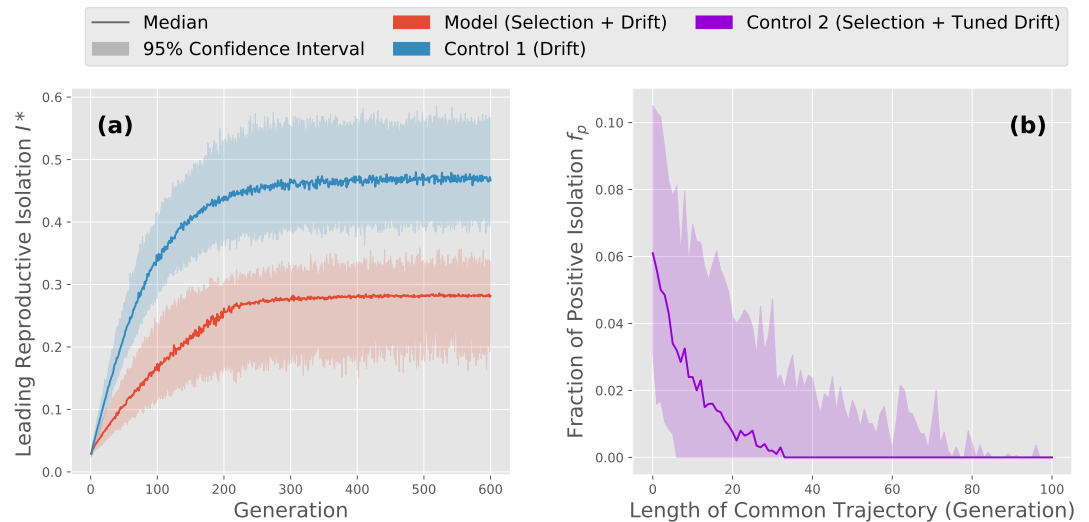


Figure 6. Early divergence of evolutionary trajectories between lineages was necessary for reproductive barriers to arise. Here we compare a statistic, termed leading reproductive isolation I^* (99th percentile of the RI distribution), measuring the degree of reproductive barrier in the original model and two designed control scenarios. Control scenarios were simulated with the same group of ancestral populations as the model, where lineages were then crossed to generate hybrids. **(a)** Leading reproductive isolation I^* among allopatric populations over time, where positive values indicate the existence of reproductive barriers. We plot the original model in red and the control scenario with a neutral environment in blue. The increasing and larger I^* uncovered in the control scenario implies that reproductive barriers were still observed when the selection forces were silenced. **(b)** Long-term fraction of positive RI f_p when the influence of random genetic drift was tuned. We simulated the evolution of lineages, but first confine them to a common trajectory of length L , which was realized by evolving a single population from the ancestors for L generations, and then simulated allopatric evolution from this now less diverse ancestral population. The original model corresponds to the case where $L = 0$, and for any positive L the effect of drift were lessened. We obtained the f_p metric when lineages evolved for 600 generations, where $f_p = 0$ suggests no barriers among populations. That f_p decreased with L to 0 shows that reducing the effect of drift diminished reproductive barriers. As a result, it implies the criticality of divergence among evolutionary trajectories for barriers to emerge.

312 barriers between lineages. We discovered that in both the model and the control scenario, the
 313 leading RI I^* increased and then saturated. Furthermore, the growth in I^* decelerated after a similar
 314 number of generations in both scenarios. That RI occurs at a higher level in the control experiment
 315 indicates that selection did not “cause” the fixation of barriers between allopatric populations,
 316 but instead suggests that selection was actually limiting chances for incompatibilities to occur
 317 in hybrids. We hypothesize that—although restricted as compared to drift—selection operating
 318 on incompatibilities likely induced the observed disconnect between viability and fitness seen in
 319 **Figure 4.**

320 We next turned to the contribution of genetic drift. This control scenario, however, was less
 321 straightforward due to technical difficulties associated with directly removing random genetic drift
 322 from the model. Neither abandoning sexual reproduction nor simulating an infinite population
 323 would result in non-trivial and/or computationally tractable GRN evolution. Alternatively, we
 324 designed a control scenario where the evolutionary influence of drift could be tuned and limited.
 325 Genetic drift results in stochasticity and causes populations to experience diverse trajectories. On
 326 the other side of the coin, if two lineages show similar evolutionary trajectories, one would say that
 327 drift effectively leads to less divergence between them. We restricted the influence of genetic drift
 328 by first confining lineages in a common trajectory for L generations, and then freed the populations
 329 and let them evolve independently, i.e., in allopatry. Varying the length of the common trajectory
 330 L tunes the overall similarity among lineages. Therefore, L quantitatively reflects the strength of
 331 genetic drift.

332 **Figure 6b** demonstrates the long-term fraction of positive reproductive isolation introduced
333 in Methods, termed f_p , as we varied the length of the common trajectory. Despite substantial
334 variation in f_p in the original model, which corresponds to the case where $L = 0$, a decline of
335 f_p was uncovered as early evolutionary confinement was extended. We discovered 50% of the
336 experiments showed a zero f_p after lineages were evolved together for 40 generations, and as the
337 length of common trajectory exceeded 80 generations positive reproductive isolation was hardly
338 found between lineages. More importantly, **Figure 6b** suggests that as the evolutionary influence of
339 genetic drift was mitigated, RI was weakened and eventually vanished. Namely, restricting early
340 divergence among populations due to genetic drift diminished reproductive barriers. This control
341 scenario consequently suggests that divergence between lineages, coupled with high diversity in
342 the ancestral population, is critical for reproductive barriers to arise.

343 **Intra-lineage Incompatibilities were Eliminated Stochastically While Inter-lineage** 344 **Incompatibilities Persisted and Led to Reproductive Barriers**

345 To better understand how reproductive barriers might be removed within a lineage, but persist
346 between lineages, we computed two quantities from the underlying genetic pool. First, the size
347 of the genetic pool, which determines how many possible genotypes a population contains. This
348 measure captures the potential genetic diversity in the population. Second, we count the number
349 potential incompatibilities in the underlying genetic pool, which are lethal allelic combinations
350 that could potentially be realized in the next generation. These incompatibilities compose the
351 source of inviable offspring and RI between allopatric populations. However, because even for
352 small GRNs searching for all possible incompatibilities quickly becomes computationally intractable,
353 we developed a novel algorithm (summarized in Methods) to compute their number in the genetic
354 pool.

355 Because our model does not contain mutation, one would expect the size of the underlying
356 genetic pool to decline in our simulated gene network evolution. Any allele in an individual was
357 inherited from its parents, and thus it must appear in the parental generation as well. Additionally,
358 a parental allele might not persist in the offspring for two possibilities: either it was not transmitted
359 because of finite population size of the progeny generation and the stochasticity during sexual
360 reproduction, i.e. drift, or it formed a lethal pathway along with other inherited alleles which made
361 the offspring inviable, i.e. selection.

362 **Figure 7a** demonstrates the size of genetic pool over time, where we compare simulations in the
363 original model (red) and in the control scenario without selection pressure, i.e., only genetic drift
364 will reduce the size of the genetic pool (blue). A rapid decline of genotypic diversity was witnessed
365 under both models. More intriguingly, little difference was found between the GRN evolution model
366 and the control scenario under a neutral environment. The two median curves nearly overlaps, and
367 for any given generation, the pool size in the original model was not significantly smaller than the
368 control counterpart. Therefore, we find additional support for our earlier finding that although both
369 natural selection and random genetic drift decreased genotypic diversity, drift was the dominant
370 driving force. However, while the effect of drift reduced diversity within a lineage, it increased the
371 divergence among lineages.

