

Title: How do biological traits affect brachiopod taxonomic
2 survival? A hierarchical Bayesian approach.

Running title: How do biological traits affect taxonomic survival?

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Abstract

While the effect of geographic range on extinction risk is well documented, the effects of other traits are less well known. Using a hierarchical Bayesian modeling approach, I also model the possible interaction between the effects of the biological traits and a taxon's time of origination. I analyze patterns of Paleozoic brachiopod genus durations and their relationship to geographic range, affinity for epicontinental seas versus open ocean environments, and body size. Additionally, I allow for environmental affinity to have a nonlinear effect on duration. My analysis framework eschews the traditional distinction between background and mass extinction, instead the entire time period is analyzed where these "states" are part of a continuum. I find evidence that as extinction risk increases, the expected strength of the selection gradient on biological traits (except body size) increases. This manifests as greater expected differences in extinction risk for each unit change in geographic range and environmental preference during periods of high extinction risk, as opposed to a much flatter expected selection gradient during periods of low extinction risk. I find weak evidence for a universally nonlinear relationship between environmental preference and extinction risk such that "generalists" have a lower expected extinction risk than either "specialists". While for the many parts of the Paleozoic this hypothesis is supported, there are many times where this hypothesized relationship is absent or even reversed. Importantly, I find that as extinction risk increases, the steepness of this relationship is expected to increase as well.

1 Introduction

How do biological traits affect extinction risk? Jablonski (1986) observed that during periods of high extinction risk, the effects of biological traits on survival

decreased in size. However, this pattern was weakest/absent in the effect of
40 geographic range on survival (Jablonski, 1986). Biological traits are defined here
as descriptors of a taxon’s adaptive zone, which is the set of biotic–biotic and
42 biotic–abiotic interactions that a taxon can experience (Simpson, 1944). In
effect, these are descriptors of a taxon’s broad-sense ecology.

44 Jablonski (1986) phrased his conclusions in terms of background versus mass
extinction, but this scenario is readily transferable to a continuous variation
46 framework as there is no obvious distinction in terms of extinction rate between
these two states (Wang, 2003). Additionally, the Jablonski (1986) scenario has
48 strong model structure requirements in order to test its proposed
macroevolutionary mechanism; not only do the taxon trait effects need to be
50 modeled, but the correlation between the trait effects need to be modeled as
well.

52 There are two end-member macroevolutionary mechanisms which may underlie
the pattern observed by Jablonski (1986): the effect of geographic range on
54 predictive survival remains constant and those of other biological traits decrease,
and the effect of geographic range in predicting survival increases and those of
56 other biological traits stay constant. Reality, of course, may fall somewhere
along the continuum between these two opposites.

58 I model brachiopod taxon durations because trait based differences in extinction
risk should manifest as differences in taxon durations. Namely, a taxon with a
60 beneficial trait should survive longer, on average, than a taxon without that
beneficial trait. Conceptually, taxon survival can be considered an aspect of
62 “taxon fitness” along with expected lineage specific branching/origination rate
(Cooper, 1984, Palmer and Feldman, 2012). Brachiopods are an ideal group for
64 this study as they are well known for having an exceptionally complete fossil
records (Foote, 2000). Specifically, I focus on the brachiopod record from most

66 of the Paleozoic, specifically from the start of the Ordovician (approximately
485 Mya) through the end Permian (approximately 252 Mya) as this represents
68 the time of greatest global brachiopod diversity (Alroy, 2010).

he analysis of taxon durations, or time from origination to extinction, falls
70 under the purview of survival analysis, a field of applied statistics commonly
used in health care (Klein and Moeschberger, 2003) but has a long history in
72 paleontology (Simpson, 1944, 1953, Van Valen, 1973, 1979).

Geographic range is widely considered the most important taxon trait for
74 estimating differences in extinction risk at nearly all times with large geographic
range associated with low extinction risk (Jablonski, 1986, 1987, Jablonski and
76 Roy, 2003, Payne and Finnegan, 2007). I expect this to hold true nearly always.

