1	Quantitative uniqueness of human brain evolution revealed through phylogenetic
2	comparative analysis
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17 Abstract

18 While the human brain is clearly large relative to body size, less is known about the 19 timing of brain and brain component expansion within primates and the relative 20 magnitude of volumetric increases. Using Bayesian phylogenetic comparative methods 21 and data for both extant and fossil species, we identified that a distinct shift in brain-body 22 scaling occurred as hominins diverged from other primates, and again as humans and 23 Neanderthals diverged from other hominins. Within hominins, we detected a pattern of 24 directional and accelerating evolution towards larger brains, consistent with a positive feedback process in the evolution of the human brain. Contrary to widespread 25 26 assumptions, we found that the human neocortex is not exceptionally large relative to 27 other brain structures. Instead, our analyses revealed a single increase in relative 28 neocortex volume at the origin of haplorrhines, and an increase in relative cerebellar 29 volume in apes. 30

31 Keywords: brain evolution, phylogenetic comparative methods, human evolution,
32 primate

33 Introduction

34 Primates vary almost a thousand-fold in endocranial volume – a measure which closely 35 approximates brain size – ranging from 1.63 mL in mouse lemurs [1] to 1478 mL in 36 humans [2]. Body size is perhaps the most important statistical predictor of brain size 37 across primates, with larger bodied species having larger brains, but substantial variation 38 remains after accounting for the effects of body size [1]. While numerous comparative 39 studies have sought to identify ecological, behavioral, and cognitive correlates of this 40 variability [3–7], much less is known about the evolutionary patterns and processes that 41 generated extant variation in brain size within the primate clade, how these differ for 42 different components of the brain, or the degree to which the brain phenotypes of 43 particular species, such as humans, are the result of exceptional patterns of evolutionary 44 change.

45 A common approach to investigating human uniqueness is to test whether humans 46 fall "significantly" far from a regression line, for example by regressing brain size on 47 body mass [8–10]. One surprising recent result reported from such an analysis is that the 48 mass of the human brain is only 10% greater than expected for a primate of human body 49 mass [8]. However, such non-phylogenetic methods may give misleading results because 50 they fail to incorporate trait co-variation among species that results from shared 51 evolutionary history. Valid analysis requires methods that account for phylogeny both 52 when estimating scaling parameters and when evaluating deviations from such scaling 53 exhibited by individual species [11-13]. An additional source of error arises if the species 54 being investigated is included in the regression model [e.g. 8], particularly when, as for 55 humans, the phenotypic trait lies at the extreme of the distribution for the other species in

the analysis. This procedure would reduce the magnitude of deviations from expected trait values for lineages that have undergone exceptional change, and in the case of humans, would bias the results toward failing to detect uniqueness.

59 Comparative methods make it possible to incorporate phylogeny into analyses and 60 to model phenotypic evolution in ways that uncover hitherto hidden patterns. Such 61 methods are now being applied to a wide variety of traits [e.g. 13–15], including brain 62 size. Pagel [14] estimated phylogenetic scaling parameters to characterize the 63 evolutionary trajectory of endocranial volume (ECV) in fossil hominins. His analyses 64 revealed that ECV evolution accelerated towards the present. As this analysis did not 65 account for body size, it is not clear to what extent this pattern reflects changes in brain 66 size independent of body size. Montgomery et al. [16] used ancestral state reconstruction 67 with fossil data to demonstrate a directional trend in primate brain size evolution and to 68 identify branches in the primate phylogeny along which exceptional evolutionary change 69 occurred. They found that while the absolute change in the mass of the human brain was 70 exceptional, the rate of change relative to body size was not. Phylogenetic methods have 71 also been used to examine how specific brain components evolved and the extent to 72 which the branch leading to humans exhibited unusual amounts or rates of change in the 73 size of these components [17,18]. Recently, Lewitus [19] suggested that comparative 74 analyses of neuroanatomical data can be improved by incorporating and comparing 75 results from different evolutionary models.

Here, we use phylogenetic methods to model the evolution of brain size and to
identify exceptional evolutionary change along phylogenetic branches. We employ three
methods: The first method models trait evolution both as a multi-optima Ornstein-

79 Uhlenbeck (OU) process (which incorporates stabilizing selection and drift) and as a 80 Brownian motion process [20], and then compares the fit of the two models. In cases 81 where the OU model is favored, exceptional patterns of trait evolution are indicated by 82 recent shifts in adaptive optima in humans' (or other species') evolutionary lineage. In 83 cases where the Brownian model is favored, we apply our second method, which is a 84 phylogenetic outlier test that uses phylogenetic generalized least squares (PGLS) to 85 predict a phenotype for a species and then compares observed and predicted values. With 86 this method, we can assess whether humans are a phylogenetic "outlier" relative to 87 expectations based on their phylogenetic position and trait covariation in other primate 88 species. Our last method tests for directional and accelerating evolution by fitting 89 phylogenetic scaling parameters to data on deviation from trait expectations and 90 evolutionary time, building on previous efforts with these approaches [14]. 91 Using the first two methods, we investigate the evolution of absolute brain size 92 and brain size relative to body mass within primates. Absolute brain volume has been 93 shown to predict cognitive ability in primates better than other metrics that account for 94 body mass [4,21]. However, brain size is highly correlated with body size [1], and as 95 such it is difficult to interpret the significance of brain size alone. Additionally, 96 accounting for body mass gives more insights into the significance of brain size in life 97 history processes, as relative brain size better approximates relative investment in 98 cognitive ability. Accounting for body mass is also important as the relationship between 99 this trait and brain size is associated with scaling effects that reflect conservation of 100 neural function, such as preservation of somatosensory acuity across large surface areas 101 [22] and compensation for increased neural conduction distances in larger animals

102 through (i) larger neuron and axon sizes, increased myelination, and increased white 103 matter volume, all of which result in reduced neuron density [23-25] and (ii) increased 104 neural resources devoted to prediction-based sensorimotor control that result from 105 escalating neural conduction delays as body size increases [26]. Other measures of 106 relative brain size such as encephalization quotients, ratios, and residuals have been used 107 in the past, but all make theoretical assumptions about the underlying relationship 108 between brain and body size evolution that may not hold. Using relative measures can 109 bias parameter estimates and is not recommended as a good statistical practice [27]. 110 Instead, an empirical approach is preferred in which the covariation of brain size with 111 body size is accounted for within a statistical model that also accounts for phylogenetic 112 history (such as PGLS).

113 We also apply the first two phylogenetic comparative methods to investigate the 114 evolution of major brain structures involving the neocortex, cerebellum, and medulla. It 115 is widely assumed that the neocortex expanded disproportionately relative to other brain 116 structures during the evolution of anthropoid primates and most particularly in human 117 evolution [28–30]. Surprisingly however, direct tests of this hypothesis are lacking, 118 despite the focus of much evolutionary and developmental neuroscience on the neocortex 119 as the site of interest for understanding human uniqueness and its developmental 120 mechanisms [31]. Recent evidence suggests that the cerebellum may have contributed 121 more to human brain evolution than previously appreciated: it underwent rapid 122 evolutionary expansion in the great ape clade including hominins [18,32] and has been 123 implicated in shape changes of the brain in hominin fossil endocasts [33,34]. Molecular 124 evidence now corroborates the proposal that selection on cerebellar function was an

important feature of hominoid and hominin brain evolution [35], with changes in proteincoding genes implicated in cerebellar development more likely to have evolved
adaptively in apes than those implicated in neocortical development [36]. It therefore
appears that the neocortex and cerebellum have had different evolutionary trajectories in
primate evolutionary history. More research is needed to document and understand these
patterns.

