

2 DR. MICHAEL G HARVEY (Orcid ID : 0000-0001-8050-6068)

4 Article type : Research Article

6 Handling editor: Natalie Cooper

10

12

Continuous traits and speciation rates:  
14 Alternatives to state-dependent diversification models

16

Michael G. Harvey<sup>1,\*</sup> and Daniel L. Rabosky<sup>1</sup>

18

20 <sup>1</sup>Department of Ecology and Evolutionary Biology and Museum of Zoology, University of  
Michigan, Ann Arbor, Michigan, 48109, USA

22

24 \*Correspondence author. E-mail: mgh272@gmail.com

26

28

This is the author manuscript accepted for publication and has undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the [Version of Record](#). Please cite this article as [doi: 10.1111/2041-210X.12949](https://doi.org/10.1111/2041-210X.12949)

This article is protected by copyright. All rights reserved

30

**Running headline:** Simple trait-dependent speciation test

32 **Abstract**

- 34 1. Many quantitative traits, for example body size, have been hypothesized to influence the  
36 diversification dynamics of lineages over macroevolutionary timescales. The Quantitative  
38 State Speciation-Extinction (QuaSSE) model and related methods provide an elegant  
40 framework for jointly modeling the relationship between change in continuous traits and  
42 diversification. However, model misspecification and phylogenetic pseudoreplication can  
44 result in elevated false discovery rates in this and other state-dependent speciation-  
46 extinction models.
- 48 2. Here, we evaluate alternative trait-dependent diversification methods that do not formally  
50 model the relationship between traits and diversification, but instead test for correlations  
52 between summary statistics of phylogenetic branching patterns and trait variation at the  
54 tips of a phylogenetic tree (hereafter tip rate correlations or TRCs). We compare  
56 alternative branching pattern statistics and significance tests, and we evaluate their  
58 performance relative to QuaSSE under a range of evolutionary scenarios.
3. We found that a simple statistic derived from branch lengths (inverse equal splits) can  
detect trait-associated rate variation, and that a simulation-based method performs better  
than phylogenetic generalized least-squares (PGLS) for testing the significance of trait-  
rate correlations. This test (*ES-sim*) had better power to detect trait-dependent  
diversification than other TRCs. By testing the approach across a diverse set of  
simulation scenarios, we found that *ES-sim* is similar to QuaSSE in statistical power.  
However, the approach rarely led to false inferences of trait-dependent diversification,  
even under conditions that are problematic for formal state-dependent models. We  
illustrate the application of *ES-sim* to real data by re-assessing the relationship between  
dispersal ability and diversification in Furnariid birds.

60 4. We conclude that simple, semi-parametric tests like *ES-sim* provide a promising approach  
62 for trait-dependent diversification analyses in groups with heterogeneous diversification  
64 histories and provide a useful alternative or complement to formal state-dependent  
speciation-extinction models.

66 **Key-words:** comparative methods, inverse equal splits statistic, trait-dependent diversification,  
68 phylogenetic generalized least squares, state-dependent speciation and extinction models

## 70 **Introduction**

72 Traits of organisms can impact their propensity for evolutionary diversification through time  
(Stanley 1975; Jablonski 2008). Many traits thought to be responsible for trait-dependent  
74 diversification are quantitative or continuous, rather than discrete. Body size may be associated  
with diversification, for example, if the higher metabolic rates or faster generation times typical  
76 of smaller-bodied species lead to higher evolutionary rates (Glazier 1987; Marzluff and Dial  
1991; Gittleman and Purvis 1998). Other examples of continuous traits with hypothesized links  
78 to diversification rates include dispersal ability (Phillimore et al. 2006; Claramunt et al. 2011),  
ecological specialization (Futuyma and Moreno 1988), strength of sexual selection (West-  
80 Eberhard 1983; Panhuis et al. 2001), range size (Rosenzweig 1995), and latitudinal range  
(Cardillo 1999).

82 Early investigations of trait-dependent diversification involved comparing the diversities  
of sister clades that differed in some trait of interest (Mitter et al 1988; Farrell et al 1991;  
84 Barraclough et al 1998). In recent years, the study of trait-dependent diversification has focused  
on jointly modeling diversification dynamics and trait evolution across a phylogeny (e.g., Paradis  
86 2005, Bokma 2008). The most recent such method for continuous traits, quantitative state  
speciation and extinction or QuaSSE (FitzJohn 2010), allows speciation and extinction rates to  
88 vary as arbitrary (user-defined) functions of trait values. The degree to which the phylogeny and  
trait data are explained by models with and without trait-dependent diversification can then be  
90 compared in a likelihood framework. QuaSSE and related state-dependent speciation-extinction

(SSE) models for binary (BiSSE) and multi-state (MuSSE) characters are powerful tests for  
92 detecting trait-dependent diversification (Maddison et al. 2007; FitzJohn et al. 2009; FitzJohn  
2012; Beaulieu and O’Meara 2016). However, various authors have found high incidences of  
94 false inference of trait-dependent relationships using SSE methods (Maddison and FitzJohn  
2015; Rabosky and Goldberg 2015; Rabosky and Huang 2016), including QuaSSE (FitzJohn  
96 2010; Machac 2014).

Recently, Beaulieu and O’Meara (2016) noted that many false inferences of state-  
98 dependent diversification ultimately follow from an incorrectly formulated hypothesis-testing  
framework. Specifically, formal tests for trait-dependent diversification have typically involved  
100 comparing a model with trait-dependent diversification (e.g., BiSSE) to a model with no  
diversification rate variation (e.g., constant-rate birth-death process). This procedure is  
102 problematic, because state-dependent models frequently provide a good fit whenever  
diversification rate variation is present in the data, even if it is unlinked to the character state of  
104 interest. As noted by Beaulieu and O’Meara (2016), this outcome is not a “false positive” in the  
statistical sense, because it reflects correct rejection of an overly simplistic null hypothesis rather  
106 than incorrect rejection of a true null hypothesis. Nonetheless, we continue to refer to “false  
positives” and “false discovery rates” in the remainder of the text, partly for brevity and partly  
108 because the biological interpretation of the result is that observed diversification dynamics are  
associated with trait variation even though in actuality they are not.

As an alternative to overly simplistic null models, Beaulieu and O’Meara developed  
110 several models (CID-2, CID-4) that allow diversification rates to vary across the phylogeny as a  
function of unobserved character states. Use of these hidden-state models in conjunction with  
112 BiSSE can dramatically reduce false inferences of trait-dependent diversification (Beaulieu and  
O’Meara 2016; Rabosky and Goldberg 2017). However, an equivalent hidden-state model has  
114 yet to be developed for quantitative characters, and modeling continuous variation in  
diversification rates across a phylogeny as a function of an unobserved latent variable poses a  
116 challenging problem in numerical analysis.

An alternative class of methods for trait-dependent diversification analyses involves  
118 assessing the correlation between variation in a trait of interest across the tips of a phylogeny and  
tip-specific estimates of speciation rates. These tip rate correlation (hereafter TRC) methods  
120 bypass the need for a fully parameterized model of diversification and trait evolution. Speciation

122 rate metrics used in TRC tests are generally simple indices based on the waiting times between  
speciation events and ignore extinction; as such, they provide a more reliable index of speciation  
124 than net diversification in many scenarios (Belmaker and Jetz 2015). Freckleton (2008)  
introduced a TRC method for continuous traits, measuring speciation rate as the mean internode  
126 distance (branch lengths) between the root and a given tip. Jetz et al. (2012) used a related  
measure (the "DR statistic") that assigns more weight to recent branch lengths than to branches  
128 early in the clade's history. Bromham et al (2016) and Hua and Bromham (2016) present a suite  
of alternative summary statistics describing phylogenetic branching patterns.

130 TRC methods involve, in addition to choice of speciation rate metrics, a strategy for  
assessing the significance of correlations between traits and diversification. Most TRC tests have  
132 used phylogenetic generalized least squares (PGLS) to assess the significance of correlations  
while accounting for shared evolutionary history among relatives (Freckleton et al. 2008, Jetz et  
134 al. 2012, Harvey et al 2017). PGLS accounts for shared history using the expected covariance of  
residuals based on the phylogenetic distance between species and assuming some model of  
136 evolutionary change (e.g. random Brownian motion). Although this strategy may be appropriate  
for modelling covariance among species in many traits, it is unclear whether Brownian motion  
138 and similar models appropriately account for covariance in comparisons involving summary  
metrics of branching patterns (hereafter "speciation rate metrics"), which change in concert  
140 between sister lineages at each node rather than randomly along branches.

