Ecological harshness mediates reproductive trade-offs in a great tit population Louis Bliard¹, Jordan S. Martin², Dylan Z. Childs³, Ella F. Cole⁴, Ben C. Sheldon⁴, Maria Paniw^{1,5}, Arpat Ozgul¹ 1 Department of Evolutionary Biology and Environmental Studies, Zurich University, Zurich, Switzerland 2 Department Fish Ecology and Evolution, Swiss Federal Institute of Aquatic Science and Technology (EAWAG), Kastanienbaum, Switzerland 3 Department of Animal and Plant Sciences, University of Sheffield, Sheffield, UK 4 Edward Grey Institute, Department of Biology, University of Oxford, Oxford, UK 5 Department of Conservation Biology, Estación Biológica de Doñana (EBD-CSIC), Seville, Spain Corresponding author: bliard.louis@gmail.com

Abstract

24 Lack's seminal work on bird clutch sizes has spurred expansive research on reproductive trade-25 offs, especially focusing on offspring quantity-quality trade-offs and the potential fitness 26 consequences for the parents. The environment is a critical driver of the expression of individual 27 reproductive traits, influencing them through plastic responses. However, the plasticity of 28 reproductive trade-offs themselves across environments has seldom been studied, and these 29 studies were often limited to experimental approaches and dichotomous environments. Using 30 58 years of detailed data from a great tit population, we employ the recently developed 31 'covariance reaction norm' (CRN) model to explore how continuous environmental variation 32 influences the shape of reproductive trade-offs among individuals. Our analysis reveals that the 33 offspring quantity-quality trade-off is predominantly stable across years, with minimal variation 34 linked to ecological harshness during the breeding season. However, the CRN also demonstrated 35 that the among-mother correlation between offspring mass and future offspring recruitment was 36 positive, but only under harsh environmental conditions, suggesting that producing larger 37 offspring provides fitness benefits when breeding conditions are suboptimal, which may reflect 38 the importance of size for early-life competition. Altogether, this work highlights that there is 39 temporal variation in some of the phenotypic correlations, mostly driven by environmental 40 conditions, which shape the expression of offspring investment across breeding seasons. Our 41 study shows the benefits of exploring old ecological questions in the light of new statistical 42 methods, highlighting the importance of understanding how environmental variation shapes the 43 expression of life history trade-offs and the evolution of plasticity in reproductive strategies.

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Introduction

46 The offspring quantity-quality trade-off has been a central area of interest in life-history biology, 47 with numerous studies exploring this long-standing topic, both theoretically (Williams, 1966; 48 Smith & Fretwell, 1974; Fischer et al., 2011), as well as empirically in various species (Lack, 1954; 49 Sinervo & Licht, 1991; Einum & Fleming, 2000) including humans (Lawson & Mulder, 2016). All 50 else being equal, selection should favor females producing more offspring, but these females also 51 require enough resources to allocate to each offspring to ensure their survival, as larger offspring 52 usually have better survival prospects (Sogard, 1997; Einum & Fleming, 2000; Marshall et al., 53 2003; Fischer et al., 2011). It was, therefore, initially proposed that each female has an inherent 54 optimal brood size, such that it yields the highest possible recruitment, whereby any deviations 55 from this brood size would lead to suboptimal offspring quality and thus lower overall 56 recruitment (Lack, 1954). Overall, while some evidence agrees with Lack's initial hypothesis 57 (Smith & Fretwell, 1974), with manipulated increases or decreases in clutch size leading to 58 changes in offspring condition and suboptimal recruitment as a consequence (Pettifor et al., 59 1988, 2001), most studies found that any increase in clutch size does not necessarily decrease 60 offspring quality, and can even lead to higher recruitment (Perrins & Moss, 1975; Boyce & Perrins, 61 1987). Recent work has also shown how selection on offspring quality across breeding seasons 62 can promote rather than constrain variability in females' clutch size in response to seasonal 63 fluctuations (Westneat et al., under review).

This potential lack of brood size optimization can have several causes. First, the offspring quantity–quality trade-off does not happen in isolation from other traits: females do not necessarily optimize the size of a single brood for highest possible recruitment, but rather 67 balance it with their own survival and thus future reproductive opportunities, maximizing their 68 lifetime reproductive success (Williams, 1966; Gustafsson & Sutherland, 1988; Dijkstra et al., 69 1990). Second, it ignores the role of mating and bi-parental care present in many avian species, 70 and thus overlooks factors such as mate quality and sexual conflicts over provisioning which can 71 influence reproductive trade-offs (Smith & Härdling, 2000; Ratikainen et al., 2018). Finally, 72 models on optimal brood size have sometimes ignored the role played by the environment in 73 mediating such reproductive trade-offs (Smith & Fretwell, 1974), as in many species, individuals 74 adjust their offspring number and size via phenotypic plasticity (Fischer *et al.*, 2011).