131 We examined volumetric change in the neocortex and cerebellum relative to both 132 body mass and the volume of the rest of the brain. As a check to establish whether 133 changes in evolutionary patterns for relative neocortex and cerebellum size are primarily 134 attributable to changes in those structures or to changes in the rest of the brain, we 135 investigated the evolution of the rest of the brain relative to body mass. We also 136 conducted analyses of the volume of the medulla relative to body mass and the volume of 137 the rest of the brain. The relative volume of the medulla does not vary significantly across 138 clades [37] and as such it has not been attributed a major role in brain expansion. For the 139 analyses of fossil species, brain component volumes are not available; thus, analyses of 140 these lineages are restricted to overall brain size (ECV).

Although our main focus is on broad patterns across primate phylogeny and on the extent to which human brain evolution fits or departs from these patterns, we also examined brain evolution in other species that are considered to be unusually largebrained, such as the aye-aye (*Daubentonia*) and capuchins (*Cebinae*) [1,38]. Our analyses also help to identify other primate species that have experienced exceptional expansion or reduction of the brain or its components, generating new hypotheses for future research on exceptional brain evolution in primates.

148	We used our third method to characterize patterns of brain evolution in humans
149	and extinct hominins. Pagel [14] conducted similar analyses of raw ECV. Our analyses
150	advance his findings in two ways. First, we incorporate body mass as a predictor.
151	Second, we focus on the deviation from brain size expectations, based on the PGLS
152	methods used to assess outlier status. Our findings therefore provide insights to the
153	evolutionary trajectory of exceptional hominin ECV relative to primate-wide brain-body
154	mass scaling relationships.
155	

156 Methods

157 <u>Comparative data</u>

158 We compiled ECV and female body mass data on non-human primates [1] as well 159 as humans and fossil hominins [2, Tables 1 and 2]. Given that sex specific body mass 160 estimates are available for ancient humans and extinct hominins [2], we used female 161 values for body mass because female values are more tightly linked to ecological and 162 life-history factors [39] and sexual selection can drive increases in male body mass 163 unlinked to ecology, obscuring brain-body scaling relationships [40]. We also compiled 164 data on neocortex, cerebellum, and medulla volume [18,41,42]. Values used to compute 165 predictor variables (described below) for analyses of brain sub-structures were taken 166 from [1]. We used several phylogenies in our analyses. For analyses of hominin ECV, 167 we constructed a "hominin phylogeny" by combining the hominin consensus tree from 168 [13] and the non-human primate consensus tree from 10kTrees version 3 [43]. To ensure 169 that our results in this set of analyses were not dependent upon the topology of the 170 hominin phylogeny, we repeated them using an "alternate hominin phylogeny,"

171 constructed in a similar manner using another hominin tree from [13]. Details of the tree 172 construction process are given in Appendix 1. In all other analyses we used either the 173 consensus primate phylogeny or a block of 100 primate phylogenies from 10kTrees, 174 version 3.

175 To determine whether patterns of exceptional evolution represent absolute or 176 relative changes in scaling, we included several predictor variables in our analyses. To 177 investigate whether the volumes of structures changed relative to body size, we used 178 body mass as a predictor variable, while we used a "rest-of-brain" metric as a predictor 179 variable to investigate whether the volumes of structures changed relative to other brain 180 structures. For the analyses of all structures other than the medulla, the "rest-of-brain" 181 was computed as whole brain volume - (neocortex volume + cerebellum volume). In 182 analyses of the medulla, we calculated "rest-of-brain" volume as brain volume - medulla 183 volume. We also analyzed the volume of the "rest-of-brain" [whole brain volume -184 (neocortex volume + cerebellum volume)] relative to body mass. The data sets used in all 185 analyses, along with more detailed descriptions, are given in Appendix 1.

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Table 1: Hominin ECV and body mass data details. All values are from [2].					
Species	ECV (mL)	Sample size	Female Body Mass (kg)	Sample size	
Australopithecus africanus	464.00	8	30	7	
Homo erectus	969.00	40	57	4	
Homo habilis	609.00	6	32	2	
Homo rudolfensis	726.00	3	51	2	
Homo sapiens neanderthalensis	1426.00	23	65	7	
Homo sapiens	1478.00	66	57	36	
Paranthropus boisei	481.00	10	34	1	
Paranthropus robustus	563.00	2	32	2	
Australopithecus afarensis	458.00	6	30	4	

188 Table 2: Human brain data

1	QQ	
	02	

Brain Trait	Sour	ce l	Notes	Dataset
ECV	1478.00 mL	[2]	Composite of values from 66 fossil specimens from locations across Eurasia and Africa	1
Brain volume	1267.65 mL	[71, calculated from 32, 72-75]	Average of measurements of modern human brains	2
Brain volume	1251.85 mL	Stephan et al. [32]	Measurement of modern human brain	3

190

191 Characterizing patterns of phenotypic evolution

192 We compared the fit of multi-optima Ornstein-Uhlenbeck (OU) models of evolution and

193 Brownian models of evolution using a developmental version of the R package bayou

194 (https://github.com/uyedaj/bayou/tree/537e373b6c15faf6a03f21d3d642d14e567ad4d8)

195 [44,45]. OU models of evolution incorporate stabilizing selection and drift, while

Brownian models only include drift. Bayou fits multi-optima OU models to a phylogeny 196

- 197 using a Markov-Chain Monte Carlo (MCMC) approach. A shift in selection regime refers
- 198 to a change in the parameters that determine the optimum trait value (towards which

199 species evolve) at a specific location on a phylogeny. Thus, inferred changes in selective

200 regime provide insights to how lineages differ. Shifts in selection regime along terminal

- 201 branches of a tree would provide particularly strong evidence for a species' uniqueness.
- 202 Grabowski et al. [46] proposed the following OU model to describe the evolution

203 of a trait, y, as a function of a predictor variable, x:

204

205	Eqn. 1: $dy = -\alpha (y - y_0) dt + \sigma^2 dB$
206	
207	Eqn. 2: $y_0 = \theta + x \beta$
208	
209	In these equations, dy is the change in the trait value, α is the magnitude of the
210	selective "pull" towards the optimum trait value, y_0 , and σ^2 is the variance of the white
211	noise process <i>dB</i> . The variables θ and β can be interpreted as the intercept and slope of
212	the optimum regression line specified in Eqn. 2. The optimum regression line represents
213	the state that a species is evolving towards rather than the actual evolutionary trajectory.
214	This model has limited utility when data for x are only available for the tips of the
215	phylogeny because the values of x must be known along the branches of the phylogeny to
216	infer the expected value of y for a lineage. We utilize two similar models implemented in
217	the developmental version of bayou - the unweighted predictor model and the weighted
218	predictor model (corresponding to "immediate" and "alphaweighted" options for
219	"slopechange" in bayou) – as these circumvent the issue of unknown phenotypes in
220	ancestral lineages while incorporating a predictor variable into the OU model. The
221	weighted predictor model considers the evolutionary history of the predictor variable
222	while fitting models, and the unweighted predictor model only considers the values of the
223	predictor variables at the tips of the phylogeny while fitting models. The details of these
224	two models are provided in Appendix 2.
225	Bayou uses a MCMC to parameterize the models to fit the data by inferring the
226	location and magnitude of concurrent shifts θ and β on a phylogeny and by inferring the