The significance of trait-speciation correlations can also be assessed by testing whether  
142 the observed correlation between trait values and speciation rate metrics lies outside a  
distribution constructed by simulation under a null evolutionary model (e.g. Garland et al. 1993).  
144 Rabosky and Huang (2016) developed a test (STRAPP) that builds a null distribution of  
associations between speciation metrics and trait variation by permuting trait values among  
146 diversification rate regimes inferred using BAMM (Rabosky 2014) or potentially other  
multiprocess diversification models, but the power of this approach is limited by the number of  
148 distinct rate regimes present in a given phylogeny. Bromham et al. (2016) and Hua and  
Bromham (2016) developed tests that construct null distributions of trait-speciation associations  
150 by backward simulation of phylogenetic trees with or without trait dependence. The FiSSE  
approach (Rabosky and Goldberg 2017) constructs a null distribution by simulating change in a  
152 binary trait across the empirical phylogeny under a simple Markovian model. Rabosky and

Goldberg (2017) demonstrated that this strategy performed well across a diverse range of testing  
154 scenarios, although FiSSE was limited to analysis of discrete characters.

Here, we explore the performance of TRC tests for trait-dependent speciation in  
156 quantitative characters. We use simulations to evaluate the performance of alternative tip-  
specific speciation rate metrics. We also compare strategies for significance testing including  
158 PGLS and simulation-based approaches to generating a null distribution of speciation-trait  
correlations. We then evaluate the performance of our best-performing TRC method relative to  
160 QuaSSE using simulated and empirical data. Our simulation scenarios encompass a range of  
possible model violations that might lead to spurious inference of relationships between traits  
162 and diversification.

164

## Methods

166

### *Tip rate correlation tests*

168

We evaluated three tip-specific metrics of speciation rate for use in TRC tests. The node  
170 density ( $ND$ ) is the simplest measure of speciation rate and is simply the ratio of the number of  
speciation events (nodes) along a particular root-to-tip path divided by the age of the clade, or

172

$$ND_i = \frac{N_i}{T}$$

174 where  $ND_i$  is the speciation rate for tip  $i$ ,  $N_i$  is the number of nodes between tip  $i$  and the root of  
the tree, and  $T$  is the total evolutionary time between the tips and the root. Alternatively, we can  
176 estimate the speciation rate for a particular tips as the inverse of the corresponding equal-splits  
(ES) measure, which was originally designed to capture the amount of unique evolutionary  
178 history that could be apportioned among each tip in a phylogenetic tree (Redding & Mooers,  
2006):

180

$$ES_i = \sum_{j=1}^{N_i} l_j \frac{1}{2^{j-1}}$$

182 Here,  $ES_i$  is the speciation rate for tip  $i$ ,  $N_i$  is the number of edges between tip  $i$  and the root of  
the tree, and  $l_j$  is the length of each edge  $j$  beginning with the terminal edge ( $j = 1$ ) and  
184 terminating with the root edge ( $j = N_i$ ). Effectively,  $ES$  represents the sum of the lengths of the  
edges subtending a tip, with each edge root-ward down-weighted by  $\frac{1}{2}$ . The log-transformed  $ES$   
186 is the diversification rate statistic (“DR statistic”) employed in trait-dependent diversification  
tests by Jetz et al. (2012). Finally, the inverse of the terminal branch lengths ( $TB$ ) can be used as  
188 a measure of the time since the last speciation event, with lineages exhibiting higher speciation  
rates expected to have shorter terminal branches. This statistic has been used recently for trait-  
190 dependent diversification analyses (e.g., Bromham et al. 2016; Gomes et al. 2016). In summary,  
 $ND$  captures splitting dynamics over the entire history of the lineage leading to a tip,  $TB$  captures  
192 only the dynamics at the tips, and  $ES$  uses information from the full root-to-tip path but is  
weighted towards branching patterns nearer the tips.

194 We evaluated two methods of determining the significance of associations between trait  
variation and speciation rate metrics: phylogenetic generalized least squares (PGLS) and a  
196 simulation test involving comparison of the observed correlation with a null set of associations  
between the speciation metrics and trait values. We used caper (Orme et al. 2013) to fit PGLS  
198 models assuming a Brownian motion model for the error structure, following prior studies  
(Freckleton et al. 2008, Jetz et al. 2012, Gomes et al. 2016). For the simulation test, we simulated  
200 Brownian trait evolution 1000 times across the empirical tree using root state and diffusion rate  
( $\sigma^2$ ) parameters from the maximum-likelihood fit of a Brownian motion model to the original  
202 data. Note that PGLS and the simulation approach need not yield identical results: PGLS  
assumes that the residuals of the relationship between traits and speciation rates can be modelled  
204 as a Brownian motion on the phylogeny (Revell 2010); the simulation approach assumes  
Brownian motion in the trait only. Two-tailed p-values were computed by comparing the  
206 Pearson’s correlation between the speciation rate metric and trait values in the original data to  
the correlation between the speciation rate metric and the simulated trait values. We note that test  
208 statistics aside from Pearson’s correlation could certainly be used, including statistics that  
accommodate non-linear associations between traits and diversification (see Discussion).

210

### *General overview of performance tests*

212

We used simulated datasets to evaluate the performance of TRC methods. First, we  
214 compared the power of the three speciation rate metrics (*ND*, *ES*, and *TB*) to detect associations  
between speciation and traits changing at different rates. Second, we evaluated the two strategies  
216 for significance testing (PGLS and simulations), based on both power and false discovery rates,  
in datasets of different sizes. Third, we evaluated whether power was reduced when the  
218 assumption of Brownian motion used in our simulation-based significance test was violated.  
Fourth, we compared the power of our best-performing TRC test to that of QuaSSE. Finally, we  
220 compared false discovery rates of the TRC test to those of QuaSSE across a wide range of  
evolutionary scenarios.

222

### *Speciation rate metrics*

224

We evaluated the ability of the three speciation rate metrics (*ND*, *ES*, and *TB*) to infer  
226 true relationships between continuous traits and speciation rates by assessing their performance  
on trees simulated with a QuaSSE process (FitzJohn 2010). Using diversitree (FitzJohn 2012),  
228 we performed forward-in-time pure-birth simulations in which speciation rate was related to trait  
values according to a linear function (slope = 0.004). Traits evolved along the tree under a  
230 Brownian motion process. Different speciation rate metrics may perform better depending on the  
rate of trait evolution and associated rate of change in diversification rates in a dataset. For  
232 example, in rapidly evolving traits we might expect trait variation at the tips to be associated  
with length variation only in the most recent branches. For such traits, *TB* may be the best  
234 diversification metric. For slowly evolving traits, *ND* may be preferred because it captures  
variation in diversification back to the root of the phylogeny. Therefore, we simulated trait-  
236 dependent diversification under a series of diffusion rates of trait change ( $\sigma^2$ ) encompassing a  
range of values (0.00006, 0.0006, 0.006, 0.06, 0.6, 6, 60) similar to the spectrum of body size  
238 evolution rates observed in empirical studies (Harmon et al. 2010). At each rate of trait change,  
we simulated 100 datasets with 250 species each and assessed the power of all three speciation  
240 rate metrics to recover the signal of trait-dependent diversification. We evaluated power by



calculating the proportion of simulated datasets for which trait-dependent diversification was  
242 correctly inferred using both of the significance testing approaches described below.

#### 244 *Significance tests*

246 We compared PGLS and simulation-based significance tests using the 250-tip datasets  
simulated at an intermediate rate of trait change ( $\sigma^2 = 0.06$ ) from the previous section, but added  
248 sets of datasets ( $n=100$ ) containing 50 tips and 1250 tips to assess the effect of dataset size on  
test performance. We also simulated datasets in which there was no relationship between  
250 speciation rate and trait values (simulated using simple Brownian motion) to measure the false  
discovery rate of each test. For clarity, a full list of the trait-dependent diversification tests  
252 examined in the study is presented in Table 1.

#### 254 *Evaluating power of TRC tests with violations of Brownian trait evolution*

256 Our simulation-based significance test relies on a simple Brownian motion process to  
generate the null distribution of trait values. Trait model misspecification can, however, lead to  
258 spurious results in comparative analyses (Diaz-Uriarte and Garland 1996, Pennell et al. 2015).  
To investigate the sensitivity of our method to misspecification of the model of trait evolution,  
260 we simulated datasets under an Ornstein-Uhlenbeck (OU) model and compared the performance  
of the Brownian motion simulation test to an alternative test in which the correct (OU) model  
262 was used to generate the null distribution. We simulated trees and OU trait evolution using  
diversitree with “pull” toward the optimum determined by the linear function  $\alpha(\hat{x} - x)$  as  
264 suggested by FitzJohn (2010). We examined  $\alpha$  values of 0.002, 0.02, and 0.2. These absolute  
values mean little because  $\alpha$  is scaled to tree depth (Cooper et al. 2016), but this range included  
266 the parameter space across which all methods lost power to detect trait dependence. At each  $\alpha$   
value we simulated 100 datasets with 250 tips with trait-dependence and examined the power of  
268 simulation-based tests using Brownian and OU models. OU models were fit using the R package  
geiger (Harmon et al. 2008) and OU simulations used phytools (Revell 2012).