372 **Figure 7b** shows the number of potential incompatibilities within a lineage's underlying genetic
373 pool (orange). We found that the amount of incompatibilities embedded in a population also
374 decreased over time. This phenomenon is understood by the continual loss of allelic diversity,
375 since removing an allele from the underlying pool always restricts the possibilities to form a lethal
376 pathway in the GRN. Furthermore, the number of potential incompatibilities fell rapidly until no
377 potential incompatibilities remained. The elimination of potential incompatibilities illuminates how
378 a population adapted to the imposed environment when GRNs evolved, as shown in **Figure 3a**.
379 Random genetic drift drove the loss of a lineage's genotypic diversity, and along with the guidance of
380 selection, it eliminated probable lethal pathways in the genetic background. Once all the potential
381 incompatibilities were eliminated, no source of inviable offspring existed and consequently the

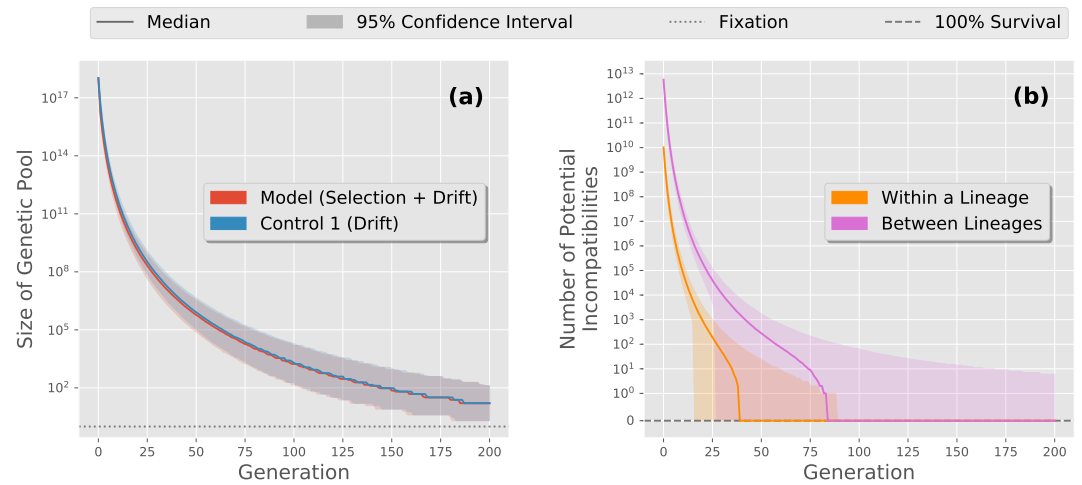


Figure 7. The underlying genetic pool lost alleles and eliminated potential incompatibilities within allopatric populations, whereas inter-lineage incompatibilities persisted. (a) Size of the underlying genetic pool for each generation, where we plot the original model in red along with the no selection control scenario in blue. Both cases show a similar reduction in the genetic pool. The similarity of these curves suggests that the continual losses of allelic diversity within a lineage was dominated by random genetic drift. **(b)** Number of potential intra-lineage (orange) and inter-lineage (pink) incompatibilities for each generation in the original model. We found that the number of potential incompatibilities also decreased as GRNs evolved, which is explained by the reduced allelic diversity in the genetic background. The vanishing intra-lineage incompatibilities implies disappearing sources of inviable hybrids, and it provides a mechanistic understanding of how a genotypically rich populations adapted to the imposed environment. Contrarily, the intra-lineage incompatibilities remained during GRN evolution. It was the persistent potential incompatibilities between allopatric populations that led to evident reproductive barriers.

Figure 7-Figure supplement 1. Inter-lineage incompatibilities were sustained throughout GRN evolution.

382 population reached 100% survival. Again, this result supports our earlier finding that natural
 383 selection was operating against incompatibilities within a lineage, but that drift was nevertheless
 384 the dominate force in structuring incompatibilities between lineages.

385 Finally, we investigated incompatibilities between underlying pools of lineages, which we call
 386 the “inter-lineage” incompatibilities, as compared to potential lethal allelic combinations within a
 387 population termed “intra-lineage” incompatibilities. **Figure 7b** presents the number of inter-lineage
 388 incompatibilities over generations (pink). We observed more incompatibilities between allopatric
 389 populations than those within a population, and similarly their amount dropped as allelic diversity
 390 decreased. In contrast, inter-lineage incompatibilities were removed at a slower pace compared
 391 to intra-lineage incompatibilities. The sustained confidence interval further suggests that some
 392 inter-lineage incompatibilities persisted, which was also the case after populations reached fixation
 393 (**Figure 7-Figure Supplement 1**). The persistence of these potential incompatibilities qualitatively
 394 explain the inviable hybrids revealed after GRN evolution. In spite of lineages adapting to the
 395 same imposed environment, hybridization can “resurrect” a lethal combination of alleles, which
 396 was eliminated in either lineages yet remained in their joint genetic background. This explanation
 397 also supports the stronger barriers uncovered in the neutrally evolving control in **Figure 6a**, since
 398 inter-lineage incompatibilities would be more persistent without the constant selection pressure
 399 (**Figure 7-Figure Supplement 1**).

400 Discussion

401 In this work, we develop a pathway-oriented construction of GRNs where alleles are represented
 402 as edges in a network. Termed the pathway framework, this model allows us to apply network
 403 science analyses to the study of speciation. Specifically, we simulate the evolutionary dynamics of
 404 GRNs under a model that includes natural selection, sexual reproduction, and genetic drift. Starting

405 from a diverse ancestral population, we show how reproductive isolation can arise rapidly between
406 allopatric populations experiencing identical selection pressure. Then, using a series of counter-
407 factual simulations, we disentangle the relative importance of each evolutionary force included
408 in our model and identify the central roles of high-dimensionality and functional redundancy,
409 even in comparatively small GRNs, for speciation. Finally, we show how higher-order genetic
410 incompatibilities can often evolve simply as a by-product of GRN evolution.

411 Our counter-factual simulations reveal that the observed reproductive barriers likely resulted
412 from divergent evolutionary trajectories and persistent, inter-lineage incompatibilities. Driven by
413 genetic drift and guided by selection, many GRNs that satisfied the same viability function were
414 sorted into parallel lineages, whereas mixing edges between them can lead to fatal pathways and
415 inviable offspring. These results highlight the importance of “functional redundancy” in evolution
416 (*Nowak et al., 1997; Láruson et al., 2020*) and agree with earlier studies that suggested alternative
417 regulatory structures can achieve the same phenotype (*True and Haag, 2001; Wagner and Wright,*
418 *2007; Schiffman and Ralph, 2018*). Indeed, both theoretical and empirical studies increasingly
419 support the role of parallel trajectories through fitness landscapes in evolution (*Elmer and Meyer,*
420 *2011; Bank et al., 2016; Ogbunugafor and Eppstein, 2016; Langerhans, 2018*).

421 More importantly, the pathway framework illustrates why degenerate genotypes can reach fix
422 through parallel evolution. Once the alleles are presented as functional pathways connecting an
423 underlying group of proteins, the conjunction between genetic factors and physiological traits is
424 no longer a bipartite mapping; the phenotype, as the collective chemical status of proteins, is a
425 convolution of active signals and external stimuli propagating on the network of genetic pathways.
426 The pathway configuration that satisfies a specific environmental input and phenotypic output is, as
427 a result, not unique. One can thus find numerous, functionally degenerate gene network structures
428 fulfilling the input-output viability relation, as *Figure 4* demonstrates. In addition, taking advantages
429 of basic network analyses, the pathway framework predicts that the number of GRNs generating
430 the same phenotype will increase more than exponentially as the system scales (*Appendix 2*).

431 The minimal model of GRN evolution we consider encapsulates selection through binary viability,
432 which is essentially a special case of holey adaptive landscapes (*Gavrilets, 1997*). *Gavrilets and*
433 *Gravner (1997)* introduced a multi-locus model where each genotype was independently assigned
434 to one of two fitness levels, whose results suggested that reproductive isolation can arise simply due
435 to the high dimensionality of the genotype space. In a similar vein, our model further connects the
436 high dimensionality of genotypes to complex genetic interactions. Under the pathway framework,
437 inviability originates via the mechanism of hybrid incompatibilities, i.e., allelic combinations that
438 form lethal pathways in a GRN. Furthermore, the pathway framework can be readily extended to
439 include alternative fitness landscapes. For example, *Barton (2001)* demonstrated that stabilizing
440 selection can generate reproductive isolation, and the pathway framework can be easily embedded
441 into such a continuous fitness landscape.

442 Our work supports the latent connection between speciation processes and ancestral genetic
443 variation. Ancient polymorphisms drive genomic divergence and confound inference of evolu-
444 tionary processes (*Guerrero and Hahn, 2017*). Additionally, these same polymorphisms and the
445 empirical evidence that incompatible alleles often far predate speciation events have recently been
446 consolidated into a “combinatorial” view of speciation (*Marques et al., 2019*). The combinatorial
447 mechanism proposes that, if there was a past admixture event or if standing genetic variation
448 persists, the reassembly of these old genetic variants can facilitate rapid speciation and adaptive
449 radiation. *Marques et al.* found that ancestral genetic variants that had undergone selection—and
450 thus are likely to be beneficial—often have higher allele frequency than *de-novo* mutations. Alter-
451 natively, we demonstrate that stochastic loss of accessible pathways resulted in the fixation of
452 incompatible GRNs due to their functional redundancy and high dimensionality. We also observed
453 that the emerging reproductive barriers required the ancestral variation to be greater than a critical
454 amount (*Appendix 3*). Our pathway framework hence adds theoretical support for the role of stable
455 polymorphisms in hybrid incompatibilities, as reviewed in *Cutter (2012)*. We therefore consider the

456 evolution of regulatory pathways as a parallel mechanism with which ancestral genetic variation
457 can facilitate the appearance of new species.