227 values of α and σ^2 , which remain constant across the phylogeny. The parameters α and

 σ^2 are used in the calculation of the variance-covariance matrices used in evaluating 228 229 model fit to the phylogeny. The phylogenetic half-life, the time needed for a trait to 230 evolve halfway to the optimum, is computed as $\ln(2) / \alpha$. We present phylogenetic half-231 life in units of tree height. A phylogenetic half-life less than tree height indicates that the 232 evolutionary processes can "pull" parameter values to the optimum within the timescale 233 in question, while a phylogenetic half-life that exceeds tree height or constitutes a large 234 percentage of tree height indicates that evolutionary processes have a weak "pull" and 235 trait values are not expected to closely approach the optimum during the timescale in 236 question. The expected variance in trait values evolving to the same optima at

237 equilibrium (stationary variance) can be computed as $\frac{\sigma^2}{2\alpha}$.

238 For each analysis, we ran the weighted and unweighted predictor models. We also 239 ran a Brownian motion model in which the strength of stabilizing selection (α) was fixed at 10⁻⁶ (resulting in a phylogenetic half-life ~9500x greater than tree height; bayou cannot 240 241 compute model likelihoods when α is 0), and no shifts away from the root regime were 242 allowed. The predictor variable is still incorporated in the Brownian motion model, but 243 no changes in its coefficient occur on the phylogeny. We used the hominin tree for the 244 analysis of ECV and the consensus tree of extant primates for all other analyses. All 245 MCMCs were run for 5,005,000 time steps, sampling every 10 time steps. The priors 246 used are given in Table 3. For each analysis, two chains were run and checked for convergence in terms of likelihood, α , and σ^2 (see Appendix 3 for discussion of chain 247 248 non-convergence issues in analyses of ECV). We also checked for correlation in branch-249 wise posterior shift probability between chains. Diagnostic plots pertaining to chain 250 convergence are given in Source data 1. The two chains were combined, with the first

- 251 30% of samples being discarded as burn in. We then obtained the likelihood of each
- model and calculated Bayes factors for each model pairing [47,48] using the
- steppingstone algorithm in bayou, which implements the method of Fan et al. [49]. We
- imposed a posterior probability cutoff of 0.3 for shift detection.
- 255

Model Parameter	Prior Distribution
α	Half-cauchy with scale factor 1. Fixed at 0 in Brownian model.
σ^2	Half-cauchy with scale factor 0.1
β	Normal distribution with standard deviation=0.5, mean=slope of linear model of trait and predictor data
θ	Normal distribution with standard deviation=1, mean=intercept of linear model of trait and predictor data
Number of shifts per branch	Fixed at one
Branch-wise shift probability	Uniform
Number of shifts	Conditional Poisson distribution ¹ with mean =0.1*number of edges on phylogeny and maximum=number of edges on phylogeny. Fixed at 0 in Brownian model.
Location of shift along branch	Uniform

257 Table 3: Priors for bayou MCMC analyses

258 ¹Calculated using "cdpois" option in bayou.

- 259
- 260
- 261 When the multi-optima OU model was selected over the Brownian motion model,
- we used the location and magnitude of shifts in adaptive optima to assess changes in
- 263 patterns of evolution. The inference of a shift on a terminal branch would indicate an
- 264 exceptional pattern of evolution for a given species.
- Ho and Ané [50] identified several potential problems with OU models, including
- 266 un-identifiability of parameters and over-fitting, but acknowledged that such models may

267	be necessary, and recommended that Bayesian models, specifically bayou, be used to
268	overcome these problems. Several other phylogenetic OU models have been developed
269	(most notably Hansen et al. [51]), but none utilized Bayesian parameter estimation.
270	Cooper et al. [52] echoed the concerns of Ho and Ané [50] and again recommended using
271	Bayesian approaches. Additionally, they recommended weighing the fit of an OU model
272	of evolution against that of a Brownian model, which do through our model selection
273	process.
274	
275	Outlier Detection using PGLS
276	When bayou indicated that the Brownian model of trait evolution was favored over the
277	multi-optima OU model, we conducted a phylogenetic outlier test. This was
278	accomplished using BayesModelS, an R script that generates distributions of predicted
279	trait values for a species or several species based on phylogenetically controlled analyses
280	of trait covariation with predictor variables [53]. BayesModelS uses a Markov-Chain
281	Monte Carlo (MCMC) to fit parameters of a PGLS model and assumes a Brownian
282	motion model of evolutionary change. The PGLS models are used to generate trait value
283	predictions for the species of interest. Uncertainty in phylogenetic structure can be
284	accounted for by sampling from a set of trees [14].
285	BayesModelS accounts for phylogenetic non-independence of residual trait values
286	by incorporating branch scaling factors when fitting PGLS models. The MCMC samples
287	between two branch length scaling factors, λ and $\kappa,$ to improve the fit of the models. The
288	parameter λ scales the internal branches of the phylogeny and measures phylogenetic
289	signal [54]. Values for λ were constrained to be in the interval [0, 1]. In the κ model

phylogenetic tree branch lengths are raised to the power κ. The value of κ has previously
been used to assess support for a "speciational" mode of evolution (see Pagel [14]).

292 When predicting the value of a trait for a species (or a group of species), its data 293 were excluded from the BayesModelS analysis to avoid biasing the predictions. 294 BayesModelS was then used to generate a posterior probability distribution of predicted 295 values for that species, based on the predictor variable, estimated phylogenetic signal, 296 and estimated trait co-variation with the other species in the analysis. Species were 297 identified as outliers when their trait value was more extreme than 97.5% of the predicted 298 trait values (i.e. when trait values fell outside 95% credible interval). A species was 299 identified as a positive outlier when its true value fell above the majority of predictions, 300 and a negative outlier when the opposite was true.

301 The analyses conducted using BayesModelS proceeded as follows. First, we 302 investigated whether hominins follow primate brain size to body mass scaling rules by 303 using BayesModelS to predict ECV based on body mass and phylogeny. We tested each 304 hominin species for outlier status while excluding data on all hominins when generating 305 predictions. When computing mean estimates for hominin ECV, we corrected for back 306 transformation bias using the quasi-maximum likelihood estimator method described in 307 [55]. We used the hominin phylogeny or the alternate hominin phylogeny in these 308 analysis, and the data spanned 225 extant primate species (including humans) and 10 309 extinct hominin species.

Next, we identified individual primate species that are evolutionary outliers for
ECV and other brain structures (neocortex, cerebellum, medulla, rest-of-brain). In these
analyses, we accounted for phylogenetic uncertainty by using the block of 100 trees,

which included *H. sapiens* and *H. neanderthalensis* but no other hominins. We iteratively
tested each species in the data set for outlier status. Our analysis for ECV included data
from 145 species, and our analyses for other brain structures structures included data
from between 39 and 53 species.
MCMC chains were run for 1,000,000 time steps, and the first 200,000 time steps
were discarded as burn in. Flat priors were used for all variables being predicted. To

319 assess whether the post-burn in results were drawn from a stable distribution, we used the

320 "heidel.diag" function in the R package coda [56]. When post-burn-in results were not

321 drawn from a stable distribution, we discarded an additional portion of the chain (as

322 indicated by "heidel-diag") so that only results drawn from a stable distribution remained.