270

#### *Power comparison with QuaSSE*

272

We compared the best-performing test of trait-dependent diversification based on the  
274 above analyses to QuaSSE (FitzJohn 2010). We used the same sets of datasets with different  
numbers of tips (50, 250, and 1250 species) and with and without trait-dependence that were  
276 examined in “Significance tests” above to evaluate the power and false discovery rates of both  
tests. We used QuaSSE to fit a model in which the trait exhibited a linear relationship with  
278 speciation versus one in which speciation was constant with respect to trait variation. We used  
likelihood ratio tests for model comparison and to determine whether trait-dependence was  
280 supported in each case.

### 282 *False discovery rate comparison with QuaSSE*

284 A major goal of this study is to evaluate methods that may overcome the erroneous  
inferences of trait-dependent diversification (“false discovery” for brevity) often observed in  
286 analyses with formal state-dependent speciation-extinction tests (Machac 2014; Rabosky and  
Goldberg 2015; but see Beaulieu and O'Meara 2016). We therefore examined false discovery  
288 rates of our best-performing TRC test and QuaSSE in datasets simulated under a broad spectrum  
of scenarios where the focal trait was unlinked to diversification rates, roughly following  
290 Rabosky and Goldberg (2017). These scenarios included sets of trees simulated under a constant  
diversification rate, a diversification rate slowdown, a QuaSSE tree with trait dependence, a  
292 BiSSE tree with trait dependence, the coral supertree from Huang and Roy (2015), the carnivore  
tree from Nyakatura and Bininda-Emonds (2012), and a set of diversity-dependent multiprocess  
294 trees with a single shift between decoupled diversification processes from Rabosky (2014).  
These were combined with each of the following trait simulation scenarios: Brownian motion,  
296 Brownian motion with a single rate shift, Brownian motion with a jump in the mean values in  
one clade, no phylogenetic signal in the trait (i.e., evolving as if along a star-shaped tree),  
298 Brownian motion across most of the tree but white noise (no phylogenetic signal) in a single  
subclade, Brownian motion but with one clade fixed for a single trait value, shifts between two  
300 discrete trait distributions (normally distributed), an OU process with a single optimum and weak  
“pull” toward the optimum, and an OU process with a single optimum and strong “pull” toward  
302 that optimum. The resulting scenarios represent 63 unique combinations of diversification and

304 trait evolution settings, but in none of the scenarios is diversification rate linked to trait values  
(Table S1). For each combination, one iteration of trait evolution was simulated on each of 50  
trees from the tree set, except in combinations involving the coral supertree, for which 50  
306 iterations of trait evolution were simulated on the single tree. Thus, 50 simulated datasets were  
generated for each of the 63 scenarios. We then ran the TRC test and QuaSSE on each iteration  
308 of each scenario and tabulated the frequency with which each method incorrectly inferred state-  
dependent diversification. In some scenarios, the find.mle optimizer from QuaSSE failed under  
310 the default settings. In these cases, we used the optim function with the Nelder-Mead algorithm  
using starting parameters estimated by QuaSSE. If both optimization strategies failed for any  
312 particular iteration, we treated the iteration as failed and excluded it from further analysis.

#### 314 *Trait-dependent diversification in Furnariidae*

316 We evaluated the results of different tests of trait-dependent diversification on an  
empirical dataset previously found to exhibit trait-dependent diversification dynamics  
318 (Claramunt et al. 2011). This dataset includes a time-calibrated phylogenetic tree of birds in the  
family Furnariidae and measurements of the hand-wing index (HWI), a morphological metric  
320 that predicts dispersal ability. In continental settings, high dispersal ability is expected to inhibit  
speciation in birds, because it allows populations to maintain genetic cohesion in the presence of  
322 biogeographic barriers. Accordingly, Claramunt et al. (2011) found that species with high HWI  
had relatively low speciation rates based on a QuaSSE analysis. In fact, their best model (log-  
324 Likelihood [lnL] = -1531.6) included a sigmoidal relationship in which lineages with high HWI  
had low speciation rates, those with low-to-moderate HWI had high speciation rates, and those  
326 with the smallest HWI again had somewhat lower speciation rates (i.e., an “intermediate  
dispersal” model). However, a simple linear model in which HWI was negatively correlated with  
328 speciation rate was still a better fit (lnL = -1535.6) than a model in which speciation was  
unrelated to HWI (lnL = 1539.7). Thus, we expect a significant negative linear correlation  
330 between HWI and speciation rate in this dataset.

We first examined the Furnariid dataset using our best-performing TRC method  
332 assuming Brownian trait evolution as described above. We removed one species (*Asthenes  
luizae*) lacking HWI information, resulting in a final set of 282 species. Although Brownian

334 simulations perform reasonably well in TRC tests even when the trait evolved under a different  
model (see Results), comparing the fit of alternative trait evolution models may still be advisable  
336 in analyses of empirical datasets. We therefore compared the fit of a model of Brownian motion,  
an OU model, an early burst model, and a white noise model assuming no covariance among  
338 species to the Furnariid dataset using AICc scores. We also used parametric bootstrapping to  
evaluate model adequacy by simulating 1000 trait datasets under the best-fit model and assessing  
340 whether the log likelihood of the real data fell outside the 95% confidence interval of log  
likelihoods from the simulated datasets. We compared the results of ES-sim using a Brownian  
342 motion, ES-sim using the best-fit trait evolution model, and QuaSSE.

344

## Results

346

### *Comparison of performance among TRC tests*

348

The most powerful tip-rate correlation (TRC) test for trait-dependent diversification  
350 combined *ES* (the inverse of the equal splits measure) with a simulation-based significance test  
(Fig. 1). We refer to this test hereafter as *ES-sim*. *TB* (the inverse of terminal branch lengths) and  
352 *ND* (node depth) both exhibited lower power than *ES* in tests using the simulation-based  
significance test. Pearson's correlation performed similar to or better than other test statistics in  
354 the simulation test (Table S2). PGLS-based tests had lower power than simulation-based tests in  
*ES* and *TB*. PGLS with *ND* actually performed better than the simulation-based test with *ND*, but  
356 was still less powerful than *ES-sim*. All tests performed better on 250-tip trees than on 50-tip  
trees, with more modest improvements on 1250-tip trees relative to 250-tip trees. Rates of false  
358 positives were low across all tests when they were used to examine datasets simulated without  
trait-dependent diversification (Table S3).

360

All TRC tests examined had the greatest power at intermediate rates of trait change given  
a linear relationship between the trait and speciation rate with a slope of 0.004 ( $\sigma^2$ ; Figs. 2, S1).  
362 In the simulation tests, all three metrics performed poorly at very slow rates ( $\sigma^2 \leq 0.0006$ )  
presumably due to minimal variation in speciation rate at this value, *ES* had the highest power at  
intermediate rates, and *ES* and *TB* performed similarly at very high rates ( $\sigma^2 \geq 6$ ; Fig. 2). *ES*,  
364

therefore, may be the best metric for use in simulation-based tests of trait-dependent  
366 diversification across a broad range of rates of trait evolution.

*ES-sim* in which Brownian motion was used for trait simulations had lower power to  
368 detect trait-dependent diversification when the true model of trait evolution was an OU model,  
particularly as the “pull” toward an optimum increased (Table 2). However, an *ES-sim* test in  
370 which the correct, OU model was used for simulations performed similarly to *ES-sim* with the  
Brownian motion model, suggesting that a mis-matched trait evolution model is not the problem  
372 but rather that the signal of trait-dependent diversification is obscured by an OU model of trait  
change. On a related note, we also found that QuaSSE showed similar reductions in power with  
374 greater deviation from Brownian motion in the trait evolution model (Table S4).