458 Recent evidence supports our findings that distributed regulatory networks are sources of
459 genetic incompatibilities between closely related taxa. For example, *Morgan et al. (2020)* identified
460 a number of disrupted gene expression modules in sub-fertile, hybrid mice and concluded that “hub”
461 genes in these modules played a central role in genetic incompatibility. Additionally, *Rougeux et al.*
462 *(2019)* showed how gene expression was disrupted in hybrids between benthic and limnetic species
463 pairs of Lake Whitefish, *Coregonus clupeaformis* and that genes underlying this disruption were
464 enriched for polymorphisms in the outgroup taxa, the European Whitefish, *Coregonus lavaretus*.
465 This pattern of gene network disruption and standing genetic variation is consistent with our
466 findings from the pathway model. Furthermore, *Guerrero et al. (2016, 2017)* found evidence for
467 the role of gene regulatory disruption and the presence of persistent antagonistic interactions in
468 speciation in *Solanum*. Lastly, *Stankowski et al. (2019)* found that genetic divergence arose rapidly
469 after population of monkeyflowers were isolated and that the evolution of regulatory-based genetic
470 incompatibilities may have been driven parallel selection pressure from a polymorphic ancestor
471 (*Stankowski et al., 2019; Jiggins, 2019*), again the mechanism identified in the pathway framework.

472 Our work is not without important caveats and there are many clear opportunities to advance
473 the pathway framework. First, our model did not include mutation, large-scale genome rearrange-
474 ments, nor whole genome duplication events, which are all known to be important for genetic
475 incompatibles and speciation (*Otto and Whitton, 2000; Noor et al., 2001; Kirkpatrick and Barton,*
476 *2006; Hoffmann and Rieseberg, 2008; Guerrero et al., 2012*). Although it is possible to draw some
477 preliminary conclusions regarding the effect of random mutations from our counter-factual sim-
478 ulation that “eliminated” genetic drift, we leave a fuller exploration of mutation for future work.
479 Second, despite the widely documented, asymmetric risk of hybrid breakdown in the heterogametic
480 sex, i.e., Haldanes rule (*Haldane, 1922; Coyne and Orr, 1997; Delph and Demuth, 2016*), our model
481 considers sexual selection with only a single sex of mating type. Third, both empirical results from
482 yeast (*Bernardes et al., 2017*) and from theoretical, population-genetic models (*Dagilis et al., 2019*)
483 point towards the importance of increased hybrid fitness, i.e., heterosis, even if only temporary,
484 during speciation (*Gavrilets, 2003*). Forth, there are studies that clearly demonstrate the importance
485 of divergent selection in the process of speciation, e.g., (*Nosil et al., 2002; Allender et al., 2003;*
486 *Gow et al., 2007*). However, the pathway framework can be readily modified to include divergent
487 selection and will almost certainly result in higher degrees of reproductive isolation. Finally, the
488 relative importance of post-zygotic, genetic incompatibilities in generating and/or maintaining
489 species remains an active area of investigation (*Servedio and Sætre, 2003; Rundle and Nosil, 2005;*
490 *Rieseberg and Willis, 2007; Magnuson-Ford and Otto, 2012; Hopkins, 2013; Seehausen et al., 2014*).

491 Our results support a growing body of literature on the theoretical importance of higher-order,
492 genetic interactions in the speciation process (*Johnson and Porter, 2000; Palmer and Feldman,*
493 *2009; Schiffman and Ralph, 2018; Blanckaert et al., 2020*) and are consistent with emerging em-
494 pirical data on genes involved in reproductive isolation (*Seehausen et al., 2014; Marques et al.,*
495 *2019*). We support calls for the increased use of high-fidelity simulation models in evolutionary
496 genetics (*Jiggins, 2019; Satokangas et al., 2020*), but stress the need for models with interpretable
497 mechanisms and that generate testable hypotheses. For example, our results on the evolution
498 of higher-order incompatibilities could serve as a null model for evaluating empirical data under
499 the relaxed assumption that genes function independently. Only by joining mathematical and
500 computational theory with comparative-level data can we uncover general patterns in speciation
501 and, potentially, resolve long-standing debates in the field.

502 Methods

503 Numerical Simulations

504 General Schema and Assumptions

505 In this work we simulated evolution GRNs in allopatric populations. Throughout evolution, we
506 assumed that individuals had a constant number of loci and thus a fixed number of edges in their
507 GRNs. The underlying set of nodes in GRNs also remained unchanged as we reasoned in *Results*.
508 We further introduced different categories of nodes/proteins to concrete the space of plausible
509 alleles. Some proteins were presumed to only be present with the environmental stimuli, which
510 were not products of any locus; on the other hand, some other proteins were presumed to have
511 mere physiological effects, and thus they were not capable of activating gene expression. We called
512 them source proteins and target proteins respectively. A plausible allele was therefore labeled
513 by a non-target protein that could activate its expression and a non-source protein that would be
514 synthesized. In our simulations we supposed only one source protein and one target protein.

515 We considered a naive model of GRN evolution incorporating natural selection, independent
516 assortment and random genetic drift. The environmental condition was set fixed over time and
517 across populations. We assumed that the environment stimulated presence of one protein and it
518 specified another protein with a lethal effect³. Viability of individuals was presumably equated to
519 the reciprocal binary state of the lethal protein. Hence given the current generation, individuals
520 were selected such that whoever did not possess a pathway from the environmental stimulus to
521 the lethal protein survived and were able to reproduce.

522 The survivors then randomly mated and formed the next generation with independent assort-
523 ment. Here we assumed individuals with haploid-dominant life cycles, where the multicellular
524 haploid stage is evident⁴. Supposed even segregation during meiosis of the diploid zygotes, we
525 modeled the process of independent assortment as follow. Two parental individuals were randomly
526 sampled from the survivors. The set of loci was first randomly partitioned into two groups of equal
527 sizes. The offspring inherited alleles of one group of loci from one of its parents and alleles of the
528 remaining loci from the other parent. Hence half of the edges in the offspring's GRN came from
529 one parent's GRN and the rest was acquired from the other. This procedure was repeated until the
530 next generation had the same constant population size as their predecessors.

531 Simulations and Parameter Setups

532 Here we summarize the two different parameter setups in our simulations:

533 **Setup 1:** We assumed 11 possibly existing proteins in the organism. A generation was composed of
534 100 individuals with 10 loci each. We generated 100 ancestral populations where individuals'
535 GRNs were randomly sampled from all plausible genotypes. For every ancestral population,
536 we in parallel ran 100 simulations from it, which were regarded as lineages evolving in isolated
537 geo-locations.

538 **Setup 2:** We assumed 5 possibly existing proteins in the organism. A generation was composed
539 of 16 individuals with 4 loci each. We generated 10^4 ancestral populations induced from a
540 genetic pool⁵ containing all plausible alleles for each locus. For every ancestral population, we
541 in parallel simulated 10^3 lineages from it.

542 The randomly generated ancestral populations encapsulate our assumption of ancestral genetic
543 variation, which reflect divergence of gene regulation that has been found in empirical studies
544 (*Gould et al., 2018*). Setup 2 aimed to examine how broadly, in terms of fixed GRNs, evolution can
545 explore in all possibilities. Thus it consisted of a larger amount of simulations starting with unbiased

³Specifically, they reconciled with the source and the target protein respectively.

⁴During reproduction, specialized haploid cells from two individuals combined and formed a diploid zygote. The zygote experienced meiosis and generated haploid spores, which then developed into multicellular-haploid-stage individuals through mitosis.

⁵We refer a population induced from a genetic pool to a sample among all possible populations that own the same underlying genetic pool.

546 ancestral populations that were induced from a maximal genetic pool. If not otherwise specified,
547 simulations shown in Results were run under Setup 1.

548 When we inspected reproductive barriers between allopatric populations by interbreeding them,
549 we first sampled 1000 pairs of lineages and then each generated F_1 1000 hybrids. The survival
550 probability of hybrids can then be obtained for all crosses. The same sampling procedure was also
551 applied when we computed the number inter-lineage potential incompatibilities between pairs of
552 allopatric populations.