Miller and Foote (2009) demonstrated that during several mass extinctions taxa
78 associated with open-ocean environments tend to have a greater extinction risk
than those taxa associated with epicontinental seas. During periods of
80 background extinction, however, they found no consistent difference between
taxa favoring either environment. These two environment types represent the
82 primary environmental dichotomy observed in ancient marine systems (Miller
and Foote, 2009, Peters, 2008, Sheehan, 2001).

84 Epicontinental seas are a shallow-marine environment where the ocean has
spread over the surface of a continental shelf with a depth typically less than
86 100m. In contrast, open-ocean coastline environments have much greater
variance in depth, do not cover the continental shelf, and can persist during
88 periods of low sea level. Because of this, it is strongly expected that taxa which
favor epicontinental seas would be at great risk during periods of low sea levels,
90 such as during glacial periods, where these seas are drained. During the
Paleozoic (approximately 541–252 My), epicontinental seas were widely spread

92 globally but declined over the Mesozoic (approximately 252–66 My) and
eventually diminished disappearing during the Cenozoic (approximately 66–0
94 My) as open-ocean coastlines became the dominant shallow-marine setting
(Johnson, 1974, Miller and Foote, 2009, Peters, 2008).

96 Given the above information, I predict that as extinction risk increases, taxa
associated with open-ocean environments should generally increase in extinction
98 risk versus those that favor epicontinental seas. Additionally, there is a possible
nonlinear relationship between environmental preference and taxon duration. A
100 long standing hypothesis is that generalists or unspecialized taxa will have
greater survival than specialists (Baumiller, 1993, Liow, 2004, 2007, Nürnberg
102 and Aberhan, 2013, 2015, Simpson, 1944). In this analysis I allowed for
environmental preference to possibly have a parabolic effect on taxon duration
104 Body size, measured as shell length (Payne et al., 2014), was also considered as
a potentially informative covariate. Body size is a proxy for metabolic activity
106 and other correlated life history traits (Payne et al., 2014). There is no strong
hypothesis of how body size effects extinction risk in brachiopods, meaning a
108 positive, negative, or zero effect are all plausible.

I adopt a hierarchical Bayesian survival modeling approach, which represents a
110 conceptual and statistical unification of the paleontological dynamic and cohort
survival analytic approaches (Baumiller, 1993, Foote, 1988, Raup, 1975, 1978,
112 Simpson, 2006, Van Valen, 1973, 1979). By using a Bayesian framework I am
able to quantify the uncertainty inherent in the estimates of the effects of
114 biological traits on survival, especially in cases where the covariates of interest
(i.e. biological traits) are themselves known with error.

116 2 Materials and Methods

2.1 Fossil occurrence information

118 The dataset analyzed here was sourced from the Paleobiology Database
(<http://www.paleodb.org>) which was then filtered based on taxonomic,
120 temporal, stratigraphic, and other occurrence information that was necessary
for this analysis. These filtering criteria are very similar to those from Foote and
122 Miller (2013) with an additional constraint of being present in the body size
data set from Payne et al. (2014). Epicontinental versus open-ocean assignments
124 for each fossil occurrence are partially based on those from Miller and Foote
(2009), with additional occurrences assigned similarly (Miller and Foote,
126 personal communication). Sampled occurrences were restricted to those with
paleolatitude and paleolongitude coordinates, assignment to either
128 epicontinental or open-ocean environment, and belonging to a genus present in
the body size dataset (Payne et al., 2014).

130 Fossil occurrences were analyzed at the genus level which is common for
paleobiological, macroevolution, or macroecological studies of marine
132 invertebrates (Alroy, 2010, Foote and Miller, 2013, Harnik et al., 2013, Kiessling
and Aberhan, 2007, Miller and Foote, 2009, Nürnberg and Aberhan, 2013, 2015,
134 Payne and Finnegan, 2007, Simpson and Harnik, 2009, Vilhena et al., 2013).
While species diversity dynamics are of much greater interest than those of
136 higher taxa, the nature of the fossil record makes accurate and precise
taxonomic assignments at the species level for all occurrences. In particular, the
simplicity of brachiopod external morphology and the quality of preservation
138 makes it very difficult for assignments below the genus level. As such, the choice
to analyze genera as opposed to species was in order to assure a minimum level
140 of confidence and accuracy in the data analyzed here.