#### 376 *Comparison of performance relative to QuaSSE*

378 QuaSSE had slightly more power to detect trait-dependent diversification in datasets of  
50 and 250 tips than *ES-sim* (Table 3). In the set of 63 diversification and trait evolution  
380 scenarios modelled after that of Rabosky Goldberg (2017), we found false discovery rates were  
substantially higher (5% or more) in QuaSSE than in *ES-sim* in 43 of 63 scenarios (Fig. 3). False  
382 discovery rates were similar (within 5%) in 8 scenarios, and were higher in *ES-sim* in 9  
scenarios. QuaSSE results failed in all iterations in the remaining 3 scenarios. The *ES-sim* false  
384 discovery was 10% or lower in all but one scenario (it was 18% in the coral tree with trait  
simulations in which one clade had trait values with no phylogenetic signal). However, QuaSSE  
386 false discovery rates were higher than 18% in 54 scenarios. The scenarios with the highest false  
discovery rates were those including the empirical carnivore tree and the simulated diversity-  
388 dependent multiprocess trees with a single shift between decoupled diversification processes,  
which were (along with the coral supertree) the largest trees examined.

390

#### *Trait-dependent diversification in Furnariidae*

392

Consistent with the results of Claramunt et al. (2011), our QuaSSE results indicated a  
394 model containing a linear association between the hand-wing index (HWI) and speciation rate  
was a better fit than a model in which speciation was constant with respect to HWI in Furnariid

396 birds (likelihood ratio test:  $\chi^2 = 8.054$ ,  $p = 0.005$ ). The best-fit model of trait evolution for HWI  
was an Ornstein-Uhlenbeck (OU) model (AICc = 1467.1 versus AICc = 1481.7 with Brownian  
398 motion; Table S5). However, OU models can be incorrectly favored over Brownian motion in  
some cases (Cooper et al. 2016). Parametric bootstrapping indicated that the real data was not  
400 distinguishable from datasets simulated under either a Brownian ( $p = 0.094$ ) or OU ( $p = 0.108$ )  
model. We therefore conducted *ES-sim* tests using both Brownian and OU models. We failed,  
402 however, to detect significant trait-dependent correlations in the Furnariid dataset using *ES-sim*  
with either OU ( $p = 0.33$ ) or Brownian motion ( $p = 0.40$ ). The Pearson's correlation coefficient  
404 [ $\rho$ ] was -0.16, indicating 2.56% of the variance in speciation rate was explained by variation in  
HWI. The slope of a linear model fit to the data was -0.02, which equates to model-based  
406 speciation rates 0.11 species/My higher in species with the lowest HWI values versus the highest  
(speciation rates observed across species in the dataset ranged from 0.04 to 1.37 species/My).  
408 Although these effect size measures do not account for covariance among related species, they  
do provide additional evidence that dispersal ability is a weak predictor of speciation rates in this  
410 group. The Furnariid tree appears to show some heterogeneity in diversification dynamics (Fig.  
4a), which might explain the inference of trait-dependent diversification with QuaSSE. QuaSSE  
412 analysis of 100 traits simulated with random Brownian motion on the Furnariid tree revealed a  
high rate (40%) of false positives. The positive result in QuaSSE may also be partly due to  
414 phylogenetic pseudoreplication; many of the points with high values of HWI and low speciation  
rates are in one clade, the Sclerurinae (Fig 4 a, b).

416

## 418 Discussion

420 We assessed the performance of a series of TRC methods for testing hypotheses about the  
relationship between continuous-valued traits and lineage diversification rates. We focused on  
422 three measurements of tip-specific speciation rate (*ND*, *ES*, and *TB*) under two general  
approaches for significance testing (PGLS and null simulations). Our results highlight  
424 differences in performance both among TRC tests and between TRC tests and QuaSSE under a  
set of simple evolutionary scenarios. Consistent with prior results (FitzJohn 2010, Machac 2014),  
426 we found that QuaSSE exhibits a high rate of false positives when trees contain diversification

rate variation unlinked to the focal trait. QuaSSE false discovery rates were especially high in  
428 datasets containing large trees with heterogeneous diversification dynamics, such as the  
carnivore trees (Nyakatura and Bininda-Emonds 2012) and the diversity-dependent multiprocess  
430 trees from Rabosky (2014). The use of more sophisticated null models is an important way  
forward in addressing false positives in SSE methods and in phylogenetic comparative methods  
432 generally (Beaulieu et al. and O’Meara 2016, Uyeda et al. 2017). This approach may be possible  
with QuaSSE, but implementations are lacking and the computational challenges associated with  
434 fitting such models in a QuaSSE framework are expected to be nontrivial.

We found that a simulation-based test using *ES* (*ES-sim*) had nearly as much power as  
436 QuaSSE to detect trait-dependence across trees of different sizes (Table 3) and was robust to  
false inferences of trait-dependent diversification across a range of evolutionary scenarios (Fig.  
438 3). The null trait-speciation associations used in *ES-sim* are simple to simulate and may be  
sufficiently realistic to avert false positives in many evolutionary scenarios. *ES-sim* performed  
440 better than simulation-based tests using the other speciation rate metrics we considered, *ND* and  
*TB*. *TB* performed as well or slightly better than *ES* at very high rates of trait evolution, and may  
442 be preferred in analyses of rapidly evolving traits, but *ES* performed better across a wide range of  
evolutionary rates. Tests that used PGLS to evaluate significance also were less powerful than  
444 simulation-based tests, a result that bears further investigation but may be related to the fact that  
speciation rate metrics change in non-Brownian fashion. Even when traits were simulated using  
446 non-Brownian models, we found that *ES-sim* with Brownian motion simulations had roughly  
equivalent power to an alternative approach where the true trait evolution model (OU) was used  
448 to construct the null distribution (Table 2). This suggests that, like FiSSE for discrete characters  
(Rabosky and Goldberg 2017), *ES-sim* may be reasonably robust to model misspecification in  
450 terms of statistical power as well as false discovery rates (Fig. 3).

*ES-sim* is a powerful test because it incorporates relatively fine-scale variation in  
452 speciation rates across phylogenies. It is therefore useful in small trees with few dramatic  
diversification rate shifts, in contrast to methods like STRAPP (Rabosky and Huang 2016).  
454 However, the sensitivity of *ES-sim* needs to be taken into account in empirical studies, and  
researchers should evaluate the effect size as well as significance of their results. Effect size in a  
456 test like *ES-sim* could correspond either to the amount of variance in speciation rate explained by  
trait variation (i.e., the spread of points away from the correlation line), or the magnitude of the

458 difference in speciation rates between lineages with the minimum and maximum trait values (the  
slope of the correlation line). Although the Pearson's correlation from *ES-sim* does not account  
460 for covariance between closely related species, it does provide an index of the amount of  
variance in speciation rate that might be explained by variation in the trait of interest. The slope  
462 of a linear model fit to the data can provide an index of the magnitude of the change in speciation  
rates across the observed range of trait values. We encourage researchers to report both the  
464 variance explained by the trait of interest and the slope of the correlation, as we did for the  
Furnariid dataset. Plotting the relationship between a trait and tip rates can also provide informal  
466 but useful insights into effect size. Moreover, sensitivity tests can provide quantitative  
information about the robustness of results to stochastic noise, measurement error, and the  
468 impact of phylogenetic pseudoreplication. Moving forward, it would be useful to develop formal  
measures of trait-diversification effect size that estimate the change in species richness – or  
470 potentially, the among-clade variance in richness – that is attributable to the correlation with  
traits. Such a metric could compare the magnitude of the observed difference in species richness  
472 to that which would be present if the clade evolved in the absence of a relationship between traits  
and diversification rates.

474 In our empirical analysis, we found that the relationship between the hand-wing index  
(HWI), a measure of dispersal ability, and speciation rate in Furnariid ovenbirds identified using  
476 QuaSSE (Claramunt et al. 2011) was not supported by *ES-sim*. However, this result does not  
conclusively reject an association between HWI and speciation in this group. The best-fit model  
478 found by Claramunt et al. (2011) included a sigmoidal relationship between HWI and speciation,  
but we tested only for a linear relationship between speciation and traits using *ES-sim* and may  
480 have failed to capture a more complex relationship. QuaSSE has higher power than *ES-sim* based  
on simulations, and it is possible our non-significant *ES-sim* result simply reflects inadequate  
482 power. Researchers should generally be wary of over-interpretation when TRC tests reveal a  
negative result. Even a strong causal relationship between traits and speciation rates could be  
484 difficult to detect with TRC methods if there is insufficient replication across the phylogeny.  
Nonetheless, there is no clear visual signal of a relationship between HWI and ES (Fig. 4b).  
486 Independent evidence supports the association between high dispersal ability and limited  
divergence in birds (Burney and Brumfield 2009, Salisbury et al. 2012, Weeks and Claramunt



488 2014), but additional study will surely reveal a more nuanced understanding of their association  
and interactions with other predictors.