553 **Metrics of Reproductive Isolation**

554 We introduce a quantitative measure of reproductive isolation between lineages which evolved
555 from a common ancestral population. Given a group of lineages and a chosen pair among them,
556 the reproductive isolation between the pair is defined as the relative difference of hybrid survival

$$I = \frac{p_c - p_h}{p_c} \quad (1)$$

557 where p_h is the survival probability of F_1 hybrids, and p_c denotes the average of survival probabilities
558 of all lineages' next generation. A positive value of reproductive isolation I implies that the hybrids
559 have less survivability than the expectation of the offspring. In the extreme case where no hybrid
560 lives, $I = 1$. It therefore serves as an indicator of reproductive barriers between two lineages.

561 Strengths of reproductive barriers among the group of lineages are described through a distribu-
562 tion of reproductive isolation, which can be obtained by sampling pairs of lineages and computing
563 their reproductive isolation I . We further introduce two indicators for the existence of reproductive
564 barriers. A quantity named leading reproductive isolation I^* is defined as the 99th percentile of the
565 reproductive isolation distribution. It signals that there is one percent of crosses with reproductive
566 isolation equal or larger than I^* . We would also like to raise a caveat that $I^* > 0$ is sufficient for the
567 existence of reproduction barriers but not a necessary condition, due to the possibility of positive
568 I in the distribution even if $I^* \leq 0$. The leading reproductive isolation metric hence summarizes
569 a high level of reproductive barriers that can be found among the lineages. On the other hand,
570 the fraction of positivity in the reproductive isolation distribution serves as a necessity indicator
571 for reproductive barriers, which we denote as f_p . The zero-value of f_p implies that none of the
572 crosses generate inviable hybrids more than the anticipation of the offspring and thus the absence
573 of reproductive barriers. Contrarily, a positive f_p does not satisfy existence of barriers considering
574 small reproductive isolation subject to noise. These two indicators are beneficial for us to identify
575 the responsible part of the model to the observed evolutionary consequences.

576 **Potential Incompatibilities within and between Genetic Pools**

577 An intra-lineage incompatibility is a group of alleles in its genetic pool, each of a unique locus, that
578 generates a lethal pathway. In our model those incompatibilities are the only source of inviability,
579 and hence the number of potential incompatibilities provides information about reproductive
580 barriers. Nevertheless, counting the number of potential incompatibilities within a genetic pool
581 through a brute-force manner is computationally intractable. Here we suggest a relatively efficient
582 algorithm when the total number of loci is small. Our strategy is to turn the task into solving a graph
583 problem. The genetic pool can be transformed to an edge-colored network where nodes once more
584 represent possibly existing proteins in the organism. The edges correspond to available alleles
585 in the pool, which are colored by their according loci. A potential incompatibility then becomes
586 a simple path from an environmental input signal to a lethal protein node, with an additional
587 constrain that no edges on the path have the same color. We call such a path an edge-colorful
588 simple path (ECSP).

589 The proposed algorithm, as demonstrated in **Appendix 4** Algorithm 1, counts the number of
590 ECSPs from the source nodes to the targets nodes by having agents propagate on the edge-colored
591 network iteratively. An agents is capable of keeping information of the trajectory, including its

592 current position on the network, the colors of edges it has traversed and the nodes that it has
593 visited⁶. Initially we deploy one agent on each source node. At every iteration, each agent is
594 substituted by all of its possible successors who are a hop away, such that the hop along with the
595 agent's memory obeys an edge-colorful simple path. Those successors can be deduced from the
596 agent's trajectory information as shown in **Appendix 4** Algorithm 2. The cautiously-designed rule of
597 agent propagation guarantees that the total number of agents locating on the target nodes at the
598 n th iteration equals to the number of the desired ECSPs of length n . Moreover, since the order of
599 an potential incompatibility is bounded above by the number of genes in the organism, iterations
600 as many as the amount of edge colors in the network are sufficient to obtain a computationally
601 feasible count of all potential incompatibilities. The efficiency of the algorithm can be further
602 improved by, instead of keeping track of numerous agents, monitoring the distribution of agent
603 states over iterations.

604 The same algorithm can be applied to count the number of inter-lineage incompatibilities
605 as well. In this case the underlying genetic pools of both lineages are transformed into a single
606 edge-colored network, whose edges then consist of alleles in the two pools and are again colored
607 by their according loci. A ECSP on this composite network either only traverses through edges
608 from one of the genetic pools, or it contains alleles from the two different pools. These two
609 scenarios correspond to a incompatibility within and between genetic pools respectively. Therefore,
610 by counting the number of ECSPs on the composite network, and subtracting by the number of
611 potential incompatibilities within the two genetic pools separately, we can compute the number of
612 incompatibilities between the two underlying genetic pools.

613 References

- 614 **Allender CJ**, Seehausen O, Knight ME, Turner GF, Maclean N. Divergent selection during speciation of Lake
615 Malawi cichlid fishes inferred from parallel radiations in nuptial coloration. *Proceedings of the National
616 Academy of Sciences*. 2003; 100(24):14074–14079.
- 617 **Bank C**, Matuszewski S, Hietpas RT, Jensen JD. On the (un) predictability of a large intragenic fitness landscape.
618 *Proceedings of the National Academy of Sciences*. 2016; 113(49):14085–14090.
- 619 **Barton NH**. The role of hybridization in evolution. *Molecular ecology*. 2001; 10(3):551–568.
- 620 **Bateson W**. Heredity and variation in modern lights. *Darwin and modern science*. 1909; .
- 621 **Bernardes J**, Stelkens R, Greig D. Heterosis in hybrids within and between yeast species. *Journal of evolutionary
622 biology*. 2017; 30(3):538–548.
- 623 **Bikard D**, Patel D, Le Mett e C, Giorgi V, Camilleri C, Bennett MJ, Loudet O. Divergent evolution of duplicate genes
624 leads to genetic incompatibilities within *A. thaliana*. *Science*. 2009; 323(5914):623–626.
- 625 **Blanckaert A**, Bank C, Hermisson J. The limits to parapatric speciation 3: Evolution of strong reproductive
626 isolation in presence of gene flow despite limited ecological differentiation. *bioRxiv*. 2020; .
- 627 **Boyle EA**, Li YI, Pritchard JK. An Expanded View of Complex Traits: From Polygenic to Omnigenic. *Cell*.
628 2017; 169(7):1177 – 1186. <http://www.sciencedirect.com/science/article/pii/S0092867417306293>, doi:
629 <https://doi.org/10.1016/j.cell.2017.05.038>.
- 630 **Brideau NJ**, Flores HA, Wang J, Maheshwari S, Wang X, Barbash DA. Two Dobzhansky-Muller genes interact to
631 cause hybrid lethality in *Drosophila*. *science*. 2006; 314(5803):1292–1295.
- 632 **Castillo DM**, Barbash DA. Moving speciation genetics forward: modern techniques build on foundational
633 studies in *Drosophila*. *Genetics*. 2017; 207(3):825–842.
- 634 **Chae E**, Bomblies K, Kim ST, Karelina D, Zaidem M, Ossowski S, Mart n-Pizarro C, Laitinen RE, Rowan
635 B, Tenenboim H, Lechner S, Demar M, Habring-M ller A, Lanz C, R tsch G, Weigel D. Species-wide
636 Genetic Incompatibility Analysis Identifies Immune Genes as Hot Spots of Deleterious Epistasis. *Cell*.
637 2014; 159(6):1341 – 1351. <http://www.sciencedirect.com/science/article/pii/S0092867414013762>, doi:
638 <https://doi.org/10.1016/j.cell.2014.10.049>.

⁶In Algorithm 1, the NEW-AGENT procedure creates an agent instance given its position, visited colors and nodes accordingly. This trajectory information is also accessible fields of the agent instance.