323 We ensured that the effective sample sizes for the PGLS model parameters (slope,

324 intercept, most frequently selected phylogenetic scaling parameter) were greater than

325 1000 using the "effectiveSize" function in coda [56]. Details of the MCMC diagnostics

are given in supplementary materials S6, along with detailed results concerning the

327 posterior predicted distribution and phylogenetic scaling parameters for each species in328 each analysis.

329

330 Characterizing the Tempo of ECV Evolution in Hominins

331 We investigated the evolutionary trajectory of brain-body scaling in hominins relative to

332 other primates. We calculated the difference between observed ECV and the mean

333 BayesModelS prediction for brain size (generated in the first described BayesModelS

analysis in which data for all hominin species was excluded while generating predictions)

335 for each of the hominin species. This difference, which we call "brain size deviation"

336 represents the magnitude and direction of the deviation in brain size from what would be 337 expected under primate brain-body scaling rules. We fit four PGLS model to hominin 338 brain size deviation to examine how brain size deviation covaried with the phylogenetic 339 distance from the hominin-Pan split: First, we fit a "Brownian" model of brain size 340 deviation with no predictor. We fixed λ at 1 in this and all subsequent models. Next, we 341 fit a "directional" model of brain size deviation predicted by phylogenetic distance from 342 the hominin-*Pan* split, expecting to find a positive relationship between these variables if 343 brain volume relative to body size has increased since the split of hominins and *Pan*. To 344 determine whether evolutionary rates in brain size deviation have accelerated over time, 345 we fit an "acceleration" model that included the phylogenetic scaling parameter δ 346 [14,57]. Values of δ greater than 1 are consistent with accelerating evolution, but not 347 necessarily directional evolution. Finally, we fit a "directional acceleration" model in 348 which we fit the parameter δ and used phylogenetic distance from the hominin-*Pan* split 349 as a predictor of brain size deviation. In this model, a positive relationship between brain 350 size deviation and phylogenetic distance, along with a value of δ greater than 1, would indicate that brain volume relative to body size has increased at an accelerating rate since 351 352 the divergence of hominins from *Pan*. We compared these models using AICc. Analyses 353 were conducted in the R package caper [58].

354

355 **Results**

356 Endocranial volume (ECV)

In the bayou analysis of ECV predicted by body mass using the homininphylogeny, the Brownian model was favored over the weighted and unweighted predictor

359 OU models with Bayes factors greater than 22. When we repeated this analysis using the 360 alternate hominin phylogeny, we found that the un-weighted predictor OU model was 361 favored over the weighted predictor OU model and the Brownian model with Bayes factors greater than 42, despite displaying poor convergence in terms of α and σ^2 . 362 363 However, both chains inferred a similar set of shifts, indicating that this is likely an issue 364 related to parameter identifiability rather than to shift identifiability. In this model, 365 progressive shifts towards larger ECV relative to body mass were detected within the 366 hominin clade along the human lineage (figure 1A,B). Shifts towards larger relative brain 367 size were also detected on the terminal branch leading to D. madagascariensis and the 368 internal branches leading to the *Lemuridae* and *Cebinae*, clades, and shifts towards 369 smaller relative brain size were detected on the branch leading to the Alouatta clade, the 370 branch leading to the clade containing the Aotidae and Callitrichidae families, and the 371 branch leading to the Colobinae sub-family (figure 1-figure supplement 1). The rejected 372 weighted predictor OU model, as well as both OU models that were rejected in the bayou 373 analysis using the hominin phylogeny, detected a very similar set of shifts that included 374 shifts towards progressively larger ECV relative to body mass along the human lineage 375 (Source data 1). Because the Brownian model was favored in the bayou analysis using 376 the hominin phylogeny, we proceeded with BayesModels analyses using both the

377 hominin and alternate hominin phylogenies.



378

379 Figure 1: OU Model of ECV Evolution in Primates

Panel A shows the location of the selection regimes identified in an OU model of ECV predicted
by body mass. Panel B shows the corresponding optimum regression lines representing the
various selection regimes, along with body mass and ECV data. Data are colored by their
corresponding selection regimes. All results are from the un-weighted predictor OU model in the
bayou analysis using the alternate hominin phylogeny. Only the great ape clade is shown;

385 selection regimes across the entire primate phylogeny are show in figures S1A,B.

387	In the BayesModelS analysis predicting ECV based on body mass while
388	excluding all hominin data, the observed values for H. sapiens and H. neanderthalensis
389	exceeded the mean values predicted by BayesModelS by 7.63 and 6.96 standard
390	deviations respectively (figure 2C). All hominin species were strongly supported positive
391	outliers, with more than 99.9% of predictions falling below the observed values for ECV.
392	The mean ECV prediction for a primate with the body mass of <i>H. sapiens</i> was 438 mL.
393	Remarkably, the observed value for humans is 1478 mL, which is 238% greater than the
394	mean of the predicted posterior distribution. A similar result was found for H .

neanderthalensis; the observed ECV for this species exceeded the mean predicted value
for a primate of their body mass by 952mL, or 201%. Humans exceeded their predicted
ECV by the greatest percentage, but all hominins exceeded predictions by at least 51%
(figure 2C, Table 4). We obtained similar results using the alternate hominin phylogeny
(figure 2-figure supplement 1, Table 5).

400 When we iteratively predicted ECV based on body mass and phylogeny for each

401 species in the data set (no hominins besides *H. sapiens* and *H. neanderthalensis* were

402 included in this analysis) and while using all data to generate predictions. We again found

403 that humans were strongly supported positive outliers (figure 4A). *H. neanderthalensis*

404 was not identified as an outlier, perhaps because these analyses included all species

405 except for the one being predicted, and thus inclusion of *H. sapiens* resulted in a wide

406 posterior distribution when predicting ECV in *H. neanderthalensis*. Indeed, when we

407 excluded *H. sapiens* in this analysis we found that *H. neanderthalensis* was identified as a

408 strongly supported positive outlier (Source data 1). We also identified several other

409 primate species as outliers (see Table 6 and Source data 1).



411 Figure 2: BayesModelS predictions of ECV in hominins

412 Panel A shows a scatter plot of primate ECV and body mass data. Panel B shows the topology of

413 the great ape portion of the hominin phylogeny used in the BayesModelS analyses of hominin

414 ECV. Panel C shows the posterior distributions of predicted ECV values generated by

415 BayesModelS for hominin species with body mass used as the predictor variable. Vertical lines

416 indicated observed values.