490 The methods examined in this study are amenable to modification and extension. *ES-sim*  
can readily accommodate missing trait information. The method can even be used with sparsely  
492 sampled trait data across a tree, provided the sample reflects the spectrum of trait variation across  
the phylogeny as a whole. However, the estimation of tip-specific speciation rates will be biased  
494 by incomplete taxon sampling. For phylogenies with substantial and/or non-random missing  
taxa, we suggest that researchers estimate speciation rates from distributions of phylogenies  
496 where the unsampled species have been placed on the tree according to constraints, but  
integrating over possible placements of the unsampled lineages (e.g., Kuhn et al, 2011; Thomas  
498 et al. 2013). The trait values for these unsampled taxa should not be included in the analyses, due  
to biases in the rate of trait evolution that can emerge when unsampled species are placed  
500 randomly on trees with respect to trait values (Rabosky 2015).

TRC methods could also be devised that allow for non-linear relationships between traits  
502 and diversification, and potentially, multiple predictor variables. In the present article, we  
assessed the performance of *ES-sim* only under scenarios where speciation rates are a strict linear  
504 function of the underlying traits. However, we should be clear that there are many potential  
functional relationships between speciation rate and phenotypes, including unimodal (hump)  
506 functions, logistic/threshold functions, step functions, and others. As noted above for the  
Furnariids, QuaSSE can already accommodate sigmoidal and other potential relationships. *ES-*  
508 *sim* could also be modified to fit non-linear models to datasets and incorporate different test  
statistics, for example the absolute difference between the upper and lower limits in a sigmoid  
510 function, to assess significance. We expect that *ES-sim* will perform better for some types of  
relationships than others, and for some functional relationships the method may fail entirely. The  
512 interpretation of parameters from *ES-sim* may be difficult if the true evolutionary process  
deviates substantially from a simple linear relationship, even if the method recovers a significant  
514 relationship. These concerns provide another argument for always visualizing the relationships  
between tip rates, phenotypes, and fitted values; simple visual inspection may help diagnose  
516 potential problems with the analyses.

In summary, *ES-sim* provides a powerful test for trait-dependent speciation with  
518 relatively low rates of false positives. *ES-sim* is also appealing because the inverse equal splits

measure provides an intuitive metric of speciation rate that is closely connected to the underlying  
520 data (e.g., the branch lengths) and lends itself to visual inspection of the trait-speciation  
relationship. It may be an appropriate alternative or supplement to likelihood-based state-  
522 dependent speciation-extinction analyses, particularly in datasets with heterogeneous  
diversification dynamics. Finally, the computational speed of *ES-sim* makes it feasible for use  
524 with very large datasets that may be computationally intractable with other methods.

526

### **Acknowledgements**

528

Santiago Claramunt generously provided access to the Furnariid dataset. We thank Brian  
530 O'Meara, Sonal Singhal, Michael Grundler, and the Rabosky lab for discussion. Three  
anonymous reviewers or editors provided helpful comments on earlier versions of the  
532 manuscript. This work was supported by the David and Lucile Packard Foundation (D.L.R.) and  
by National Science Foundation grant DBI-1523893 (M.G.H.).

534

### **Authors' contributions**

538 MGH and DLR developed the method and developed the simulation scenarios, MGH and DLR  
implemented the method, MGH ran analyses, MGH and DLR wrote the manuscript. Both  
540 authors contributed critically to subsequent drafts and approved the final publication.

542

### **Data accessibility**

544

R scripts and simulated data are available on Github (<https://github.com/mgharvey/ES-sim>, doi:  
546 10.5281/zenodo.1067144).

548

### **References**

550

Barraclough, T. G., Nee, S., & Harvey, P.H. (1998) Sister-group analysis in identifying  
552 correlates of diversification. *Evolutionary Ecology*, 12, 751-754.

554 Beaulieu J. M., & O'Meara, B. C. (2016) Detecting hidden diversification shifts in models of  
trait-dependent speciation and extinction. *Systematic Biology*, 65, 583-601.

556

Belmaker, J., & Jetz, W. (2015) Relative roles of ecological and energetic constraints,  
558 diversification rates, and region history on global species richness gradients. *Ecology Letters*, 18,  
563-571.

560

Bokma, F. (2008) Detection of “punctuated equilibrium” by Bayesian estimation of speciation  
562 and extinction rates, ancestral character states, and rates of anagenetic and cladogenetic evolution  
on a molecular phylogeny. *Evolution*, 62, 2718-2726.

564

Bromham, L., Hua, X., & Cardillo, M. (2016) Detecting macroevolutionary self-destruction  
566 from phylogenies. *Systematic Biology*, 65, 109-127.

568

Burney, C. W., & Brumfield, R. T. (2009) Ecology predicts levels of differentiation in  
Neotropical birds. *American Naturalist*, 174, 358-368.

570

Cardillo, M. (1999) Latitude and rates of diversification in birds and butterflies. *Proceedings of*  
572 *the Royal Society of London B*, 266, 1221-1225.

574

Claramunt, S., Derryberry, E. P., Remsen, J. V., & Brumfield, R. T. (2012) High dispersal ability  
inhibits speciation in a continental radiation of passerine birds. *Proceedings of the Royal Society*  
576 *of London B*, 279, 1567-1574.

578

Cooper, N., Thomas, G. H., Venditti, C., Meade, A., & Freckleton, R. P. 2016. A cautionary note  
on the use of Ornstein Uhlenbeck models in macroevolutionary studies. *Biological Journal of the*  
580 *Linnean Society*, 118, 64-77.

- 582 Diaz-Uriarte, R., & Garland, T. (1996) Testing hypotheses of correlated evolution using  
phylogenetically independent contrasts: Sensitivity to deviations from Brownian motion.  
584 *Systematic Biology*, 45, 27-41.
- 586 Farrell, B. D., Dussourd, D. E., & Mitter, C. (1991) Escalation of plant defense: Do latex and  
resin canals spur plant diversification? *American Naturalist*, 138, 881-900.
- 588  
590 FitzJohn, R. G. (2010) Quantitative traits and diversification. *Systematic Biology*, 59, 619-633.
- 592 FitzJohn R. G. (2012) Diversitree: Comparative phylogenetic analyses of diversification in R.  
*Methods in Ecology and Evolution*, 3, 1084-1092.
- 594 FitzJohn, R. G., Maddison, W. P., & Otto, S. P. (2009) Estimating trait-dependent speciation and  
extinction from incompletely resolved phylogenies. *Systematic Biology*, 58, 595-611.
- 596  
598 Freckleton, R. P., Phillimore, A. B., & Pagel M. (2008) Relating traits to diversification: A  
simple test. *American Naturalist*, 172, 102-115.
- 600 Futuyma, D. J., & Moreno, G. (1988) The evolution of ecological specialization. *Annual Review  
of Ecology and Systematics*, 19, 207-233.
- 602  
604 Garland, T. G., Dickerman, A. W., Janis, C. M. & Jones, J. A. (1993) Phylogenetic analysis of  
covariance by computer simulation. *Systematic Biology*, 42, 265-292.
- 606 Gittleman, J. L., & Purvis A. (1998) Body size and species-richness in carnivores and primates.  
*Proceedings of the Royal Society of London B*, 265, 113-119.
- 608  
610 Glazier, D. S. (1987) Energetics and taxonomic patterns of species richness. *Systematic Zoology*,  
36, 62-71.