- 639 **Coyne JA**, Allen Orr H. The evolutionary genetics of speciation. *Philosophical Transactions of the Royal Society*
640 *of London Series B: Biological Sciences*. 1998; 353(1366):287–305.
- 641 **Coyne JA**, Orr HA. “Patterns of speciation in *Drosophila*” revisited. *Evolution*. 1997; 51(1):295–303.
- 642 **Cutter AD**. The polymorphic prelude to Bateson–Dobzhansky–Muller incompatibilities. *Trends in ecology &*
643 *evolution*. 2012; 27(4):209–218.
- 644 **Dagilis AJ**, Kirkpatrick M, Bolnick DI. The evolution of hybrid fitness during speciation. *PLoS genetics*. 2019;
645 15(5).
- 646 **Dagilis AJ**, Matute DR. Incompatibilities between emerging species. *Science*. 2020; 368(6492):710–711.
- 647 **Davidich M**, Bornholdt S. The transition from differential equations to Boolean networks: A case study in
648 simplifying a regulatory network model. *Journal of Theoretical Biology*. 2008; 255(3):269 – 277. <http://www.sciencedirect.com/science/article/pii/S0022519308003652>, doi: <https://doi.org/10.1016/j.jtbi.2008.07.020>.
- 649
- 650 **Davies B**, Hatton E, Altemose N, Hussin JG, Pratto F, Zhang G, Hinch AG, Moralli D, Biggs D, Diaz R, et al.
651 Re-engineering the zinc fingers of PRDM9 reverses hybrid sterility in mice. *Nature*. 2016; 530(7589):171–176.
- 652 **De Bruijn NG**. A combinatorial problem. In: *Proc. Koninklijke Nederlandse Academie van Wetenschappen*, vol. 49;
653 1946. p. 758–764.
- 654 **Delph LF**, Demuth JP. Haldane’s rule: genetic bases and their empirical support. *Journal of Heredity*. 2016;
655 107(5):383–391.
- 656 **Dobzhansky T**. Studies on hybrid sterility. II. Localization of sterility factors in *Drosophila pseudoobscura*
657 hybrids. *Genetics*. 1936; 21(2):113.
- 658 **Duranton M**, Allal F, Valière S, Bouchez O, Bonhomme F, Gagnaire PA. The contribution of ancient admixture to
659 reproductive isolation between European sea bass lineages. *BioRxiv*. 2019; p. 641829.
- 660 **Elmer KR**, Meyer A. Adaptation in the age of ecological genomics: insights from parallelism and convergence.
661 *Trends in ecology & evolution*. 2011; 26(6):298–306.
- 662 **Gavrilets S**. Evolution and speciation on holey adaptive landscapes. *Trends in ecology & evolution*. 1997;
663 12(8):307–312.
- 664 **Gavrilets S**. Perspective: models of speciation: what have we learned in 40 years? *Evolution*. 2003; 57(10):2197–
665 2215.
- 666 **Gavrilets S**, Gravner J. Percolation on the fitness hypercube and the evolution of reproductive isolation. *Journal*
667 *of theoretical biology*. 1997; 184(1):51–64.
- 668 **Gould BA**, Chen Y, Lowry DB. Gene regulatory divergence between locally adapted ecotypes in their native
669 habitats. *Molecular Ecology*. 2018; 0(0). <https://onlinelibrary.wiley.com/doi/abs/10.1111/mec.14852>, doi:
670 [10.1111/mec.14852](https://doi.org/10.1111/mec.14852).
- 671 **Gow JL**, Peichel CL, Taylor EB. Ecological selection against hybrids in natural populations of sympatric threespine
672 sticklebacks. *Journal of evolutionary biology*. 2007; 20(6):2173–2180.
- 673 **Guerrero RF**, Hahn MW. Speciation as a sieve for ancestral polymorphism. *Molecular Ecology*. 2017; 26(20):5362–
674 5368.
- 675 **Guerrero RF**, Muir CD, Josway S, Moyle LC. Pervasive antagonistic interactions among hybrid incompatibility
676 loci. *PLoS genetics*. 2017; 13(6):e1006817.
- 677 **Guerrero RF**, Posto AL, Moyle LC, Hahn MW. Genome-wide patterns of regulatory divergence revealed by
678 introgression lines. *Evolution*. 2016; 70(3):696–706.
- 679 **Guerrero RF**, Rousset F, Kirkpatrick M. Coalescent patterns for chromosomal inversions in divergent populations.
680 *Philosophical Transactions of the Royal Society B: Biological Sciences*. 2012; 367(1587):430–438.
- 681 **Haldane J**. Sex ratio and unisexual sterility in hybrid animals. *Journal of genetics*. 1922; 12(2):101–109.
- 682 **Han F**, Lamichhaney S, Grant BR, Grant PR, Andersson L, Webster MT. Gene flow, ancient polymorphism, and
683 ecological adaptation shape the genomic landscape of divergence among Darwin’s finches. *Genome research*.
684 2017; 27(6):1004–1015.

- 685 **Hoffmann AA**, Rieseberg LH. Revisiting the impact of inversions in evolution: from population genetic markers
686 to drivers of adaptive shifts and speciation? *Annual review of ecology, evolution, and systematics*. 2008;
687 39:21–42.
- 688 **Hopkins R**. Reinforcement in plants. *New Phytologist*. 2013; 197(4):1095–1103.
- 689 **Hopkins R**, Rausher MD. Identification of two genes causing reinforcement in the Texas wildflower *Phlox*
690 *drummondii*. *Nature*. 2011; 469(7330):411–414.
- 691 **Jamie GA**, Meier JI. The Persistence of Polymorphisms across Species Radiations. *Trends in Ecology & Evolution*.
692 2020; .
- 693 **Jiggins CD**. Can genomics shed light on the origin of species? *PLoS biology*. 2019; 17(8):e3000394.
- 694 **Johnson NA**, Porter AH. Rapid speciation via parallel, directional selection on regulatory genetic pathways.
695 *Journal of Theoretical Biology*. 2000; 205(4):527–542.
- 696 **Kaeuffer R**, Peichel CL, Bolnick DI, Hendry AP. Parallel and nonparallel aspects of ecological, phenotypic, and
697 genetic divergence across replicate population pairs of lake and stream stickleback. *Evolution: International*
698 *Journal of Organic Evolution*. 2012; 66(2):402–418.
- 699 **Kalirad A**, Azevedo RBR. Spiraling Complexity: A Test of the Snowball Effect in a Computational Model of RNA
700 Folding. *Genetics*. 2017; 206(1):377–388. <http://www.genetics.org/content/206/1/377>, doi: [10.1534/genetics.116.196030](https://doi.org/10.1534/genetics.116.196030).
- 702 **Kelly DE**, Hansen ME, Tishkoff SA. Global variation in gene expression and the value of diverse sampling.
703 *Current opinion in systems biology*. 2017; 1:102–108.
- 704 **Kirkpatrick M**, Barton N. Chromosome inversions, local adaptation and speciation. *Genetics*. 2006; 173(1):419–
705 434.
- 706 **Kuzmin E**, VanderSluis B, Wang W, Tan G, Deshpande R, Chen Y, Usaj M, Balint A, Mattiazzi Usaj M, van Leeuwen
707 J, Koch EN, Pons C, Dagilis AJ, Pryszyk M, Wang JZY, Hanchard J, Riggi M, Xu K, Heydari H, San Luis BJ, et al.
708 Systematic analysis of complex genetic interactions. *Science*. 2018; 360(6386). [http://science.sciencemag.org/](http://science.sciencemag.org/content/360/6386/eaao1729)
709 [content/360/6386/eaao1729](http://science.sciencemag.org/content/360/6386/eaao1729), doi: [10.1126/science.aao1729](https://doi.org/10.1126/science.aao1729).
- 710 **Langerhans RB**. Predictability and parallelism of multitrait adaptation. *Journal of Heredity*. 2018; 109(1):59–70.
- 711 **Langfelder P**, Horvath S. WGCNA: an R package for weighted correlation network analysis. *BMC bioinformatics*.
712 2008; 9(1):559.
- 713 **Láruson ÁJ**, Yeaman S, Lotterhos KE. The Importance of Genetic Redundancy in Evolution. *Trends in Ecology &*
714 *Evolution*. 2020; .
- 715 **Livingstone K**, Olofsson P, Cochran G, Dagilis A, MacPherson K, Seitz KA. A stochastic model for the development
716 of Bateson–Dobzhansky–Muller incompatibilities that incorporates protein interaction networks. *Mathematical*
717 *Biosciences*. 2012; 238(1):49 – 53. <http://www.sciencedirect.com/science/article/pii/S0025556412000491>,
718 doi: <https://doi.org/10.1016/j.mbs.2012.03.006>.
- 719 **Lowry DB**, Hernandez K, Taylor SH, Meyer E, Logan TL, Barry KW, Chapman JA, Rokhsar DS, Schmutz J, Juenger TE.
720 The genetics of divergence and reproductive isolation between ecotypes of *Panicum hallii*. *New Phytologist*.
721 2015; 205(1):402–414.
- 722 **Lowry DB**, Modliszewski JL, Wright KM, Wu CA, Willis JH. The strength and genetic basis of reproductive isolating
723 barriers in flowering plants. *Philosophical Transactions of the Royal Society B: Biological Sciences*. 2008;
724 363(1506):3009–3021.
- 725 **Magnuson-Ford K**, Otto SP. Linking the investigations of character evolution and species diversification. *The*
726 *American Naturalist*. 2012; 180(2):225–245.
- 727 **Marques DA**, Meier JI, Seehausen O. A combinatorial view on speciation and adaptive radiation. *Trends in*
728 *ecology & evolution*. 2019; .
- 729 **Meier JI**, Marques DA, Mwaiko S, Wagner CE, Excoffier L, Seehausen O. Ancient hybridization fuels rapid cichlid
730 fish adaptive radiations. *Nature communications*. 2017; 8:14363.
- 731 **Mogil LS**, Andaleon A, Badalamenti A, Dickinson SP, Guo X, Rotter JI, Johnson WC, Im HK, Liu Y, Wheeler HE. Ge-
732 netic architecture of gene expression traits across diverse populations. *PLoS genetics*. 2018; 14(8):e1007586.