142 Genus duration was calculated as the number of geologic stages from first
 appearance to last appearance, inclusive. Durations were based on geologic
 144 stages as opposed to millions of years because of the inherently discrete nature
 of the fossil record; dates are not assigned to fossils themselves but instead
 146 fossils are known from a geological interval which represents some temporal
 range. Stages are effectively irreducible temporal intervals in which taxa may
 148 occur. Genera with a last occurrence in or after Changhsingian stage were right
 censored at the Changhsingian. Genera with a duration of only one stage were
 left censored (Appendix ??). The covariates used to model genus duration were
 150 geographic range size (r), environmental preference (v, v^2), and body size (m).
 Geographic range was calculated using an occupancy approach. First, all
 occurrences were projected onto an equal-area cylindrical map projection. Each
 154 occurrence was then assigned to one of the cells from a 70×34 regular raster
 grid placed on the map. Each grid cell represents approximately 250,000 km².
 156 The map projection and regular lattice were made using shape files from
<http://www.natureearthdata.com/> and the **raster** package for R (Hijmans,
 158 2015). For each stage, the total number of occupied grid cells was calculated.
 Then, for each genus, the number of grid cells occupied by that genus was
 160 calculated. Dividing the genus occupancy by the total occupancy gives the
 relative occupancy of that genus. Mean relative genus occupancy was then
 162 calculated as the mean of the per stage relative occupancies of that genus.
 Sampling was calculated as the average relative number of occurrences per
 164 temporal unit. That is, for each geographic unit between the first and last
 appearance of a taxon, the total number of occurrences of that taxon is divided
 166 by the total number of occurrences during that temporal unit. The average of
 all these ratios is that taxon's average sampling s . Sampling was included as a
 168 covariate along with its interactions with geographic range and environmental

preference. No other interaction terms were considered.

170 Environmental preference v was defined as probability of observing the ratio of
 epicontinental occurrences to total occurrences (e_i/E_i) or greater given the
 172 background occurrence probability θ'_i as estimated from all other taxa occurring
 at the same time (e'_i/E'_i). This measure of environmental preference is
 174 expressed.

$$\begin{aligned} p\left(\theta'_i \left| \frac{e'_i}{E'_i} \right.\right) &\propto \text{Beta}(e'_i, E'_i - e'_i) \text{Beta}(1, 1) \\ &= \text{Beta}(e'_i + 1, E'_i - e'_i + 1) \\ v &= p(\theta_i > \theta'_i) \end{aligned} \tag{1}$$

Body size data was sourced directly from Payne et al. (2014).

176 Prior to analysis, geographic range r and sampling s were both logit
 transformed and body size m was natural-log transformed prior to analysis. All
 178 covariates were standardized by subtracting the mean from all values and
 dividing by twice its standard deviation, which follows Gelman and Hill (2007).
 180 This standardization means that all regression coefficients are comparable as the
 expected change per 1-unit change in any of the covariates.

182 2.2 Analytical approach

Hierarchical modelling is a statistical approach which explicitly takes into
 184 account the structure of the observed data in order to model both the within
 and between group variance (Gelman et al., 2013, Gelman and Hill, 2007). The
 186 units of study (e.g. genera) each belong to a single grouping (e.g. origination
 cohort). These groups are considered draws from a shared probability
 188 distribution (e.g. all cohorts, observed and unobserved). The group-level
 parameters are then estimated simultaneously as the other parameters of

190 interest (e.g. covariate effects) (Gelman et al., 2013). The subsequent estimates
are partially pooled together, where parameters from groups with large samples
192 or effects remain large while those of groups with small samples or effects are
pulled towards the overall group mean.

194 This partial pooling is one of the greatest advantages of hierarchical modeling.
By letting the groups “support” each other, parameter estimates then better
196 reflect our statistical uncertainty. Additionally, this partial pooling helps control
for multiple comparisons and possibly spurious results as effects with little
198 support are drawn towards the overall group mean (Gelman et al., 2013,
Gelman and Hill, 2007).