- 612 Gomes, A. C. R., Sorenson, M. D., & Cardoso, G. C. (2016) Speciation is associated with  
changing ornamentation rather than stronger sexual selection. *Evolution*, 70, 2823-2838.
- 614
- Harmon, L. J., Losos, J. B., Davies, T. J., Gillespie, R. G., Gittleman, J. L., Jennings, W. B.,  
616 Kozak, K. J., McPeck, M. A., Moreno-Roark, F., Near, T. J., Purvis, A., Ricklefs, R. E.,  
Schluter, D., Schulte II, J. A., Seehausen, O., Sidlauskas, B. L., Torres-Carvajal, O., Weir, J. T.,  
618 & Mooers, A. O. (2010) Early bursts of body size and shape evolution are rare in comparative  
data. *Evolution*, 64, 2385-2396.
- 620
- Harmon, L. J., Weir, J. T., Brock, C. D., Glor, R. E., & Challenger, W. (2008) GEIGER:  
622 Investigating evolutionary radiations. *Bioinformatics*, 24, 129-131.
- 624 Harvey, M. G., Seeholzer, G. F., Smith, B. T., Rabosky, D. L., Cuervo, A. M., & Brumfield, R.  
T. (2017) Positive association between population genetic differentiation and speciation rates in  
626 New World birds. *Proceedings of the National Academy of Sciences*, 114, 6328-6333.
- 628 Hua, X., & Bromham, L. (2016) Phylometrics: An R package for detecting macroevolutionary  
patterns, using phylogenetic metrics and backward tree simulation. *Methods in Ecology and*  
630 *Evolution*, 7, 806-810.
- 632 Huang, D., & Roy, K. (2015) The future of evolutionary diversity in reef corals. *Philosophical*  
*Transactions of the Royal Society B*, 370, 20140010.
- 634
- Jablonski, D. (2008) Species selection: Theory and data. *Annual Review of Ecology, Evolution,*  
636 *and Systematics*, 39, 501-524.
- 638 Jetz, W., Thomas, G. H., Joy, J. B., Hartmann, K., & Mooers, A. O. (2012) The global diversity  
of birds in space and time. *Nature*, 491, 444-448.
- 640
- Kuhn, T. S., Mooers, A. O., & Thomas, G. H. (2011) A simple polytomy resolver for dated  
642 phylogenies. *Methods in Ecology and Evolution*, 2, 427-436.

- 644 Maddison, W. P., & FitzJohn, R. G. (2015) The unsolved challenge to phylogenetic correlation  
tests for categorical characters. *Systematic Biology*, 64, 127-136.
- 646
- 648 Maddison, W. P., Midford, P. E., & Otto, S.P. (2007) Estimating a binary character's effect on  
speciation and extinction. *Systematic Biology*, 56, 701-710.
- 650 Marzluff, J. M., & Dial, K. P. (1991) Life history correlates of taxonomic diversity. *Ecology*, 72,  
428-439.
- 652
- 654 Machac, A. (2014) Detecting trait-dependent diversification under diversification slowdowns.  
*Evolutionary Biology*, 41, 201-211.
- 656 Mitchell, J. S., & Rabosky D. L. (2016) Bayesian model selection with BAMM: Effects of the  
model prior on the inferred number of diversification shifts. *Methods in Ecology and Evolution*,  
658 8, 37-46.
- 660 Mitter, C., Farrell, B., & Wiegmann, B. (1988) The phylogenetic study of adaptive zones: Has  
phytophagy promoted insect diversification? *American Naturalist*, 132, 107-128.
- 662
- 664 Nyakatura, K., & Bininda-Emonds, O. R. P. (2012) Updating the evolutionary history of  
Carnivora (Mammalia): A new species-level supertree complete with divergence time estimates.  
*BMC Biology*, 10, 12.
- 666
- 668 Orme, D., Freckleton, R., Thomas, G., Petzoldt, T., Fritz, S., Isaac, N., & Pearse, N. (2013)  
caper: Comparative analyses of phylogenetics and evolution in R. R package Version 0.5.2  
<https://CRAN.R-project.org/package=caper>.
- 670
- 672 Panhuis, T. M., Butlin, R., Zuk, M., & Tregenza, T. (2001) Sexual selection and speciation.  
*Trends in Ecology and Evolution*, 16, 364-371.

- 674 Paradis, E. (2005) Statistical analysis of diversification with species traits. *Evolution*, 59, 1-12.
- 676 Pennell, M. W., FitzJohn, R. G., Cornwell, W. K., & Harmon, L. J. (2015) Model adequacy and  
the macroevolution of angiosperm functional traits. *American Naturalist*, 186, E33-E50.
- 678  
Phillimore, A. B., Freckleton, R. P., Orme, C. D. L., & Owens, I. P. F. (2006) Ecology predicts  
680 large-scale patterns of phylogenetic diversification in birds. *American Naturalist*, 168, 220-229.
- 682 Rabosky, D. L. (2014) Automatic detection of key innovations, rate shifts, and diversity-  
dependence on phylogenetic trees. *PLoS One*, 9, e89543.
- 684  
Rabosky, D. L. (2015) No substitute for real data: a cautionary note on the use of phylogenies  
686 from birth-death polytomy resolvers for downstream comparative analyses. *Evolution*, 69, 3207-  
3216.
- 688  
Rabosky, D. L., & Goldberg, E. E. (2015) Model inadequacy and mistaken inferences of trait-  
690 dependent speciation. *Systematic Biology*, 64, 340-355.
- 692 Rabosky, D. L., & Goldberg, E. E. (2017) FiSSE: A simple non-parametric test for the effects of  
a binary character on lineage diversification rates. *Evolution*, 71, 1432-1442.
- 694  
Rabosky, D. L., & Huang, H. (2016) A robust semi-parametric test for detecting trait-dependent  
696 diversification. *Systematic Biology*, 65, 181-193.
- 698 Rabosky, D. L., Mitchell, J. S., & Chang, J. (2017) Is BAMM flawed? Theoretical and practical  
concerns in the analysis of multi-rate diversification models. *Systematic Biology*, 66, 477-498.
- 700  
Redding, D. W., & Mooers, A. O. (2006) Incorporating evolutionary measures into conservation  
702 prioritization. *Conservation Biology*, 20, 1670-1678.

704 Revell, L. J. (2010) Phylogenetic signal and linear regression on species data. *Methods in Ecology and Evolution*, 1, 319-329.

706

708 Revell, L. J. (2012) phytools: An R package for phylogenetic comparative biology (and other things). *Methods in Ecology and Evolution*, 3, 217-223.

710 Rosenzweig, M. L. (1995) *Species diversity in space and time*. Cambridge, UK: Cambridge University Press.

712

714 Salisbury, C. L., Seddon, N., Cooney, C. R., Tobias, J. A. (2012) The latitudinal gradient in dispersal constraints: Ecological specialization drives diversification in tropical birds. *Ecology Letters*, 15, 847-855.

716

718 Thomas, G. H., Hartmann, K., Jetz, W., Joy, J. B., Mimoto, A., & Mooers, A. (2013) PASTIS: An R package to facilitate phylogenetic assembly with soft taxonomic inferences. *Methods in Ecology and Evolution*, 4, 1011-1017.

720

722 Uyeda, J. C., Zenil-Ferguson, R., & Pennell, M. W. (2017) Rethinking phylogenetic comparative methods. *bioRxiv* doi: 10.1101/222729.

724 Weeks, B. C. & Claramunt, S. (2014) Dispersal has inhibited avian diversification in Australasian archipelagos. *Proceedings of the Royal Society B*, 281, 20141257.

726

728 West-Eberhard, M. J. (1983) Sexual selection, social competition, and speciation. *Quarterly Review of Biology*, 58, 155-183.

730

732

734



**Table 1.** Trait-dependent diversification tests examined in this study.

	<b>Test</b>	<b>Reference</b>
Joint model of trait evolution and diversification		
1	QuaSSE	FitzJohn 2010
Tip rate correlation (TRC) tests		
PGLS Tests		
2	<i>ES-pgls</i>	Jetz et al. 2012
3	<i>ND-pgls</i>	Freckleton 2008
4	<i>TB-pgls</i>	Gomes et al. 2016
Simulation Tests		
5	<i>ES-sim</i>	this study
6	<i>ND-sim</i>	this study
7	<i>TB-sim</i>	this study

736

738

740

742

744

746 **Table 2.** Performance of *ES-sim* when trait analyzed was simulated under OU model.

	<i>ES-sim</i> (Brownian)		<i>ES-sim</i> (OU)	
	<b>Power</b>	<b>FDR</b>	<b>Power</b>	<b>FDR</b>
OU with alpha = 0.002	0.89	0.04	0.85	0.05
OU with alpha = 0.02	0.33	0.01	0.36	0.01
OU with alpha = 0.2	0.01	0.00	0.04	0.03

FDR, false discovery rate

"Brownian" and "OU" in parentheses reflect the trait evolution model used for the

simulation-based significance test

748

750

752

754

756

758

760

**Table 3.** Power of *ES-sim* relative to QuaSSE.

	<b>50 tips</b>	<b>250 tips</b>	<b>1250 tips</b>
<i>ES-sim</i>	0.38	0.93	1.00
QuaSSE	0.45	0.98	1.00

762

764

766

768

770

772

774

776

778

780 **Figure 1.** A comparison of the power of tip rate correlation (TRC) tests of trait-dependent  
782 diversification differing in the speciation rate metrics examined and in the approach for  
784 significance testing. The diversification metrics examined were the inverse of the equal splits  
786 metric (ES), node density (ND), and the inverse of the terminal branch length (TB). The  
significance tests examined were phylogenetic generalized least squares (PGLS) and a  
simulation test in which the observed correlation was compared to a null distribution of trait-  
diversification correlations.