- 733 **Morgan K**, Harr B, White MA, Payseur BA, Turner LM. Disrupted gene networks in subfertile hybrid house mice.
734 *Molecular biology and evolution*. 2020; 37(6):1547–1562.
- 735 **Moyle LC**, Nakazato T. Comparative genetics of hybrid incompatibility: sterility in two *Solanum* species crosses.
736 *Genetics*. 2008; 179(3):1437–1453.
- 737 **Muller H**. Isolating mechanisms, evolution, and temperature. In: *Biol. Symp.*, vol. 6; 1942. p. 71–125.
- 738 **Nelson TC**, Cresko WA. Ancient genomic variation underlies repeated ecological adaptation in young stickleback
739 populations. *Evolution Letters*. 2018; 2(1):9–21.
- 740 **Noor MA**, Feder JL. Speciation genetics: evolving approaches. *Nature Reviews Genetics*. 2006; 7(11):851–861.
- 741 **Noor MA**, Grams KL, Bertucci LA, Reiland J. Chromosomal inversions and the reproductive isolation of species.
742 *Proceedings of the National Academy of Sciences*. 2001; 98(21):12084–12088.
- 743 **Nosil P**, Crespi BJ, Sandoval CP. Host-plant adaptation drives the parallel evolution of reproductive isolation.
744 *Nature*. 2002; 417(6887):440–443.
- 745 **Nosil P**, Schluter D. The genes underlying the process of speciation. *Trends in ecology & evolution*. 2011;
746 26(4):160–167.
- 747 **Nowak MA**, Boerlijst MC, Cooke J, Smith JM. Evolution of genetic redundancy. *Nature*. 1997; 388(6638):167–171.
- 748 **Ogbunugafor CB**, Eppstein MJ. Competition along trajectories governs adaptation rates towards antimicrobial
749 resistance. *Nature ecology & evolution*. 2016; 1(1):1–8.
- 750 **Orr HA**. The population genetics of speciation: the evolution of hybrid incompatibilities. *Genetics*. 1995;
751 139(4):1805–1813. <http://www.genetics.org/content/139/4/1805>.
- 752 **Otto SP**, Whitton J. Polyploid incidence and evolution. *Annual review of genetics*. 2000; 34(1):401–437.
- 753 **Palmer ME**, Feldman MW. DYNAMICS OF HYBRID INCOMPATIBILITY IN GENE NETWORKS IN A CONSTANT
754 ENVIRONMENT. *Evolution*. 2009; 63(2):418–431. <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1558-5646.2008.00577.x>,
755 <https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1558-5646.2008.00577.x>, doi: 10.1111/j.1558-5646.2008.00577.x.
- 756 **Powell DL**, García-Olazábal M, Keegan M, Reilly P, Du K, Díaz-Loyo AP, Banerjee S, Blakkan D, Reich D, Andolfatto
757 P, et al. Natural hybridization reveals incompatible alleles that cause melanoma in swordtail fish. *Science*.
758 2020; 368(6492):731–736.
- 759 **Presgraves DC**. The molecular evolutionary basis of species formation. *Nature Reviews Genetics*. 2010;
760 11(3):175–180.
- 761 **Rieseberg LH**, Sinervo B, Linder CR, Ungerer MC, Arias DM. Role of gene interactions in hybrid speciation:
762 evidence from ancient and experimental hybrids. *Science*. 1996; 272(5262):741–745.
- 763 **Rieseberg LH**, Willis JH. Plant speciation. *science*. 2007; 317(5840):910–914.
- 764 **Rougeux C**, Gagnaire PA, Praebel K, Seehausen O, Bernatchez L. Polygenic selection drives the evolution of
765 convergent transcriptomic landscapes across continents within a Nearctic sister species complex. *Molecular*
766 *ecology*. 2019; 28(19):4388–4403.
- 767 **Rundle HD**, Nosil P. Ecological speciation. *Ecology letters*. 2005; 8(3):336–352.
- 768 **Ryu KH**, Huang L, Kang HM, Schiefelbein J. Single-cell RNA sequencing resolves molecular relationships among
769 individual plant cells. *Plant physiology*. 2019; 179(4):1444–1456.
- 770 **Satokangas I**, Martin S, Helanterä H, Saramäki J, Kulmuni J. Multi-locus interactions and the build-up of
771 reproductive isolation. *arXiv preprint arXiv:200513790*. 2020; .
- 772 **Schiffman JS**, Ralph PL. System drift and speciation. *bioRxiv*. 2018; [https://www.biorxiv.org/content/early/2018/](https://www.biorxiv.org/content/early/2018/01/26/231209)
773 [01/26/231209](https://www.biorxiv.org/content/early/2018/01/26/231209), doi: 10.1101/231209.
- 774 **Schlitt T**, Brazma A. Current approaches to gene regulatory network modelling. *BMC bioinformatics*. 2007;
775 8(S6):S9.
- 776 **Schluter D**. Evidence for Ecological Speciation and Its Alternative. *Science*. 2009; 323(5915):737–741. [http://](http://science.sciencemag.org/content/323/5915/737)
777 science.sciencemag.org/content/323/5915/737, doi: 10.1126/science.1160006.

- 778 **Seehausen O**, Butlin RK, Keller I, Wagner CE, Boughman JW, Hohenlohe PA, Peichel CL, Saetre GP, Bank C,
779 Brännström Å, et al. Genomics and the origin of species. *Nature Reviews Genetics*. 2014; 15(3):176–192.
- 780 **Servedio MR**, Sætre GP. Speciation as a positive feedback loop between postzygotic and prezygotic barriers to
781 gene flow. *Proceedings of the Royal Society of London Series B: Biological Sciences*. 2003; 270(1523):1473–
782 1479.
- 783 **Sicard A**, Kappel C, Josephs EB, Lee YW, Marona C, Stinchcombe JR, Wright SI, Lenhard M. Divergent sorting of
784 a balanced ancestral polymorphism underlies the establishment of gene-flow barriers in *Capsella*. *Nature*
785 *communications*. 2015; 6:7960.
- 786 **Stankowski S**, Chase MA, Fuiten AM, Rodrigues MF, Ralph PL, Streisfeld MA. Widespread selection and gene
787 flow shape the genomic landscape during a radiation of monkeyflowers. *PLoS biology*. 2019; 17(7):e3000391.
- 788 **Tong AHY**, Lesage G, Bader GD, Ding H, Xu H, Xin X, Young J, Berriz GF, Brost RL, Chang M, et al. Global mapping
789 of the yeast genetic interaction network. *science*. 2004; 303(5659):808–813.
- 790 **True JR**, Haag ES. Developmental system drift and flexibility in evolutionary trajectories. *Evolution & develop-*
791 *ment*. 2001; 3(2):109–119.
- 792 **Turner LM**, White MA, Tautz D, Payseur BA. Genomic Networks of Hybrid Sterility. *PLOS Genetics*. 2014 02;
793 10(2):1–23. <https://doi.org/10.1371/journal.pgen.1004162>, doi: 10.1371/journal.pgen.1004162.
- 794 **Tyler AL**, Ji B, Gatti DM, Munger SC, Churchill GA, Svenson KL, Carter GW. Epistatic networks jointly influence
795 phenotypes related to metabolic disease and gene expression in diversity outbred mice. *Genetics*. 2017;
796 206(2):621–639.
- 797 **Vaid N**, Laitinen RA. Diverse paths to hybrid incompatibility in *Arabidopsis*. *The Plant Journal*. 2019; 97(1):199–
798 213.
- 799 **Wagner A**, Wright J. Alternative routes and mutational robustness in complex regulatory networks. *Biosystems*.
800 2007; 88(1-2):163–172.
- 801 **Wang B**, Mojica JP, Perera N, Lee CR, Lovell JT, Sharma A, Adam C, Lipzen A, Barry K, Rokhsar DS, et al. Ancient
802 polymorphisms contribute to genome-wide variation by long-term balancing selection and divergent sorting
803 in *Boechera stricta*. *Genome biology*. 2019; 20(1):126.
- 804 **Wang RJ**, White MA, Payseur BA. The pace of hybrid incompatibility evolution in house mice. *Genetics*. 2015;
805 201(1):229–242.
- 806 **Wilf HS**. *Generating functionology*. Elsevier; 2013.
- 807 **Wittbrodt J**, Adam D, Malitschek B, Mäueler W, Raulf F, Telling A, Robertson SM, Schartl M. Novel puta-
808 tive receptor tyrosine kinase encoded by the melanoma-inducing Tu locus in *Xiphophorus*. *Nature*. 1989;
809 341(6241):415–421.
- 810 **Wolf JB**, Lindell J, Backström N. Speciation genetics: current status and evolving approaches. *Phil Trans R Soc B*.
811 2010; 365:1717–1733.
- 812 **Yamamoto E**, Takashi T, Morinaka Y, Lin S, Wu J, Matsumoto T, Kitano H, Matsuoka M, Ashikari M. Gain of
813 deleterious function causes an autoimmune response and Bateson–Dobzhansky–Muller incompatibility in
814 rice. *Molecular Genetics and Genomics*. 2010; 283(4):305–315.