200 All covariate effects (regression coefficients), as well as the intercept term
(baseline extinction risk), were allowed to vary by group (origination cohort).
202 The covariance/correlation between covariate effects was also modeled. This
hierarchical structure allows inference for how covariates effects may change
204 with respect to each other while simultaneously estimating the effects
themselves, propagating our uncertainty through all estimates.

206 Genus durations were modeled as time-till-event data (Klein and Moeschberger,
2003), with covariate information used in estimates of extinction risk as a
208 hierarchical regression model. Genus durations were assumed to follow a
Weibull distribution. While the exponential distribution assumes that extinction
210 risk is independent of duration, the Weibull distribution allows for age
dependent extinction (Klein and Moeschberger, 2003). The Weibull distribution
212 has two parameters: a scale σ , and a shape α . When $\alpha = 1$, σ is equal to the
expected duration of any taxon. α acts as a time dilation effect where values
214 greater than 1 indicate that extinction risk increases with age, and values less
than 1 indicate that extinction risk decreases with age. Note that the Weibull
216 distribution is equivalent to the exponential distribution when $\alpha = 1$.

The scale parameter σ was modeled as a regression with both varying intercept
 218 and varying slopes. The following variables are defined: y_i is the duration of
 genus i in geologic stages, X is the matrix of covariates including a column of
 220 ones for the intercept/constant term, B_j is the vector of regression coefficients
 for origination cohort j , μ is the vector of means of each regression coefficient, Σ
 222 is the covariance matrix of the regression coefficients, τ is the vector of the
 standard deviations of the between-cohort variation of the regression coefficient
 224 estimates, and Ω is the correlation matrix of the regression coefficients. The
 elements of the vector μ were given independent normally distributed priors.
 226 The effects of geographic range size and the breadth of environmental preference
 were given informative priors. The correlation matrix Ω was given an almost flat
 228 LKJ distributed prior following CITATION STAN manual.

The shape parameter α was also modeled as a regression with intercept α' and
 230 standard deviation σ^α . The effect of origination cohort a_j is modeled as draws
 from a shared normal distribution with mean 0 and standard deviation σ^a . γ is
 232 the regression coefficient for the effect of the rescaled logarithm of the number
 of samples s of taxon i .

234 Except where noted, regression coefficients were given a weakly informative
 normally distributed prior, scale (e.g. standard deviation) parameters were
 236 given a weakly informative half-Cauchy prior following the CITATION Gelman
 textbook, STAN manual.

238 The full sampling statement, along with all necessary transformations and

priors, is expressed as

$$\begin{aligned}
y_i &\sim \text{Weibull}(\alpha_i, \sigma_i) \\
\sigma_i &= \exp\left(\frac{-(\mathbf{X}_i B_{j[i]})}{\alpha_i}\right) \\
B_j &\sim \text{MVN}(\mu, \Sigma) \\
\mu_0 &\sim \mathcal{N}(0, 5) \\
\mu_r &\sim \mathcal{N}(-1, 1) \\
\mu_v &\sim \mathcal{N}(0, 1) \\
\mu_{v^2} &\sim \mathcal{N}(1, 1) \\
\mu_m &\sim \mathcal{N}(0, 1) \\
\Sigma &= \text{Diag}(\tau)\Omega\text{Diag}(\tau) \\
\tau &\sim \text{C}^+(1) \\
\Omega &\sim \text{LKJ}(2) \\
\alpha_i &= \exp\left(\mathcal{N}(\alpha' + a_{j[i]} + \gamma s_i, \sigma^\alpha)\right) \\
\alpha' &\sim \mathcal{N}(0, 1) \\
a_j &\sim \mathcal{N}(0, \sigma^a) \\
\sigma^a &\sim \text{C}^+(1) \\
\gamma &\sim \mathcal{N}(0, 1) \\
\sigma^\alpha &\sim \text{C}^+(1).
\end{aligned} \tag{2}$$

240 The joint posterior was approximated using a Markov-chain Monte Carlo
routine that is a variant of Hamiltonian Monte Carlo called the No-U-Turn
242 Sampler (Hoffman and Gelman, 2014) as implemented in the probabilistic
programming language Stan (Stan Development Team, 2014). The posterior
244 distribution was approximated from four parallel chains run for 10,000 draws

each, split half warm-up and half sampling and thinned to every 10th sample for
246 a total of 5000 posterior samples. Chain convergence was assessed via the scale
reduction factor \hat{R} where values close to 1 ($\hat{R} < 1.1$) indicate approximate
248 convergence. Convergence means that the chains are approximately stationary
and the samples are well mixed (Gelman et al., 2013).