Table 4: Predicted Hominin ECV values

	true value (ml)	corrected prediction (ml)	difference (ml)	% difference
Australopithecus africanus	464.00	294.73	169.27	57.43
Homo erectus	969.00	438.24	530.76	121.11
Homo habilis	609.00	306.83	302.17	98.48
Homo rudolfensis	726.00	409.63	316.37	77.23
Homo sapiens	1478.00	437.76	1040.24	237.63
Homo sapiens neanderthalensis	1426.00	474.46	951.54	200.55
Paranthropus boisei	481.00	319.00	162.00	50.78
Paranthropus robustus	563.00	307.60	255.40	83.03
Australopithecus afarensis	458.00	288.52	169.48	58.74

Table 5: Predicted Hominin ECV values from BayesModelS analysis using the alternate hominin phylogeny.

	true value (ml)	corrected prediction (ml)	difference (ml)	% difference
Australopithecus africanus	464.00	288.18	175.82	61.00
Homo erectus	969.00	431.04	537.96	124.81
Homo habilis	609.00	300.16	308.84	102.89
Homo rudolfensis	726.00	401.94	324.06	80.62
Homo sapiens	1478.00	431.20	1046.80	242.76
Homo sapiens neanderthalensis	1426.00	468.41	957.59	204.44
Paranthropus boisei	481.00	311.41	169.59	54.46
Paranthropus robustus	563.00	299.74	263.26	87.83
Australopithecus afarensis	458.00	281.59	176.41	62.65

426 Table 6: Summary of evidence for exceptional brain evolution among non-human

427 primates

Species/Clade	Exceptional Trait	Evidence
Alouatta	Reduced ECV relative to body mass	Shift in OU model
Aotidae and Callitrichidae	Reduced ECV relative to body mass	Shift in OU model
Cacajao calvus	Increased ECV relative to body mass	Outlier Detection
Cebinae	Increased ECV relative to body mass	Shift in OU model
Cebus albifrons	Increased cerebellum relative to body mass	Outlier detection
Chiropotes satanas	Reduced ECV relative to body mass	Outlier Detection
Colobinae	Reduced ECV relative to body mass	Shift in OU model
Daubentonia madagascariensis	Increased ECV relative to body mass	Shift in OU model
Gorilla beringei ^a	Reduced ECV relative to body mass	Outlier Detection
Gorilla gorilla ^a	Reduced neocortex relative to body mass	Outlier Detection
Lemuridae	Increased ECV relative to body mass	Shift in OU model
Loris tardigradus	Reduced medulla relative to the rest of brain	Outlier Detection
Microcebus murinus	Reduced medulla relative to the rest of brain	Outlier Detection
Nasalis larvatus	Reduced neocortex relative to the rest of the brain	Shift in OU model
Otolemur crassicaudatus	Reduced neocortex, cerebellum relative to body mass	Outlier Detection
Pan troglodytes schweinfurthii	Increased ECV relative to body mass	Outlier Detection
Pan troglodytes troglodytes	Reduced ECV relative to body mass	Outlier Detection

428 ^a Only one *Gorilla* species was included in this analysis, i.e. with outlier analyses

429 conducted separately for each *Gorilla* species.

431 In the bayou analysis of ECV with no predictor variable using the hominin 432 phylogeny, the Brownian model was selected over the un-weighted predictor OU models 433 (in which the influence of the predictor was set to 0) with a Bayes factor > 10. No 434 weighted predictor model was run, as it would have been equivalent to the unweighted 435 model given that no predictor variable was incorporated. An equivalent result was found 436 when we repeated the analysis using the alternate hominin phylogeny. We then 437 proceeded with the BayesModelS analysis, iteratively testing the outlier status of each 438 species in the data set. We used the tree block for this analysis, and as such *H. sapiens* 439 and *neanderthalensis* were the only hominins included. We found that neither humans 440 nor Neanderthals were detected as an outlier (figure 4-figure supplement 1, Source data 441 1), indicating that without correcting for body mass, the variance in ECV across primates 442 is great enough to prevent humans' brains from being detected as exceptionally large.

443

444 Evolutionary trajectory of ECV in Hominins

445 We conducted PGLS analyses of brain size deviation conducted to characterize 446 the evolution of exceptional brain size in hominins (data shown in figure 3). The analyses 447 revealed evidence for both accelerated evolution of brain size deviation and directional 448 evolution towards larger brain size deviations, as indicated by the directional acceleration 449 model (AICc = -23.38) being favored over the acceleration (AICc = -21.93), directional 450 (AICc = -17.56), and Brownian (AICc = -14.58) evolution models. In this best model, 451 there was evidence of directional evolution towards larger brain size relative to body size 452 (slope = 0.04) over time, and of accelerating evolution (δ =8.36). These results suggest 453 that the exceptionality of the human brain evolved recently. We found similar results

454 when we repeated this analysis using the alternate hominin phylogeny (figure 3-figure

455 supplement 1). These analyses therefore support a model of accelerating evolution

456 towards larger brain volume relative to body mass in *Homo sapiens*.







466 Figure 4: Human Outlier Status for Brain Traits

467 Predicted distributions of trait values generated by BayesModelS are show as histograms.

468 Vertical bars represent the observed values.

469

470 <u>Neocortex</u>

471 In the bayou analysis of neocortex volume as predicted by body mass, the Brownian

472 motion model was strongly favored over the weighted and unweighted predictor OU

473 models, with Bayes factors > 18. Humans were detected as strongly supported positive

- 474 outliers for neocortex volume by BayesModelS when body mass was used as the
- 475 predictor variable (figure 4B).
- 476 In the bayou analysis of neocortex volume with "rest-of-brain" as the predictor
- 477 variable, the weighted predictor model was selected over the unweighted predictor and

478	Brownian motion models with Bayes Factors > 9.2 . In the weighted predictor model,
479	different scaling patterns were detected for strepsirrhines and haplorhines, with the
480	optimum regression line for haplorhines falling above that of strepsirrhines. The only
481	other detected transition in scaling occurred on the terminal branch leading to Nasalis
482	larvatus, indicating a shift towards lower relative neocortex size (figure 5A,B).
483	
484	Cerebellum
485	In the bayou analysis of cerebellar volume predicted by body mass, the Brownian motion
486	model was favored over the weighted predictor and unweighted predictor OU models,
487	with Bayes factors of 11.96 and 22.79, respectively. BayesModelS identified humans as
488	strongly supported positive outliers for cerebellum volume when body mass was used as
489	the predictor variable (figure 4C).
490	In the bayou analysis of cerebellum volume relative to the rest-of-brain, the
491	comparison between the unweighted predictor model and the Brownian motion model
492	gave a Bayes factor of 10.65, while the comparison between the unweighted and
493	weighted predictor models gave a Bayes factor of 0.20. This indicates that the OU models
494	clearly outperform the Brownian model, but that neither OU model performs significantly
495	better than the other. Both OU models detected a shift on the branch leading to apes
496	associated with an increase in optimum cerebellar volume relative to the "rest-of-brain"
497	volume (figure 5C,D).
498	

499 <u>Medulla</u>

- 500 In the bayou analysis of medulla volume predicted by body mass, the Brownian motion
- 501 model was selected over the two OU models with Bayes factors > 7.4. BayesModelS
- 502 identified humans as strongly supported positive outliers for medulla volume (figure 4D).
- 503 No other species were identified as exceptional in this analysis. When medulla was
- 504 predicted by the "rest-of-brain" volume, the Brownian motion model was again selected
- 505 over the OU models, with Bayes factors > 3.8. Humans were identified as strongly
- 506 supported negative outliers (figure 4E).
- 507

508 <u>Rest-of-brain</u>

509 In the bayou analyses of the rest-of-brain relative to body mass, the OU models were

selected over the Brownian motion model, with Bayes factors >13. However, the

511 comparison between the two OU models gave a Bayes factor of 0.20, indicating that

- 512 neither model is supported relative to the other. No shifts were detected in either model
- 513 (figure 5E,F).
- 514



516 Figure 5: OU Models of Brain Structure Evolution in Primates

517 A and B correspond to the OU weighted predictor model of neocortex volume predicted by the

rest-of-brain. C and D correspond to the OU unweighted predictor model of cerebellum volume

519 predicted by the rest-of-brain. E and F correspond to the OU weighted predictor model of the

520 rest-of-brain volume predicted by body mass. A,C, and E show the location of selection regimes

521 on the primate phylogeny. B,D, and F show the optimum regression lines associated with the

522 selection regimes. Points show primate trait and predictor data; colors correspond to the selection

523 regimes. Colors in A,C, and E match those in B, D, and F.