815 Appendix 1

816 Hybrid inviability against a single incompatibility

817 Here we analytically evaluate the probability that a hybrid is inviable presuming that multiple
 818 incompatibilities are rarely embedded in two parental gene regulatory networks. In addition,
 819 this naive analysis explains the pattern of RI distribution, **Figure 5a** in the main text.

820 Assume that there is only one incompatibility I between the two parental gene networks
 821 G_1 and G_2 . For convenience we suppose there are an even number of loci in the organisms,
 822 denoted by $2m$, and let the incompatibility I be of order $k - 1$ so it consists of k alleles to
 823 form a lethal combination. We also suppose that, among the k alleles in I , k_1 of them come
 824 from G_1 and the other k_2 alleles are from G_2 .

825 Following the rule of recombination between haploid GRNs in our model, the hybrid is
 826 generated by randomly segregating alleles of m loci from G_1 and then mixing with alleles
 827 of the other m loci from G_2 . Hence if $m < k_1$ or $m < k_2$, then there is no chance that the
 828 incompatibility I appears in the hybrid. Otherwise, among all plausible segregation, we
 829 can compute the number of achievable ways that the k_1 and k_2 alleles from G_1 and G_2
 830 respectively are sorted into the hybrid. The probability that the hybrid is inviable due to the
 831 only incompatibility I is thus

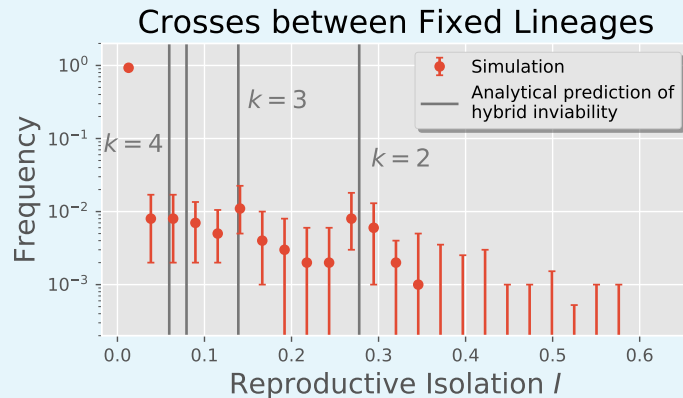
$$832 P(I) = \begin{cases} \frac{\binom{2m-k}{m-k_1}}{\binom{2m}{m}}, & \text{if } k_1, k_2 \leq m \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

835 If we further assume that $m \gg 1$ and $m \gg k$, applying the Stirling's approximation we have
 836 an estimate of the hybrid inviability

$$837 P(I) = \frac{m!(2m-k)!}{(m-k_1)!(m-k_2)!(2m)!} \approx 2^{-k} \quad (3)$$

840 This plain derivation shows that, should there be only one incompatibility concealing between
 841 two parental GRNs, the survivability of a hybrid is predominantly determined by the order of
 842 the incompatibility.

843 Here **Figure 1** shows good agreement between our analytical prediction of hybrid inviability
 844 and the “bulges” from the observed RI distribution. Our simple derivation explains the
 845 higher likelihood of certain RI levels relative to their neighboring regions. It also manifests
 846 how the discreteness nature of hybrid incompatibilities shapes the RI distribution and that
 847 this characteristic has major effects on the strength of reproductive barriers.



848 **Appendix 1 Figure 1.** Comparison between the uncovered RI distribution in our simulations and the
 849 predicted hybrid inviability **Equation 2**.
 850

852 Appendix 2

853 Estimating functional redundancy of GRNs under extreme selection

854 Our pathway framework not only resonates with existing studies of the functional redun-
 855 dancy of GRNs (*True and Haag, 2001; Wagner and Wright, 2007; Schiffman and Ralph, 2018;*
 856 *Láruson et al., 2020*), but it also estimates how many GRNs generate a given phenotype
 857 under the Boolean-state assumption. Here we consider an extreme case where every protein
 858 is either required present or absent, except those that are stimulated by the environment.
 859 This scenario depicts a strong selection force, and a weaker selection can be easily reached
 860 by relaxing the phenotypic constraint on proteins. Note that this extreme scenario hence
 861 provides a lower bound of the number of GRNs that produce the same phenotype.

862 Suppose there are n_+ and n_- proteins that are required present and absent respectively,
 863 and let there be n_0 present-state proteins due to the environmental stimuli. A GRN that
 864 generates this given phenotype can be viewed as a composition of two parts: First, it contains
 865 alleles, i.e., edges, building up pathways from any of the n_0 stimulated proteins to every
 866 of the n_+ required-present proteins. Second, edges associated with the required-absent
 867 proteins, if any, must not be alleles activated by the required-present/stimulated proteins
 868 and producing the required-absent ones. Assuming m haploid loci ($m \geq n_+$), the number of
 869 GRNs generating the given phenotype is

$$870 \quad f(m, n_0, n_+, n_-) = \sum_{k=n_+}^m \binom{m}{k} [n_- (n_- + n_+)]^{m-k} f(k, n_0, n_+, 0), \quad (4)$$

871 where $f(k, n_0, n_+, 0)$ corresponds to the special case where no protein is required absent, it is
 872 equivalently the number of directed, edge-labeled graphs with $n_0 + n_+$ nodes and k edges
 873 such that every of the n_+ nodes are reachable from any of the n_0 nodes.
 874

875 Although one may compute $f(k, n_0, n_+, 0)$ through a recursive relation general-
 876 ized from existing literature (e.g., *Wilf, 2013*), an analytical solution is hardly accessible. Here
 877 we instead assess the lower and upper bound of $f(m, n_0, n_+, n_-)$. First, $f(m, n_0, n_+, n_-)$ accounts
 878 for all graphs satisfying the reachability criterion, and it is bounded below by the amount
 879 of those graphs which are also forests^a. Finding all such forests is equivalent to finding all
 880 possibilities to grow a network from n_0 initial nodes, where edges are added incrementally,
 881 pointing from an existing node to a not-yet-existing (newly added) one. So we have

$$882 \quad f(m, n_0, n_+, n_-) \geq \binom{m}{n_+} [n_- (n_- + n_+)]^{m-n_+} f(n_+, n_0, n_+, 0) \\ 883 \quad = \binom{m}{n_+} [n_- (n_- + n_+)]^{m-n_+} \frac{n_+! (n_0 + n_+)!}{n_0!}. \quad (5)$$

884 Second, incrementally adding $k - n_+$ edges to every of such forests is essentially an
 885 enumeration of the k -edge graphs. This process generates all possible graphs with k labeled-
 886 edges, but they might be over-counted since adding edges to two different forests can
 887 produce the same graph. Computing all possible ways to add k edges to every forest
 888 satisfying the reachability criterion leads to an upper bound of $f(k, n_0, n_+, 0)$:

$$889 \quad f(k, n_0, n_+, 0) \leq [n_+ (n_0 + n_+)]^{k-n_+} \frac{n_+! (n_0 + n_+)!}{n_0!}, \quad (6)$$

890 and $f(m, n_0, n_+, n_-)$ is hence bounded above by

$$891 \quad f(m, n_0, n_+, n_-) \leq \sum_{k=n_+}^m \binom{m}{k} [n_- (n_- + n_+)]^{m-k} [n_+ (n_0 + n_+)]^{k-n_+} \frac{n_+! (n_0 + n_+)!}{n_0!}. \quad (7)$$

898 Combined, under an extreme scenario where the binary states of all proteins are con-
899 strained, we see super-linearly or even exponentially many GRNs generating the same
900 phenotype. The pathway framework therefore concludes that, for any phenotype derived
901 from the binary states of proteins, the number of functionally redundant GRNs grows faster
902 than super-linearly/exponentially as the system scales.

^aA *forest* is a graph which only has trees as its connected components, where trees are graphs without cycles.