250 The fit of the above model (Eq. 2; the “full” model) was compared to the fits of
three other sub-models: constant α across cohorts, no sampling or sampling
252 interaction terms as covariates, or both constant α and no sampling covariates.
These models were compared for predicted out-of-sample predictive accuracy
254 using both the widely-applicable information criterion (WAIC) and
leave-one-out cross-validation estimated via Pareto-smoothed importance
256 sampling CITATIONS.

Model adequacy was evaluated using a couple of posterior predictive checks.
258 The posterior predictive checks are estimates of model adequacy in that
replicated data sets using the fitted model should be similar to the original data
260 where systematic differences between the simulations and observations indicate
weaknesses of the model fit (Gelman et al., 2013). 1000 posterior predictive
262 datasets were generated from 1000 unique draws from the posterior distribution
of each parameter. The two posterior predictive checks used in this analysis are
264 a comparison of a non-parameteric estimate of the survival function $S(t)$ from
the empirical dataset to the non-parameteric estimates of $S(t)$ from the 1000
266 posterior predictive datasets, and comparison of the observed genus durations to
estimates of $\log(\sigma)$ of each observation (Eq. 2). The former is to see if simulated
268 data has a similar survival pattern to the observed, and the latter is to see if the
model systematically over or under estimates taxon survival.

270 3 Results

As stated above, posterior approximations for both the exponential and Weibull
272 models achieved approximate stationarity after 10,000 steps, as all parameter
estimates have an $\hat{R} < 1.1$.

274 Comparisons of the survival functions estimated from 1000 posterior predictive
data sets to the estimated survival function of the observed genera demonstrates
276 that both the exponential and Weibull models approximately capture the
observed pattern of extinction (Fig. ??). The major difference in fit between the
278 two models is that the Weibull model has a slightly better fit for longer lived
taxa than the exponential model.

280 Additionally, the Weibull model is expected to have slightly better out-of-sample
predictive accuracy when compared to the exponential model (WAIC 4576
282 versus 4604, respectively). ??). Because the difference in WAIC between these
two models is large, while results from both the exponential and Weibull models
284 will be presented, only those from the Weibull model will be discussed.

Estimates of the overall mean covariate effects μ can be considered
286 time-invariant generalizations for brachiopod survival during the Paleozoic (Fig.
??). Consistent with prior expectations, geographic range size has a negative
288 effect on extinction risk, where genera with large ranges having greater
durations than genera with small ranges.

290 I find that while the mean estimate of the effect of body size on extinction risk
is negative, implying that increasing body size decreases extinction risk, this
292 estimate is within 2 standard deviations of 0 (mean $\mu_m = -0.09$, standard
deviation 0.09; Fig. ??). Because of this, I infer that body size has no
294 distinguishable effect on brachiopod taxonomic survival.

Interpretation of the effect of environmental preference v on duration is slightly
 296 more involved. Because a quadratic term is the equivalent of an interaction
 term, both μ_v and μ_{v^2} have to be interpreted together because it is illogical to
 298 change values of v without also changing values v^2 . To determine the nature of
 the effect of v on duration I calculated the multiplicative effect of environmental
 300 preference on extinction risk.

Given mean estimated extinction risk $\tilde{\sigma}$, we can define the extinction risk
 302 multiplier of an observation with environmental preference v_i as

$$\frac{\tilde{\sigma}_i}{\tilde{\sigma}} = f(v_i) = \exp\left(\frac{-(\mu_v v_i + \mu_{v^2} v_i^2)}{\alpha}\right). \quad (3)$$

This function $f(v_i)$ has a y-intercept of $\exp(0)$ or 1 because it does not have a
 304 non-zero intercept term. Equation 3 can be either concave up or down. A
 concave down $f(v_i)$ may indicate that genera of intermediate environmental
 306 preference have greater durations than either extreme, and *vice versa* for
 concave up function.