524 Discussion

525 Our phylogenetic analyses revealed that the human brain is 238% larger than the size 526 expected for a primate of similar body mass and phylogenetic position. The exceptional 527 size of the human brain was achieved through progressive scaling shifts towards larger 528 size over several million years of hominin evolution, and the evolution towards increased 529 brain size relative to expectations based on primate scaling patterns accelerated over 530 time. These findings add an important dimension to previous observations of gradual 531 phyletic increases in hominin brain size. Du et al. [59] fit six evolutionary models to 532 within- and between-lineage change in hominin brain sizes (random walk, gradualism, 533 stasis, punctuated equilibrium, stasis-random walk and stasis-gradualism), obtaining the 534 best fit for a gradualism model. However, their non-phylogenetic analysis did not test 535 explicitly for accelerating directional increase. Our findings extend the results obtained 536 by Pagel (2002) on absolute cranial volume, as the pattern of accelerating evolution is 537 found even after accounting for body size. The pattern of accelerating brain size increase 538 documented here is consistent with hypotheses that postulate a co-evolutionary positive 539 feedback process driving human brain evolution, such as feedback between brain size and 540 culture or language [60,61] or between the brain sizes of conspecifics engaged in a socio-541 cognitive evolutionary arms race [62,63].

542 While humans clearly have the largest relative brain size among extant primates, 543 anatomically modern humans were closely matched by *H. neanderthalensis*. However, 544 even when accounting for the close phylogenetic relationship between humans and *H*. 545 *neanderthalensis* and the exceptionally large brain of the latter, the human brain is still 546 much larger than expected: humans were identified as strongly supported outliers when

their ECV (relative to body mass) was predicted by phenotypic data from all primates,

548 including *H. neanderthalensis*. This pattern was not reciprocal, however; *H.*

neanderthalensis was not significantly different from other primates when *H. sapiens* wasincluded in the model.

551 Significant variation exists between estimates of ECV and body mass made from 552 different fossil specimens of the same hominin species [2]. Thus, using single specimens 553 to represent a species would not be a good statistical practice. We used a dataset in which 554 almost all mean species values were calculated from multiple fossil specimens (Table 1). 555 Unfortunately, we could not explicitly account for intraspecific variation in our analyses, 556 as the multi-optima OU model fitting approach and the outlier test are unable to account 557 for variation in both a trait and predictor variable. It would therefore be worthwhile to 558 revisit our analyses as new phylogenetic comparative methods that can account for 559 intraspecific variation become available. Additionally, data quality will likely improve 560 over time. More hominin fossils will be discovered, increasing sample sizes for estimated 561 ECV and body mass.

562 The hominin phylogeny will also likely become better resolved and more 563 complete. We accounted for some phylogenetic uncertainty by repeating our analyses 564 with an alternate phylogeny. The use of different phylogenies influenced outcomes of 565 some statistical tests, as the Brownian model favored when we used the hominin 566 phylogeny and OU model was favored when we used the alternate hominin phylogeny. 567 However, we found that all of the OU models we fit inferred the same pattern of 568 evolution towards larger ECV along the human lineage. The results of our outlier tests 569 and PGLS model fitting – which assume a Brownian mode of evolution – also detected

this pattern on different phylogenies. Collectively, these results indicate that our findings
are likely to be robust to variations in assumed evolutionary relationships, and potentially
to assumptions about the mode of evolution.

573 It is widely assumed that primate brain size evolution in general, and the large 574 size of the human brain in particular, reflects expansion of the neocortex relative to other 575 brain structures [28,64]. Our results contradict this assumption: human neocortical 576 volume was exceptionally large relative to body mass, but not exceptional relative the 577 volume of the rest of the brain. We documented only one shift in neocortex size relative 578 to the rest of the brain during primate evolution: an increase at the origin of all 579 haplorrhines. This shift may be related to the visual specializations of haplorrhines for 580 high-acuity photic vision, mediated by extensive cortical visual areas that make up over 581 50% of the cortex in these species [65–67]. On branches postdating the split between 582 haplorrhines and strepsirrhines, neocortex size is largely predictable from its scaling 583 relationship to the rest of the brain, in line with the proposed importance of cortical-584 subcortical connectivity in primate brain evolution [68].

585 In contrast, we found that the cerebellum increased in size relative to the rest of 586 the brain on the branch leading to apes. This finding is consistent with the results of 587 recent studies implicating the cerebellum, and especially the lateral cerebellum, in brain 588 expansion in apes and some other mammalian lineages [18,32,69]. Our findings also 589 reinforce the argument that subcortical structures should be given greater consideration in 590 studies of mammalian brain evolution and cognition [23,70]. Cerebellar specialization in 591 apes may have been initiated by the demands on motor control and route-planning 592 imposed by arboreal below-branch locomotion and/or by complex extractive foraging

593 [18,23]. The fact that shifts in the relative size of neocortex and cerebellum occurred on
594 different parts of the tree supports the theory of mosaic brain evolution [71] and suggests
595 that no single adaptive hypothesis is likely to be capable of accounting for primate brain
596 evolution; rather, different selection pressures, on different information-processing
597 capacities, likely operated at different times on different lineages.

598 Consistent with previous studies, we found that the medulla expanded in humans 599 (positive outlier status for medulla volume relative to body mass), but to a lesser degree 600 than other structures (negative outlier status for medulla volume relative to the rest of the 601 brain). Relative to body mass, medulla volume has been shown to be much less variable 602 across taxa than other brain structures, particularly compared to the neocortex and 603 cerebellum. For example, unlike neocortex and cerebellum, medulla volume does not 604 differ significantly between insectivores, strepsirrhines and haplorrhines [37]. 605 Accordingly, we found that after controlling for either body mass or brain size, the 606 evolution of the medulla was not modulated by selection towards a stationary optimum in 607 the primate clade. These results further support mosaic brain evolution [71], and also 608 suggest that scaling constraints related to connectivity with other brain regions [72] was 609 less critical for the medulla than for the neocortex and cerebellum.

Several non-human primate species exhibited exceptional brain evolution in one
trait or another, but only humans showed exceptional brain evolution for multiple brain
components. As predicted, we detected shifts towards larger brain size on the terminal
branches leading to *D. madagascariensis*, and on the branch leading to the *Cebinae* clade.
Large brain size in *Daubentonia* and *Cebinae* has been attributed to extractive foraging
and tool use [73–75]. Although not one of our *a priori* expectations, we also documented

616 shifts towards smaller brain size on branches leading to several clades, including 617 Alouatta. We also found that two Gorilla species exhibit a smaller brain or neocortex size 618 relative to body mass than expected. Given the extremely large body mass of Gorilla 619 species, these unique traits may be the byproduct of a body mass increase rather than a 620 reduction in brain size. Also unexpectedly, two *Pan troglodytes* sub-species were found 621 to have exceptionally large and small ECV relative to body mass respectively. However, 622 because more closely related species are weighed more heavily when BayesModelS 623 generates distributions of predicted trait values, sister taxa deviating from expectations in 624 opposite directions could result in both taxa being identified as outliers, even if they both 625 conform to patterns of brain-body scaling for other primates. If the trait distributions for 626 each species overlap significantly, then accounting for intraspecific variation in future 627 analyses could remedy this problem.