75 The expression of trade-offs can change over time and and space due to phenotypic plasticity (Service & Rose, 1985; Björklund, 2004). These plastic changes in trait expression as a 76 77 response to environmental variability can lead to changes in the variance and covariance 78 between traits (de Jong, 1989; Martin, 2023), with the latter being determined by the relative 79 amount of variance in resource acquisition vs. resource allocation between the given traits (van 80 Noordwijk & de Jong, 1986). The environment influences the evolution of traits such as optimal 81 offspring size, optimal clutch size, and their plasticity (Parker & Begon, 1986), which have since 82 been widely studied (Braby, 1994; Fox & Czesak, 2000; Taborsky et al., 2007; Allen et al., 2008; 83 Marshall et al., 2008; Leips et al., 2009). However, little is known about the influence of the 84 environment on reproductive trade-offs themselves (i.e., on the correlation between traits) in 85 wild populations, with most explorations limited to experimental approaches with discrete environments, or a dichotomization of the underlying continuous environmental variation 86 87 (Messina & Slade, 1999; Czesak & Fox, 2003; Houslay et al., 2018; Mitchell & Houslay, 2021). 88 Discretizing continuous processes is rarely justifiable (MacCallum et al., 2002; Beltran & Tarwater, 2024). Historically this was done largely for practical reasons when studying trade-offs, as no modeling approach was available to easily study the influence of continuous environmental variation on genetic or phenotypic covariances (i.e., trade-offs) (Martin, 2023). However, it is likely that reproductive trade-offs in wild populations are influenced by the continuous environmental variation experienced by reproductive females. We, therefore, aim to use a new multivariate statistical approach that allows us to explore the role of continuous variation in environmental harshness on such reproductive trade-offs.

96 Here, we used one of the largest individual-based datasets of wild birds with the aim of 97 applying a new statistical tool — the covariance reaction norm (CRN) model (Martin, 2023; Bliard 98 et al., 2024) — to revisit longstanding questions related to reproductive trade-offs faced by 99 reproductive individuals in wild populations. The CRN model provides a novel framework to 100 examine how continuous environmental variation influences the covariance between traits, 101 allowing us to test longstanding hypotheses about trade-offs in a more ecologically realistic 102 context (Martin, 2023; Bliard et al., 2024). Here, we explored the dependence on key 103 environmental variables of the among-individual (i.e., among-mother) correlations between 104 three key traits: brood size, offspring mass, and offspring recruitment, with each trait viewed as 105 a maternal character (i.e., analysed at the level of the brood). Overall, based on prior work, we 106 hypothesized that we would find a trade-off (i.e., negative correlation) between brood size and 107 offspring mass (Nur, 1984; Smith et al., 1989), and that this correlation would become more 108 negative in years of harsh ecological conditions (i.e., high density, low precipitation, low 109 temperature, low beech mast), as trade-offs have often been shown to be stronger in poor 110 conditions (Cohen et al., 2020). We also hypothesized that the among-mother correlation

111 between offspring mass and recruitment would be positive overall, as females producing larger 112 offspring should have an improved recruitment, with more of these offspring surviving and 113 reproducing in following years (Perrins & Moss, 1975; Nur, 1984). Importantly, we expected this 114 correlation to be more positive under harsh ecological conditions, as in such conditions producing 115 larger offspring might be key for their survival. When ecological conditions are milder or 116 favorable (i.e., low density, high precipitation, high temperature, high beech mast), this 117 correlation is expected to become null, as even smaller offspring might be as likely to survive in 118 such conditions. Finally, we expected a slightly positive correlation between brood size and 119 recruitment, as past studies have shown that mothers with the highest brood size had higher 120 recruitment for this specific brood, even though it potentially leads to lower fitness across 121 multiple broods (Boyce & Perrins, 1987). We also expected the correlation between brood size 122 and recruitment to become more positive in breeding seasons with a low population density.

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Methods

125 In this study, we explored whether the among-individual correlations between three main traits 126 linked to reproduction depended on the environmental context. To this aim, we used 58 years of 127 individual demographic and life-history data from the monitoring of a great tit population in 128 Wytham Woods and applied a CRN model to brood size, offspring mass, and recruitment of 129 offspring into the population in following years. In this model, we explored the role of ecological 130 and environmental variables in governing the among-individual correlations between these 131 traits.