The expected effect of environmental preference as a multiplier of expected
 308 extinction risk can then be visualized (Fig. ??). This figure depicts 1000
 310 posterior predictive estimates of Eq. 3 across all possible values of v . The
 number indicates the posterior probability that the function is concave down,
 312 with generalists having lower extinction risk/greater duration than either type
 of specialist. Note that the inflection point/optimum of Fig. ?? is approximately
 314 $x = 0$, something that is expected given the estimate of μ_v (Fig. ??).

The matrix Σ describing the covariance between the different coefficients
 316 describes how these coefficients might vary together across the origination
 cohorts. Similar to how this was modeled (Eq. ??, 2), for interpretation
 318 purposes Σ can be decomposed into a vector of standard deviations $\vec{\tau}$ and a

correlation matrix Ω .

320 The estimates of the standard deviation of between-cohort coefficient estimates
321 τ indicate that some effects can vary greatly between-cohorts (Fig. ??).
322 Coefficients with greater values of τ have greater between-cohort variation. The
323 covariate effects with the greatest between origination cohort variation are β_r ,
324 β_v , and $\beta_{v,2}$. Estimates of β_m have negligible between cohort variation, as there
325 is less between cohort variation than the between cohort variation in baseline
326 extinction risk β_0 . However the amount of between cohort variation in estimates
327 of $\beta_{v,2}$ means that it is possible for the function describing the effect of
328 environmental affinity to be upward facing for some cohorts (Eq. 3), which
329 corresponds to environmental generalists being shorter lived than specialists in
330 that cohort.

The correlation terms of Ω (Fig. ??) describe the relationship between the
332 coefficients and how their estimates may vary together across cohorts. The
333 correlations between the intercept term β_0 and the effects of the taxon traits are
334 of particular interest for evaluating the Jablonski (1986) scenario (Fig. ?? first
335 column/last row). Keep in mind that when β_0 is low, extinction risk is low; and
336 conversely, when β_0 is high, then extinction risk is high.

Marginal posterior probabilities of the correlations between the level of baseline
338 extinction risk β_0 and the effects of the taxon traits indicate that the correlation
339 between expected extinction risk and both geographic range β_r and $\beta_{v,2}$ are of
340 particular note (Fig. ??).

There is approximately a 98% probability that β_0 and β_r are negatively
342 correlated (Fig. ??), meaning that as extinction risk increases, the
343 effect/importance of geographic range on genus duration increases. This means
344 that increases in baseline extinction rate are correlated with an increased

importance of geographic range size. There is a 93% probability that β_0 and β_{v^2}
 346 are negatively correlated (Fig. ??), meaning that as extinction risk increases,
 the peakedness of $f(v_i)$ increases and the relationship tends towards concave
 348 down. Additionally, there is a 97% probability that values of β_r and β_{v^2} are
 positively correlated (Mean correlation 0.51, standard deviation 0.23).

350 While the overall group level estimates are of particular importance when
 defining time-invariant differences in extinction risk, it is also important and
 352 useful to analyze the individual level parameter estimates in order to better
 understand how parameters actually vary across cohorts.

354 In comparison to the overall mean extinction risk μ_0 , cohort level estimates β_0
 show some amount of variation through time as expected by estimates of τ_0
 356 (Fig. ??). A similar, if slightly greater, amount of variation is also observable in
 cohort estimates of the effect of geographic range β_r (Fig. ??). Again, smaller
 358 values of β_0 correspond to lower expected extinction risk. Similarly, smaller
 values of β_r correspond to greater decrease in extinction risk with increasing
 360 geographic range

How the effect of environmental affinity varies between cohorts can be observed
 362 by using the cohort specific coefficients estimates. Following the same procedure
 used earlier (Fig. ??), but substituting cohort specific estimates of β_v and β_{v^2}
 364 for μ_v and μ_{v^2} , the cohort specific effect of environmental preference as a
 multiplier of mean extinction risk can be calculated. This was done only for the
 366 Weibull model, though the observed pattern should be similar for the
 exponential model.