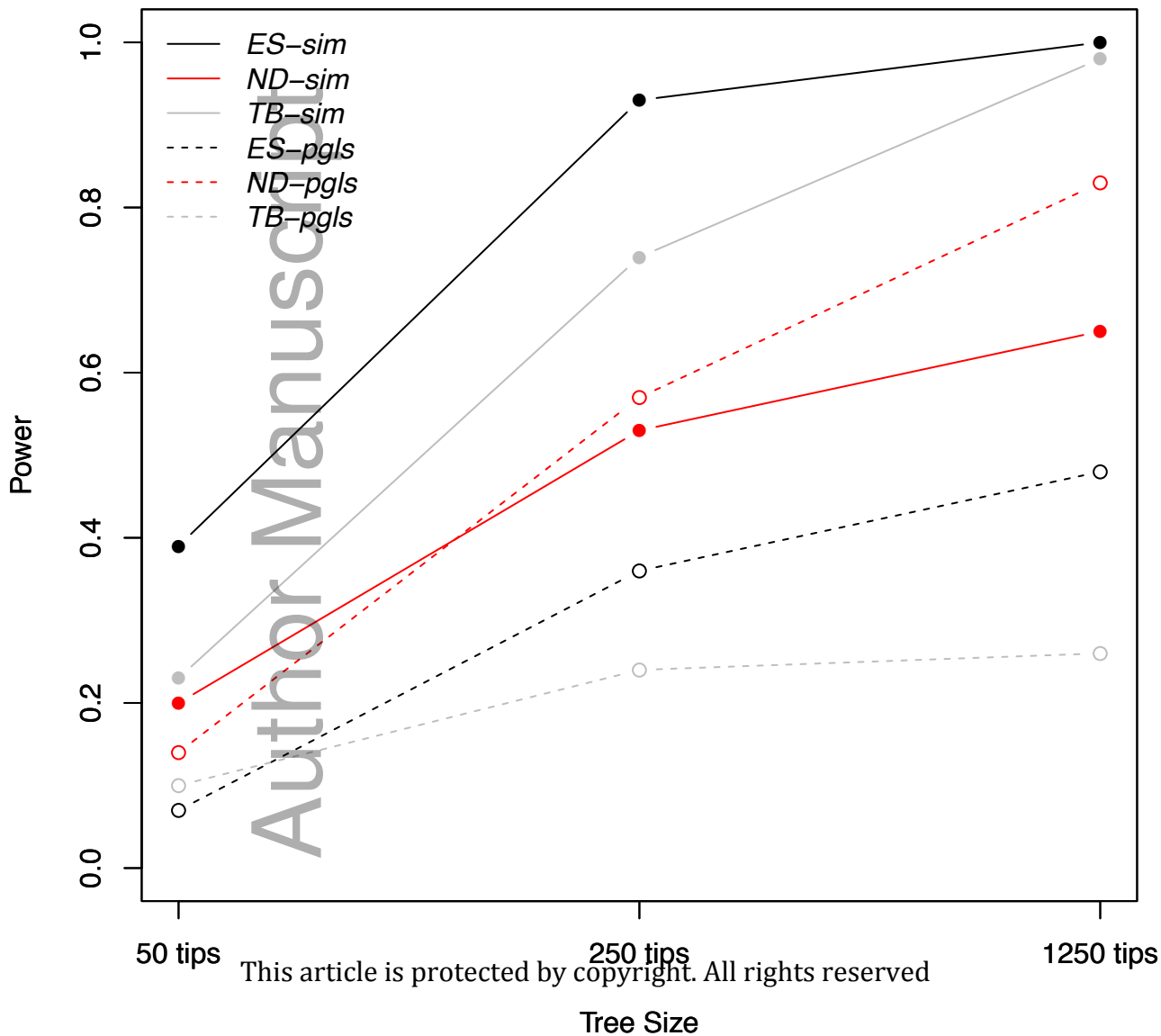
788 **Figure 2.** A comparison of the power of simulation-based TRC tests with alternative speciation  
790 rate metrics across different rates of trait evolution and associated rates of change in  
diversification dynamics.

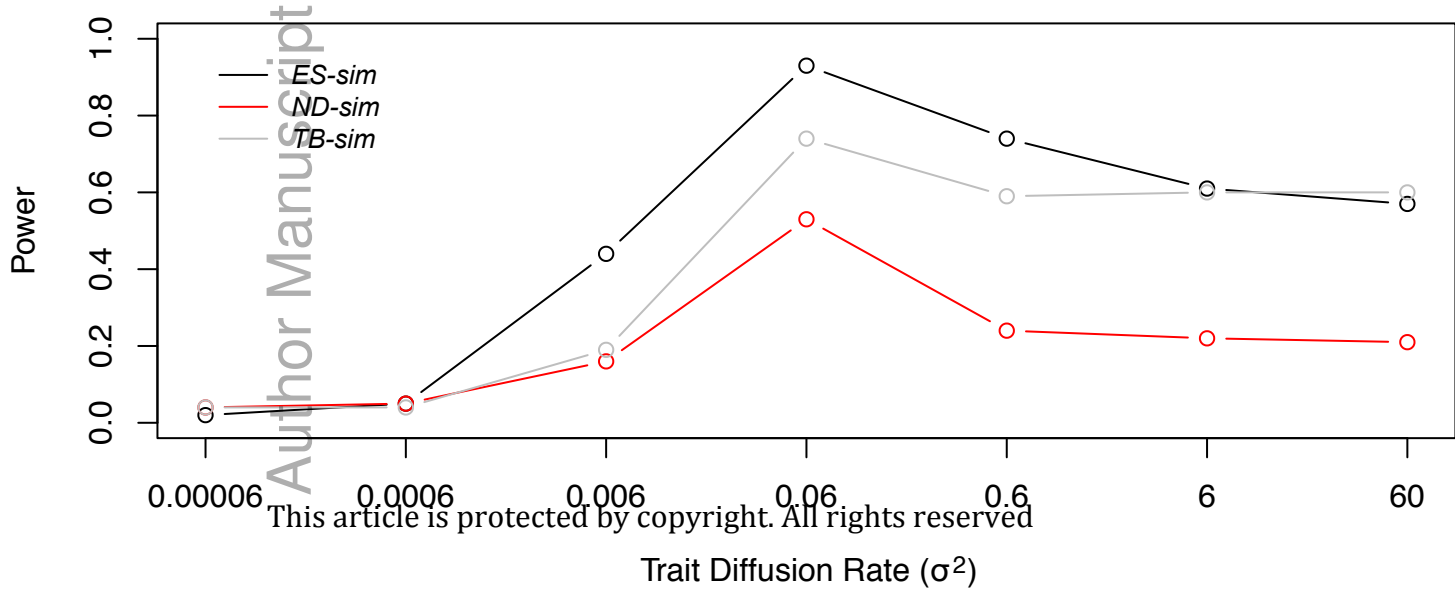
792 **Figure 3.** False discovery rates of *ES-sim* compared to QuaSSE across 63 diversification and  
794 trait evolutionary scenarios. Scenarios are numbered across the bottom axis, and vertical lines  
796 connect the false discovery rates of *ES-sim* and QuaSSE. The numbers above individual points  
798 denote the number of iterations for that scenario (of 50) for which no QuaSSE results could be  
obtained due to numerical failures; no number is given for scenarios where QuaSSE worked for  
all iterations. In the four scenarios furthest to the right, QuaSSE failed on all replicates and no  
point is presented for QuaSSE.