132 Study system

133 The great tit is a common and widespread species across Eurasia, member of the Paridae family 134 (Gosler et al., 2020), and is one of the most widely studied passerines, that has become a model 135 species for the study of behavioral and evolutionary ecology. It dwells in woodland and wooded 136 farmland, as well as urban areas (Gosler et al., 2020), and nests in tree cavities and artificial nest 137 boxes. Great tits are annual breeders, forming pairs and breeding in the spring, usually producing 138 a single clutch per year consisting of 5-12 eggs, even though second clutches later in the spring 139 sometimes occur (Perrins, 1965). The study population is from Wytham Woods (Oxfordshire, 140 United Kingdom, 51°77'N, 1°32'W), which has been monitored since 1947 (Perrins, 1965), and 141 the monitoring has been standardized with a stable number of nest boxes since 1961 (Perrins, 142 1965; Perrins & McCleery, 1989). The curated and standardized data used in this study were 143 accessed through SPI-Birds: study name "Wytham Woods", study ID "WYT", version 1.1.0 on 144 October 16th 2023 (Culina et al., 2021). As part of this long-term individual-based monitoring, 145 individuals were fitted with unique metal rings to allow individual identification and followed 146 throughout their lifespan (Lack, 1964). All breeding attempts were monitored until offspring 147 fledged, and both parents and offspring were usually caught, identified, and individually 148 measured (e.g., mass, tarsus length).

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150 Individual and environmental variables

Using 58 years of individual-based monitoring data from 1961 to 2018, we analyzed three different traits. These were the response variables in our model (see "Data analysis" section) and include the size of the brood (number of nestlings), the mass of offspring (g), and the subsequent number of successful recruits from the brood. The mass of offspring was restricted to weight 155 measurements of 14 days old offspring. Each brood size was recorded 14 days after hatching, 156 and the fate of offspring from the brood was tracked, with recruitment defined as the number of 157 offspring in a brood seen breeding within the population in subsequent years, a good measure 158 of reproductive success that is often used as a proxy of parental fitness (McCleery & Clobert, 159 1990; Both & Visser, 2000; Wilkin et al., 2006; but see Wolf & Wade, 2001 for a critical 160 perspective). It is important to note that this measurement of offspring recruitment has often 161 been used but is imperfect for many reasons, such as being confounded by natal dispersal. 162 However, this bias is expected to be limited, as natal dispersal is limited in great tits, with many 163 offspring dispersing short distances and therefore likely staying within the study population 164 (Greenwood et al., 1979; Verhulst et al., 1997). In total, this yielded a final dataset encompassing 165 7287 broods from 5032 females across 58 years, with individual measures of mass and 166 recruitment in the population in following years for 53753 offspring.

167 The explanatory variables in our model included both individual and environmental 168 variables. The individual variables were the mass of the mother (g) of each brood, as well as the 169 breeding age of the mother, which has an influence on reproductive success (Bouwhuis *et al.*, 170 2009). All breeding individuals were aged as first year breeders (1 year old) or older breeders (>1 171 year old), and this categorisation was based on plumage characteristics during captures when 172 the exact age was not known from the ring number (Crates *et al.*, 2016; Simmonds *et al.*, 2020). 173 The environmental variables were spring temperature, spring precipitation, population

density, beech mast index, and synchrony of laying dates with the caterpillar peak, which are all known to be important for great tit reproduction. These predictors were chosen because they directly influence resource availability, breeding timing, or parental effort in great tits. For 177 instance, lower spring temperatures and precipitation may limit caterpillar abundance, a key 178 food source, increasing the cost of brood provisioning, while population density may reflect 179 competition for resources. Spring temperature and precipitation were obtained from the nearby 180 Radcliffe Meteorological Station (Burt & Burt, 2019). Spring precipitation was defined as the sum 181 of precipitation from April 1st to May 31st, the period when offspring are in the nest (Simmonds 182 et al., 2020). Following Simmonds et al. (2020) analysis of climatic windows critical for great tits 183 (Bailey & Pol, 2016; van de Pol et al., 2016; Simmonds et al., 2020), spring temperature was defined as the daily mean temperature from March 1st to May 9th. As usually estimated in this 184 185 system, population density in a given year was calculated as the number of females hatching at 186 least one egg (Simmonds et al., 2020). Beech mast index has been routinely collected in Wytham 187 Woods and across Europe (Lack, 1964; Perdeck et al., 2000; Grøtan et al., 2009), and is scored as 188 an ordinal variable of increasing beech mast ranging from 0 to 2. Years of high beech mast are 189 expected to be beneficial for fledgling survival in the fall and over winter by providing abundant 190 food resources, and is therefore an important factor for offspring recruitment. Finally, synchrony 191 is an individual's measure of phenological timing in relation to an annual, population-wide, 192 measure of caterpillar abundance. More precisely, we calculated it as the difference between the 193 half-fall date, which is the median date of capture of 5th instar caterpillars of the of winter moth 194 Opheroptera brumata larvae, which indexes the timing of peak abundance of this species (Van 195 Noordwijk et al., 1995; Hinks et al., 2015), and the female's laying date.