368 As expected based on the estimates of τ_v and τ_{v^2} , there is greater variation in
 the peakedness of $f(v_i)$ than there is variation between concave up and down
 370 functions (Fig. ??). 12 of the 33 cohorts have less than 50% posterior

probability that generalists are potentially expected to be shorter lived than
 372 specialists, though two of those cases have approximately a 50% probability of
 being either concave up or down. This is congruent with the 0.72 posterior
 374 probability that μ_{v^2} is positive/ $f(v_i)$ is concave down.

Additionally, for some cohorts there is a quite striking pattern where the effect
 376 of environmental preference v has a nearly-linear relationship (Fig. ??). These
 are primarily scenarios where one of the end member preferences is expected to
 378 have a greater duration than either intermediate or the opposite end member
 preference. Whatever curvature is present in these nearly-linear cases is due to
 380 the definition of $f(v)$ as it is not defined for non-negative values of σ (Eq. 3). For
 all stages between the Emsian through the Viséan, inclusive, intermediate
 382 preferences are of intermediate extinction risk when compared with
 epicontinental specialists (lowest risk) or open-ocean specialists (highest risk).
 384 This time period represents most of the Devonian through the early
 Carboniferous.

386 4 Discussion

My results demonstrate that both the effects of geographic range and the
 388 peakedness/concavity of environmental preference are both negatively
 correlated with baseline extinction risk, meaning that as baseline extinction risk
 390 increases the effect sizes of both these traits are expected to increase (Fig. ??).
 This result supports neither of the two proposed macroevolutionary mechanisms
 392 for how biological traits should correlate with extinction risk. The observed
 correlation between the two effects as well as between the effects and baseline
 394 extinction risk instead implies that as baseline extinction risk increases, the
 strength of the total selection gradient on biological traits (except body size)

396 increases. This manifests as greater differences in extinction risk for each unit
difference in the biological covariates during periods of high extinction risk,
398 while a relatively flatter selection gradient during periods of low extinction risk.

For the approximately 233 My period analyzed there is an approximate 75%
400 posterior probability that brachiopod genera with intermediate environmental
preferences are expected to have a lower extinction risk than either end
402 members. However, the over all curvature of $f(v_i)$ is not very peaked meaning
that when averaged over the entire Phanerozoic this relationship may not lead
404 to large differences in extinction risk (Fig. ??). Note that the duration of the
period analyzed is approximately four times then length of the Cenozoic (e.g.
406 time since the extinction of the non-avian dinosaurs). This result gives weak
support for the universality of the hypothesis that environmental generalists
408 have greater survival than environmental specialists (Liow, 2004, 2007,
Nürnberg and Aberhan, 2013, 2015, Simpson, 1944).

410 The posterior variance in the estimate of overall $f(v_i)$ reflects the large between
cohort variance in cohort specific estimates of $f(v_i)$ (Fig. ??). Given that there
412 is only a 75% posterior probability that the expected overall estimate of $f(v_i)$ is
concave down, it is not surprising that there are some stages where the
414 estimated relationship is in fact the reverse of the prior expectation.

Additionally, some of those same stages where $f(v_i)$ does not resemble the prior
416 expectation of a concave down nonlinear relation are instead is highly skewed
and effectively linear (Fig. ??). These results demonstrate that, while the
418 group-level estimate may only weakly support one hypothesis, the cohort-level
estimates may exhibit very different characteristics. These results are also
420 consistent with aspects of Miller and Foote (2009) who found that the effect of
environmental preference on extinction risk was quite variable and without
422 obvious patterning during times of background extinction.

There are two mass extinction events that are captured within the time frame
424 considered here: the Ordovician-Silurian and the Frasnian-Famennian. The
cohorts bracketing these events are worth considering in more detail.

426 The proposed mechanism for the end Ordovician mass extinction is a decrease
in sea level and the draining of epicontinental seas due to protracted glaciation
428 (Johnson, 1974, Sheehan, 2001). My results are broadly consistent with this
scenario with both epicontinental and open-ocean specialists having a much
430 lower expected duration than intermediate taxa (Fig. ??). All of the stages
between the Darriwillian and the Llandovery, except the Hirnantian, have a
432 high probability (90+%) that $f(v)$ is concave down. The pattern for the
Darriwillian, which proceeds the supposed start of Ordovician glacial activity,
434 demonstrates that taxa tend to favor open-ocean environments are expected to
have a greater duration than either intermediate or open-ocean specialists, in
436 decreasing order.