628 The unexpected patterns that we observed amongst non-human primates raise 629 several questions for further research. Given the well-established positive correlation 630 between overall brain size and extended life history [76–78], what are the life history 631 implications of mosaic shifts in the sizes of different structures, and do these support any 632 specific interpretations of the correlation between brain size and life histories? One 633 hypothesis, the developmental costs hypothesis, is that large brains simply take longer to 634 grow and mature, leading to extended periods of maternal investment and slower 635 maturation, with other life history correlates of brain size being byproducts of 636 developmental prolongation. Support for this hypothesis is provided by the finding that, 637 amongst mammals, the durations of gestation and lactation have independent effects on 638 pre- and postnatal brain growth, and once these effects are accounted for, other life

history correlates are non-significant [79]. Despite their generally correlated evolution
[68], we found shifts in the relative size of neocortex and cerebellum on different parts of
the phylogenetic tree. Because these two structures have different developmental
trajectories, the developmental costs hypothesis predicts different life history correlates;
this prediction has now received support [80]. Further work is needed to establish exactly
what developmental changes allowed for the neocortex and cerebellum to rest-of-brain
scaling rules to change at the origin of haplorrhines and hominoids, respectively.

Another area of interest concerns the cases we found of brain or brain component size reduction. Montgomery et al. [16] found that brain size reductions were rare during primate evolution, and that there was a general trend for brain size to increase across multiple branches of the phylogeny. This raises questions for future work concerning the causes, developmental mechanisms and functional implications of specific types of size reduction, such as those that we uncovered in brain size relative to body size in *Alouatta* and other clades, and in neocortex size relative to the rest of the brain in *N. larvatus*.

653 Finally, a key question that has attracted considerable attention concerns the 654 ecological and social drivers of brain size and structure across large-scale evolutionary 655 radiations. It has become increasingly apparent that correlations between overall brain 656 size and behavioral ecology needed to be treated with caution [6,81,82]. However, as 657 suggested by the hypothesis of mosaic brain evolution, correlations between ecology and 658 individual, less functionally heterogenous brain components may be more reliable and 659 robust [18,23,66,67,71,83]. Our analyses focused on gross subdivisions within the brain, 660 and we suggest that further insights could be obtained by applying the phylogenetic 661 methods used in this paper to more fine-grained neuro-anatomical data, using this

662 approach to tease apart the contributions of correlated and mosaic change among brain 663 components [72] and by incorporating ecological, behavioral, and developmental 664 predictor variables that may account for additional variation in the traits of interest. 665 In conclusion, we provided robust evidence for directional and accelerating 666 selection towards larger brain size over the course of human evolution, resulting in the 667 human brain being exceptionally large for a primate of similar body mass. We also found 668 that the sizes of human brain components – including the neocortex, cerebellum, and the 669 rest of the brain – are not larger or smaller than expected relative to the size of the rest of 670 the brain, but all are larger than expected for a primate of similar body mass. These 671 results suggest that relative neocortical expansion is not a hallmark of our species. The 672 diversity of evolutionary patterns for various brain components that we observed within 673 primates suggests that no single factor fully explains primate brain evolution; instead, 674 comparative research should investigate how different selection pressures influenced the 675 evolution of different neuroanatomical components at different times on different parts of 676 the phylogenetic tree. Additionally, future work should seek to analyze the evolution of 677 other brain traits, including neuronal composition, using similar phylogenetic 678 comparative methods that account for the non-independence of data from related species. 679 680 Competing interests: We have no competing interests to declare. 681 682 Acknowledgments: We are grateful to Josef Uyeda for advice on using the 683 developmental version of bayou. We would also like to thank Tom Milledge and Duke 684 Research Computing for assistance with the Duke computing cluster.

685

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- 907

909 Supplementary figure legends

910

911 Figure 1-figure supplement 1: OU Model of ECV Evolution in Primates

912 Results are shown for the un-weighted predictor OU model of ECV predicted by body

913 mass. Figure 1 displays the same results, but only for great apes. Panel A shows the

914 location of the selection regimes. Panel B shows the optimum regression lines

915 representing the various selection regimes, along with body mass and ECV data. Data in

916 panel B are colored according to the corresponding regimes shown in panel A.

917

918 Figure 2-figure supplement 1: BayesModelS predictions of ECV in hominins

919 Panel A shows a scatter plot of primate ECV and body mass data. Panel B shows the

920 topology of the great ape portion of the alternate hominin phylogeny used in the

921 BayesModelS analyses of hominin ECV. Panel C shows the posterior distributions of

922 predicted ECV values generated by BayesModelS for hominin species with body mass

923 used as the predictor variable. Vertical lines indicated observed values. The observed

value for *H. sapiens s* exceeded the mean value predicted by BayesModelS by more than

seven standard deviations. All hominin species were strongly supported positive

926 outliers, with >99.9% of predictions falling below the observed values for ECV.

927

928 Figure 3-figure supplement 1: Accelerating Evolution of Brain Size Deviation in

929 Hominins (alternate hominin phylogeny).

930 A: Brain size deviation was calculated as the difference between the mean BayesModelS

931 prediction (made while excluding all hominin data from analysis and using the alternate

hominin phylogeny) and the observed value. Phylogenetic distance was measured as time

933 since the shared ancestor of hominins and Pan at 9.28 mya. B: Hominin portion of the

- alternate hominin phylogeny after δ transformation, with δ =3.745 following the
- 935 directional acceleration model. Among the PGLS models fit to this data, the directional
- 936 acceleration model (AICc = -23.88) was favored, as it outperformed the Brownian
- 937 (AICc = -15.71), directional (AICc = -22.12), and accelerating (AICc = -22.38) evolution
- 938 models. This model gave evidence for both evolution towards larger brain volume
- relative to body mass (slope = 0.06) and for accelerating evolution (δ =3.745).
- 940

941 Figure 4-figure supplement 1: Human outlier status for ECV

942 In the BayesModelS analysis of ECV with no predictor variable, humans were not

943 detected as outliers. Results for other species are given in Source data 1. Because

944 BayesModelS requires a predictor variable, we assigned each species a random number

945 for the predictor trait. This resulted in the predictor variable not being included in the

946 PGLS model in ~98% of post burn-in MCMC samples. We discarded the remaining

samples that included the predictor in the PGLS model before generating predictions.

950 Appendix 1: Data Compilation

All data and trees used in our analyses are included in the Source data 2 file. We

952 compiled three data sets for our analyses. The first was used for the analyses of

953 endocranial volume (ECV), the second was used for the analyses of the neocortex and

954 cerebellum, and the third was used for the analyses of the medulla.