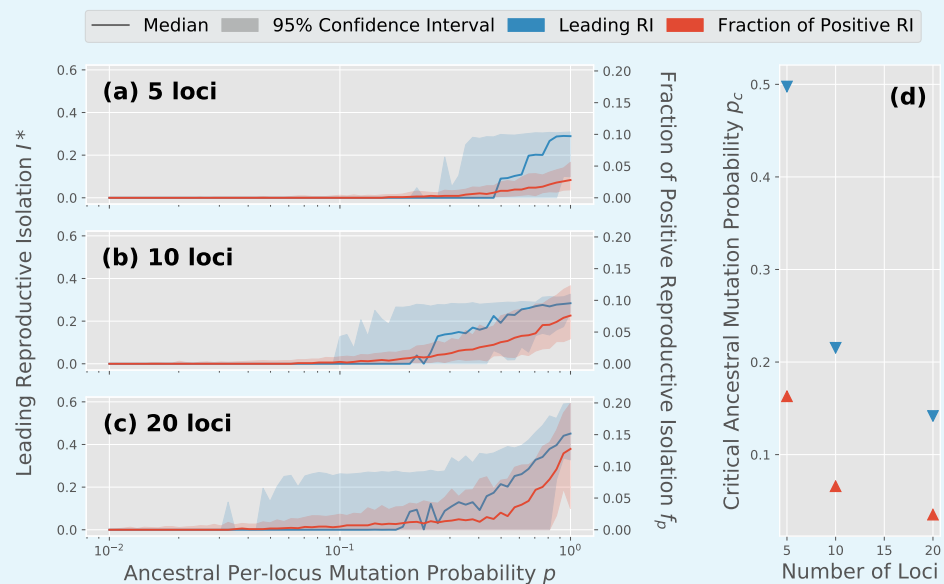
903 Appendix 3

904 Reproductive barriers and ancestral genetic variation

905 Here we demonstrate our examination on how the extent of ancestral genetic variation
906 influences the appearance and strength of reproductive barriers. To begin with, we designed
907 a pipeline to produce ancestral populations whose amount of genetic variation are tunable.
908 A fixed population was first obtained from our GRN evolution model starting with randomly
909 generated individual GRNs. For every locus, the allele might then mutate into any other
910 possible allele with a per-locus mutation probability p . The resulting population was regarded
911 as the ancestral population, where the mutation probability p became a tunable parameter
912 to assess the degree of ancestral variation.

913 We followed the same methodology to simulate generational dynamics of GRNs and to
914 compute reproductive isolation between allopatric lineages as in the main text. **Figure 1a-c**
915 below shows, for different number of loci, the reproductive barriers consequent to the
916 varying ancestral mutation probability p . Here we present two indicators of barriers: the
917 leading RI (blue, left axis) and the fraction of positive RI (red, right axis). On a first glance
918 the simulations evince that, for a organism with a larger number of loci, the barriers only
919 required a smaller ancestral mutation probability yet more apparent barriers were observed.

920 **Figure 1a-c** furthermore suggest some critical level of ancestral variation associated with
921 the constant population size, such that reproductive barriers would hardly appear between
922 lineages evolving from an ancestral population with less polymorphisms. We quantify the
923 critical level of genetic variation through a critical mutation probability p_c : this is the smallest
924 ancestral mutation probability with which a barrier indicator has non-zero median value.
925 Nevertheless, due to the lack of a both sufficient and necessary indicator, we could only
926 estimate the interval that this critical level fell into. The critical level of ancestral variation
927 would be bounded above by p_c for the leading RI (a sufficient indicator of barriers) and
928 bounded below by one for the fraction of positive RI (a necessary indicator of barriers).
929 **Figure 1d** presents the interval estimation that the critical ancestral variation fell into for
930 organisms with different number of loci.



931 **Appendix 3 Figure 1.** Varying the extent ancestral variation and its corresponding strength of
932 reproductive barriers. The GRN evolution was simulated under Setup 1 described in Methods. (a-c)
933 Indicators of barriers for 5, 10 and 20 loci. (d) Estimation of their critical level of ancestral variation.
934

936 Appendix 4

937

Algorithms of counting potential incompatibilities

938

Algorithm 1 COUNT-ECSP

940

Require: A set of source nodes S ; a set of target nodes T ; a map I from nodes to their incident outgoing edges; a set of path lengths of interests L .

941

942

Ensure: A map C from L to the number of edge-colorful simple paths from S to T , which are of the corresponding length.

943

944

1: $C \leftarrow$ an empty map

945

2: $l_{max} \leftarrow$ the largest element of L

946

3: $A \leftarrow$ an empty list

▷ Initialize agents.

947

4: **for all** node $s \in S$ **do** $A.$ INSERT(NEW-AGENT($s, \emptyset, \{s\}$))

948

5: **end for**

949

6: **for** $l \leftarrow 1$ to l_{max} **do** ▷ Iterate over the number of hops agents have made from the source nodes.

950

951

7: $n \leftarrow 0$

952

8: $N \leftarrow$ an empty list

▷ Update the list of agents.

953

9: **for all** agent $a \in A$ **do**

954

10: **for all** agent $a' \in$ NEXT-POSSIBILITIES(a, I) **do**

955

11: $N.$ INSERT(a')

956

12: **if** $a'.position \in T$ **then** $n \leftarrow n + 1$

957

13: **end if**

958

14: **end for**

959

15: **end for**

960

16: $A \leftarrow N$

961

17: **if** $l \in L$ **then** $C.$ INSERT(l, n)

▷ Update counting.

962

18: **end if**

963

19: **end for**

964

20: **return** C

966

Algorithm 2 NEXT-POSSIBILITIES

967

Require: An agent a ; a map I from nodes to their incident outgoing edges.

968

Ensure: A set P of agents who are of all the possible states that can be reached through a hop from the given agent a , such that

969

970

1. The hop only goes through an edge of a color that has not been visited by the agent.

971

2. The position after the hop has not been visited by the agent.

972

1: $P \leftarrow$ an empty set

973

2: **for all** edge $e \in I.$ GET(a) **do**

974

3: **if** $e.color \notin a.colors-visited$ and $e.target \notin a.nodes-visited$ **then**

975

4: $a' \leftarrow$ NEW-AGENT($e.target, a.colors-visited \cup \{e.color\}, a.nodes-visited \cup \{e.target\}$)

976

5: $P.$ INSERT(a')

977

6: **end if**

978

7: **end for**

979

8: **return** P

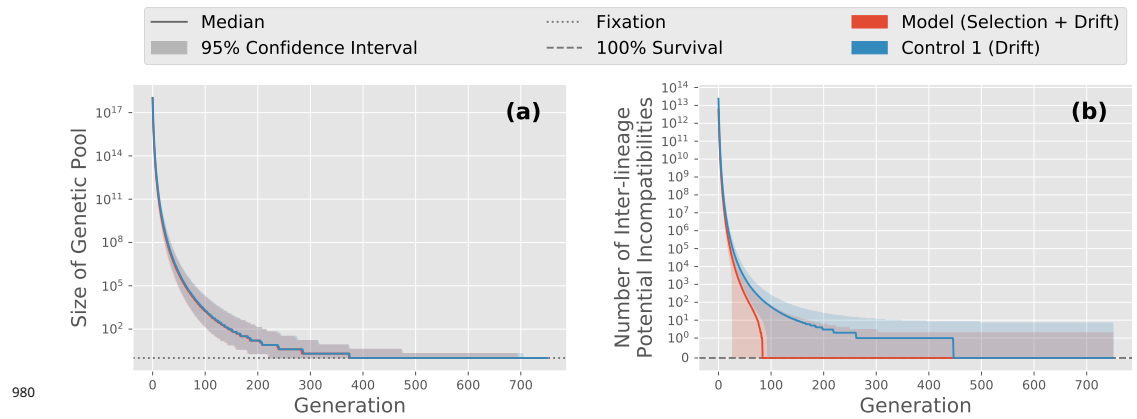


Figure 7-Figure supplement 1. (a) The size the underlying genetic pool continually shrank until there was only one accessible genotype. At this stage a population fixated a single GRN, and no significant difference was found between the model and the control scenario without selection, i.e., drift only. **(b)** In our model, inter-lineage incompatibilities persisted throughout evolution (red), which accounts for the sustained confidence interval of their abundance even after populations reach fixation. Interestingly, in the control scenario where natural selection was silenced, inter-lineage incompatibilities were eliminated at a slower pace. We hypothesize that due to the lack of guidance by selection, inter-lineage incompatibilities only became inaccessible through random genetic drift. This scenario led to fatal allelic combinations that were more persistent than those in the model and hence stronger reproductive barriers were observed.