For nearly the entire Devonian estimates of $f(v)$ indicate that one of the
438 environmental end members is favored over the other end member of
intermediate preference (Fig. ??). This is consistent with the predictions of
440 Miller and Foote (2009). For almost the entire the Givetian through the end of
the Devonian and into the Viséan, I find that epicontinental favoring taxa are
442 expected to have a greater duration than either intermediate or open-ocean
specialists. Additionally, for nearly the entire Devonian and through to the
444 Viséan, the cohort-specific estimates of $f(v)$ are concave-up. This is the opposite
pattern than what is expected (Fig. ??). This result, however, seems to reflect
446 the intensity of the seemingly nearly-linear difference in expected duration
across the range of v) as opposed to an inversion of the weakly expected
448 curvilinear pattern.

Of concern is the use of genera as the unit of the study and how to exactly

450 interpret the effects of the biological traits. For example, if any of the traits
analyzed here are associated with increases in speciation rates, this might
452 “artificially” increase the duration of genera through self-renewal (Raup, 1991,
1994). This could lead to a trait appearing to decrease generic level extinction
454 risk by increasing species level origination rate instead of decreasing species
level extinction risk. However, given the nature of the brachiopod fossil record
456 and the difficulty of identifying individual specimens to the species level, there
is no simple solution to decreasing this uncertainty in the interpretations of how
458 the biological traits studied here actually affect extinction risk.

This model could be improved through either increasing the number of analyzed
460 taxon traits, expanding the hierarchical structure of the model to include other
major taxonomic groups of interest, and the inclusion of explicit phylogenetic
462 relationships between the taxa in the model as an additional hierarchical effect.

An example taxon trait that may be of particular interest is the affixing
464 strategy or method of interaction with the substrate of the taxon. This trait has
been found to be related to brachiopod survival (Alexander, 1977) so its
466 inclusion may be of particular interest.

It is theoretically possible to expand this model to allow for comparisons within
468 and between major taxonomic groups. This approach would better constrain the
brachiopod estimates while also allowing for estimation of similarities and
470 differences in cross-taxonomic patterns. The major issue surrounding this
particular expansion involves finding an similarly well sampled taxonomic group
472 that is present during the Paleozoic. Example groups include Crinoidea,
Ostracoda, and other “Paleozoic” groups (Sepkoski Jr., 1981).

474 Taxon traits like environmental preference or geographic range (Hunt et al.,
2005, Jablonski, 1987) are most likely heritable, at least phylogenetically

476 (Housworth et al., 2004, Lynch, 1991). Without phylogenetic context, this
analysis assumes that differences in extinction risk between taxa are
478 independent of those taxa’s shared evolutionary history (Felsenstein, 1985). In
contrast, the origination cohorts only capture shared temporal context. The
480 inclusion of phylogenetic context as an additional individual level hierarchical
structure independent of origination cohort would allow for determining how
482 much of the observed variability is due to shared evolutionary history versus
actual differences associated with these taxonomic traits.

484 In summary, patterns of Paleozoic brachiopod survival were analyzed using a
fully Bayesian hierarchical survival modelling approach while also eschewing the
486 traditional separation between background and mass extinction. I modeled both
the overall mean effect of biological covariates on extinction risk while also
488 modeling the correlation between cohort-specific estimates of covariate effects. I
find that as baseline extinction risk increases, the strength of the selection
490 gradient on biological traits (except body size) increases. This manifests as
greater differences in extinction risk for each unit difference in the biological
492 covariates during periods of high extinction risk, while a much flatter total
selection gradient during periods of low extinction risk. I also find some support
494 for “survival of the unspecialized” (Liow, 2004, 2007, Nürnberg and Aberhan,
2013, 2015, Simpson, 1944) as a general characterization of the effect of
496 environmental preference on extinction risk (Fig. ??), though there is
heterogeneity between origination cohorts with most periods of time conforming
498 to this hypothesis (Fig. ??).

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