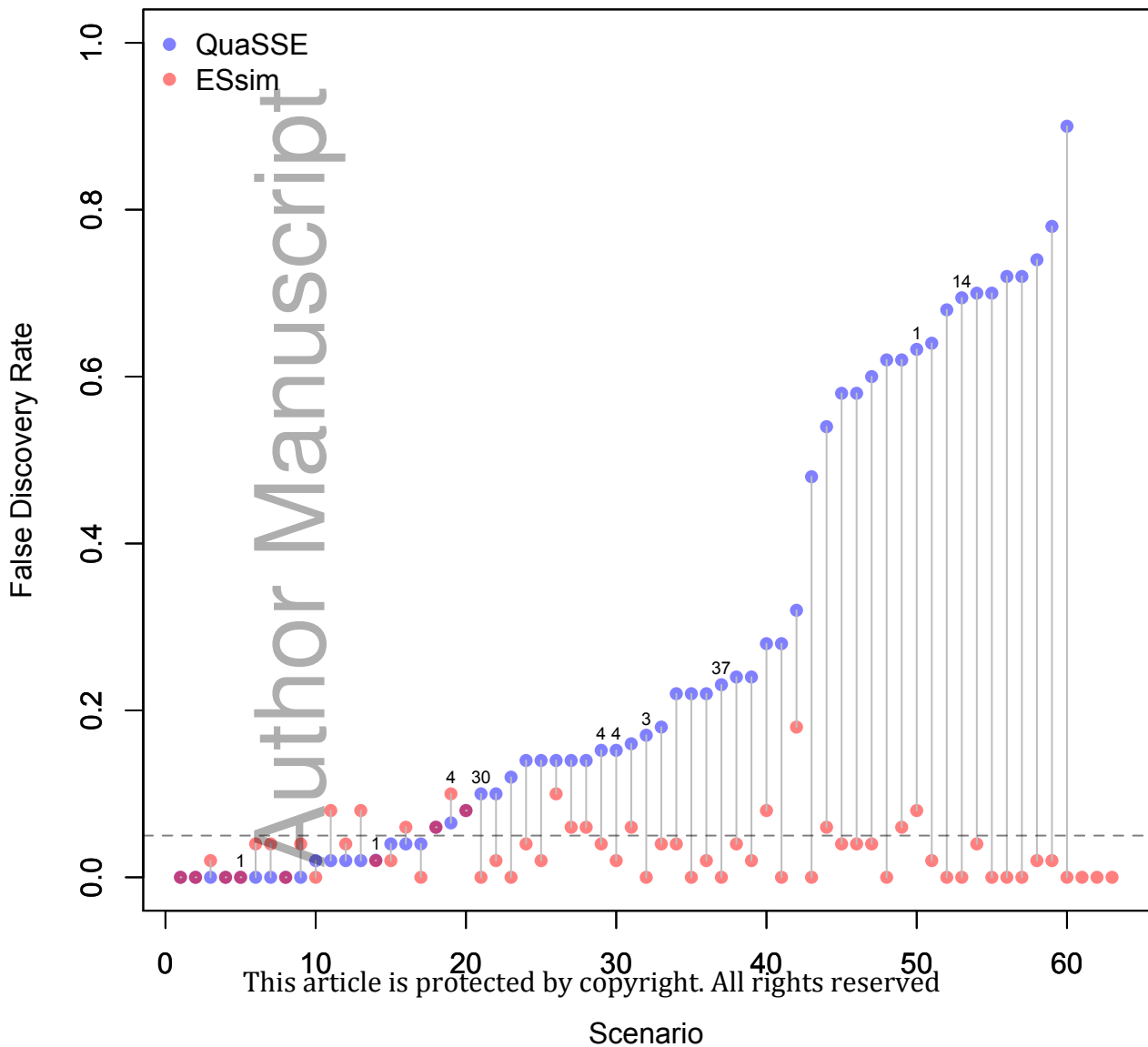
800 **Figure 4.** Plots of the empirical dataset from Furnariid ovenbirds. (a) The time-calibrated  
802 phylogeny of ovenbirds with a bar graph indicating the value of a morphological measure of  
dispersal ability (hand-wing index; HWI) for each tip. (b) A scatterplot showing the association  
804 between ES and the HWI. An association between diversification and HWI was significant based  
on QuaSSE analysis, but not *ES-sim*. This is likely because the simple null model used in

806 QuaSSE failed to account for the complex diversification dynamics evident across the Furnariid tree. In addition, many of the large values of HWI were confined to one slowly diversifying clade (Sclerurinae), colored red on the phylogeny and in the scatter plot.

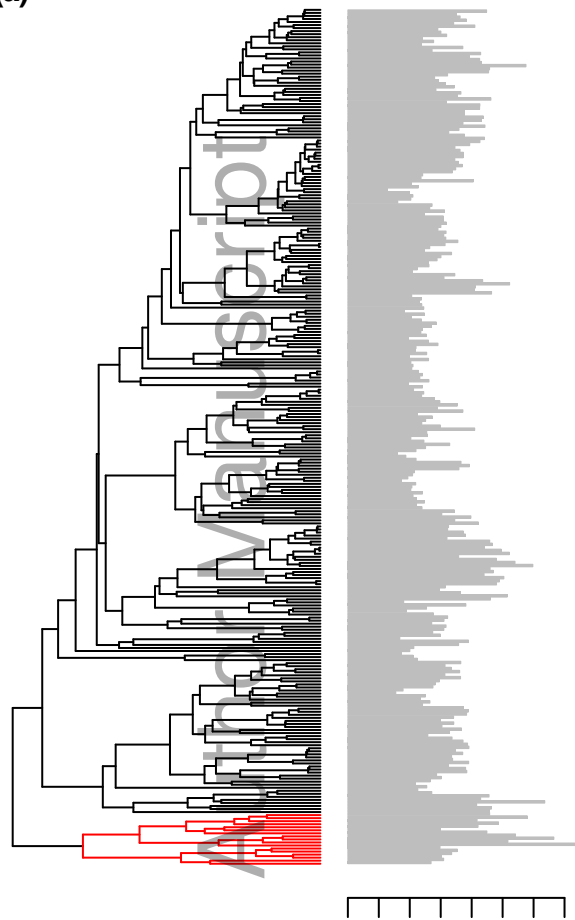
Author Manuscript







(a)

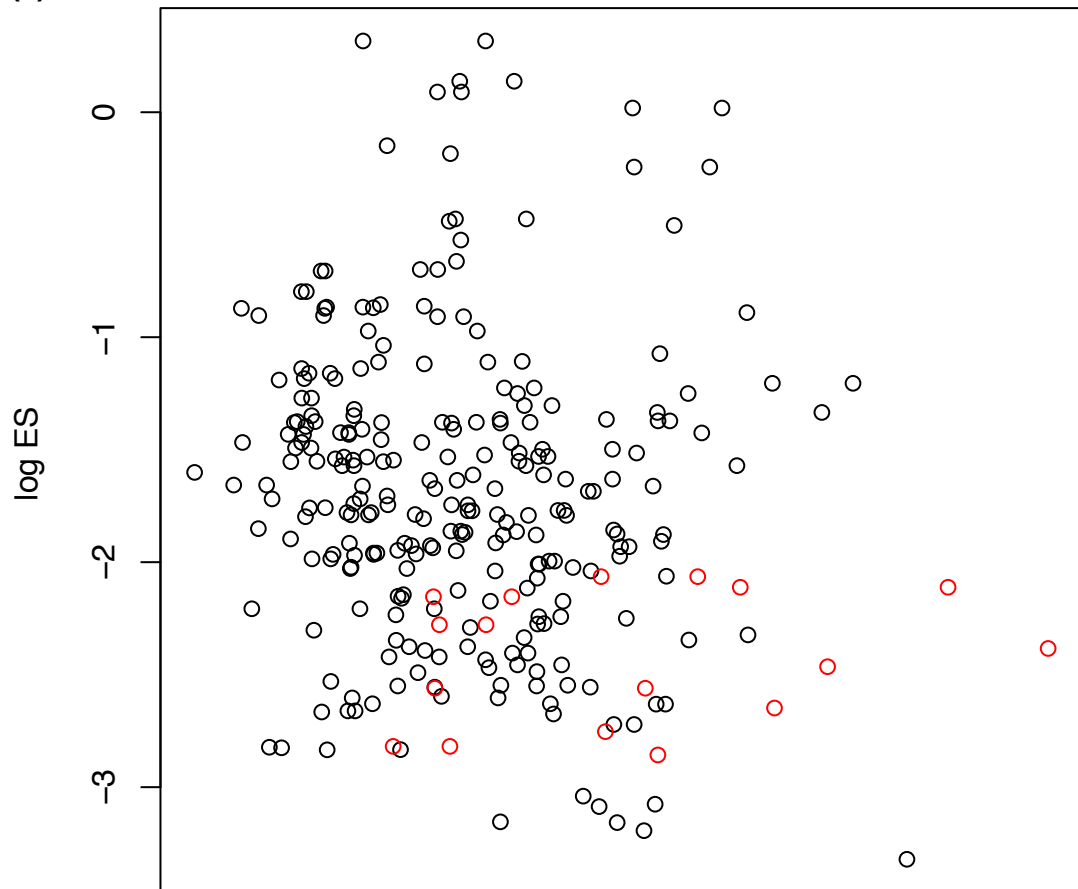


This article is protected by copyright. All rights reserved

HWI

(b)

mee3\_12949\_f4.pdf



HWI