955 In the first data set ("data set 1.csv"), we compiled ECV and female body mass 956 values for non-human primates from [1], who compiled their data set in part from Araújo 957 [84], Gordon [39], Smith and Jungers [85], and Thalmann and Geissmann [86]. This 958 dataset was supplemented with fossil data for ancient humans and extinct hominins from 959 Robson and Wood [2]. These authors provided two taxonomies: one that recognized 960 more species of hominins (the "splitting taxonomy"), and another that lumped hominin 961 lineages into fewer taxonomic categories (the "lumping taxonomy"). We extracted values 962 from the splitting taxonomy, except those for Australopithecus africanus, which were 963 only available from the lumping taxonomy. We also chose to use values for Homo 964 *erectus (sensu lato)* from the lumping taxonomy, as these values was calculated from 965 fossils attributed to both *H. erectus* and *H. ergaster*, two species that are not 966 differentiated in our phylogeny. We did not include *H. heidelbergensis* in our analyses 967 because its phylogenetic position is unresolved [87]. Sample sizes are given in Table 1. 968 Museum numbers for the specimens used in calculating species mean values are given in 969 Appendix I of [2].

In the second data set ("data set 2.csv"), body mass, neocortical volume, and
cerebellar volume for humans and extant non-human primates were compiled from the
data set of Barton and Venditti [88]. We also complied brain volumes to use in the

973 calculation of the "rest-of-brain" predictor trait in the analyses of these brain structures.
974 These values were calculated as an average of the values given in [41,89–92]. The second
975 data set was limited to extant primates and included values for 55 species, including
976 humans.

977 The third data set ("data set 3.csv") included body mass, brain volumes, and 978 medulla volumes from Stephan et al. [41]. This data set spanned 41 species.

A summary of all human ECV and body mass estimates and the analyses in whichthey were used is given in Tables 1 and 2.

All trait and predictor values were log₁₀ transformed prior to analyses. When
differences between component volumes were used in analyses, we calculated the
logarithms after subtraction.

984 We used several different phylogenetic trees and tree blocks in our analyses. We 985 constructed a "hominin phylogeny" ("hominin.phylogeny.txt") that included humans, 986 extinct hominins, and extant primates for use in the analyses of hominin ECV (including 987 the analyses of directional and accelerating evolution); this phylogeny was produced by 988 grafting the "combined dataset consensus time tree" of hominin evolution from Organ et 989 al. [13] onto the time-scaled consensus tree of extant primates from version 3 of 10kTrees 990 [43]. We grafted the clade (including the root branch) containing *Pan* and all fossil 991 hominins onto the node at which Gorilla diverged from the Pan lineage, and then re-992 scaled this pasted clade so that the human tip lined up with those of extant primates. We 993 also constructed an "alternative hominin phylogeny" ("alt.hominin.phylogney.txt" using 994 the "morphology and molecular graft time tree" from Organ et al. [13]. To construct this 995 tree, we again grafted the clade (including the root branch) containing *Pan* and all fossil

996	hominins onto the node at which Gorilla diverged from the Pan lineage, and then
997	shortened the root branch so that the human tip lined up with those of extant primates.
998	We were not able to use this method for constructing the hominin phylogeny because it
999	would have resulted in the branch leading to the clade containing Pan and hominins
1000	having a negative length. Both hominin phylogenies we constructed include humans, 300
1001	other extant primates, and 13 extinct hominin species. In other analyses, we used a
1002	consensus tree ("consensus.tree.txt") of extant primates (for OU model fitting) or a block
1003	of 100 primate trees ("tree.block.txt") downloaded from version 3 of 10kTrees [43, for
1004	phylogenetic prediction].
1005	
1006	Appendix 2: Details of Bayou models
1007	The un-weighted predictor model is described by the following equation:
1008	
1009	Eqn. 1 E[y] = W $\theta_M + x \beta_n$
1010	
1011	E[y] is the expected value of a species trait. W and θ_M represent the evolutionary weight
1012	matrix and θ matrix described in [93]. W is a 1 x <i>n</i> matrix whose entries are the weights
1013	given to each of the n selection regimes through which the species of interest evolved.
1014	The weight of each regime is dependent upon the phylogeny and the value of α . More
1015	recent regimes have greater weights, especially when α is high. θ_M is an $n \ge 1$ matrix of
1016	the θ values of the regimes through which the species of interest evolved. The product of
1017	W and θ_M gives the effective θ value for a species that evolved towards the various
1018	optimum θ values specified in θ_M . β_n is the β value of the parameter regime at the tip of

1019	the phylogeny. Therefore, in this model, the expected phenotype for a species is a
1020	function of the evolutionarily weighted effective θ value, the coefficient of the predictor
1021	variable of the current selection regime, and the value of the predictor at the tip of the
1022	phylogeny.
1023	
1024	The weighted predictor model is described by a similar equation:
1025	
1026	Eqn. 2 E[y] = W θ_M + $x W \beta_M$
1027	
1028	β_M is an <i>n</i> x 1 matrix of the optimum β values of the n regimes through which the species
1029	evolved, and is analogous to θ_M . Thus, in this model the expected trait value of each
1030	species is a function of the species evolutionarily weighted effective θ and β values, and
1031	the value of the predictor variable x at the tip of the phylogeny.
1032	
1033	Appendix 3: Problems with MCMC convergence in bayou
1034	Bayou returned several MCMC chains during the analyses of ECV that did not converge
1035	in terms of likelihood, α , and σ^2 . To address this issue, we generated up to six MCMC
1036	chains in each analysis for both for the un-weighted predictor, weighted predictor, and
1037	Brownian models. Several chains with exceptionally high mean likelihood had σ^2 values
1038	approaching zero and very high α values that appeared to be bounded by a maximum
1039	value. We infer from these patterns that the chains were settling on an unrealistic pattern
1040	of evolution with the stationary variance approaching zero. These chains also inferred
1041	shifts erratically; they predicted shifts with posterior probability greater than 0.1 on many

- 1042 branches, but no shifts had a posterior probability greater than 0.3. We discarded these
- 1043 chains, and then selected the two chains with the highest mean likelihood for each
- analysis for subsequent use.
- 1045
- 1046

1047 Additional files

1048 Source code 1. Representative Code.

- 1049 Representative R code files for the bayou analyses ("representative bayou code.R"),
- 1050 BayesModelS analyses ("representative BayesModels code.R"), and pgls model fitting
- 1051 ("pgls models.R"), are contained in the this file, along with the BayesModelS code
- 1052 ("mult.spec.BayesModelS_v24.R") and other necessary data files.
- 1053

1054 Source data 1. Bayou and BayesModelS Results Details.

- 1055 Bayou Results details: Diagnostic plots giving details of chain convergence are provided
- 1056 in the "bayou results summary.html" file along with detailed information on all OU and
- 1057 Brownain motion models for each trait and predictor pair.
- 1058 BayesModelS Results Details: Details of the BayesModelS results and diagnostic
- 1059 parameters of MCMC chains are given in the "BayesModelS.results.csv" and
- 1060 "BayesModelS.results.hominins.removed.csv" files.
- 1061

1062 Source data 2. All data and trees used in our analyses.

- 1063 Contains the following files:
- 1064 1. data set 1.csv
- 1065 2. data set 2.csv
- 1066 3. data set 3.csv
- 1067 4. consensus.tree.txt
- 1068 5. tree.block.txt
- 1069 6. grafted.tree.txt