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197 Missing data imputation

198 The final datasets contained missing data for some variables. More specifically, out of a total of 199 7287 broods, the mass of the mother was missing for 1147 observations (15.7%), while the 200 breeding age was not known for 210 observations (2.9%). Regarding the environmental variables 201 across the 58 years of monitoring, 14 years had an unknown half fall date (24.1%) and 5 years 202 had a missing beech mast index (8.6%). We imputed these missing data points using predictive 203 mean matching with the R package mice (Buuren & Groothuis-Oudshoorn, 2011; Buuren et al., 204 2023). To account for imputation uncertainty, we generated 20 alternative imputed datasets 205 using this method, and each of these datasets was then analyzed and subsequently combined, 206 successfully propagating imputation uncertainty in the results throughout the analysis.

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208 Data analysis

209 We aim to explore the ecological correlates of phenotypic correlations between maternal traits 210 linked to reproduction in great tits, more precisely the phenotypic correlations between brood 211 size and offspring quality (using mass as a proxy), and between offspring quality and offspring 212 recruitment in the population in following years. To this aim, we used a multivariate Covariance 213 Reaction Norm (CRN) model, which is a recently developed model (Martin, 2023) that we have 214 previously tailored to routinely collected demographic data (Bliard et al., 2024), allowing 215 phenotypic covariances to vary through time or space in response to environmental variation. 216 We apply this method on the three traits of interest in this study: brood size, offspring mass, and 217 offspring recruitment (all treated as maternal traits, analysed at the level of the brood).

We first modeled offspring mass at day 14 with a Gaussian distribution (equation 1), as a function of **X**₁ (a N x P matrix of N measurements of P predictors, including an intercept), with 220 predictors being spring temperature, spring precipitation, population density, beech mast index, 221 synchrony and its quadratic effect, the mass of the mother and the age of the mother. All the 222 continuous variables were standardized. In addition, we included a year random effect δ_1 and a 223 nestbox random effect y_1 . The year random effect accounts for inter-annual variability in 224 environmental conditions, while the nestbox random effect controls for potential variation in 225 territory quality or non-random selection of specific nestboxes by reproductive individuals. These 226 random effects ensure that observed phenotypic correlations are not biased by unmeasured 227 temporal or spatial factors. We also added a year-specific mother random effect $\alpha_{1(Y)}$ structured 228 across repeated measurements by W (a N x J matrix of J mothers), which as explained further 229 below could vary in response to year-specific ecological conditions. Finally, σ is the residual 230 variation describing the within-brood variance.

$$\mu_1 = X_1 \beta_1 + \delta_1 + \gamma_1 + W \alpha_{1(Y)}$$
(1)
offspring mass ~ Normal(μ_1, σ_{μ_1})

231

232 As our second trait, brood size, is underdispersed relative to a Poisson distribution, we modeled 233 it using an ordinal regression (also called cumulative logistic regression; equation 2), as a function 234 of X₂, with covariates being the same as in X₁, but not containing an intercept and differing in the 235 number of observations. Similarly, we also included a year random effect δ_2 and a nestbox 236 random effect y_2 . In the absence of repeated measurement for each mother in a given year (a 237 single brood per female in a breeding season), as indicated by the exclusion of W, we included a 238 year-specific observation-level random effect $o_{2(Y)}$. Here, the cumulative probability of having at 239 most *i* offspring is given as a function of the thresholds θ_i and the matrix of covariates X_2 , as well 240 as the random effects.

$$logit(Pr(N_{offspring} \le i)) = \theta_i - (X_2\beta_2 + \delta_2 + \gamma_2 + o_{2(Y)})$$
(2)

242 We modeled the third trait, offspring recruitment, describing the number of offspring from a 243 given brood found breeding in the population in following years, with a zero-inflated Poisson 244 distribution (equation 3). Recruitment data were expected to be heavily zero-inflated because 245 many broods produced no recruits, due to factors such as brood predation and low offspring survival. The zero-inflation term ψ was included because posterior predictive checks with a 246 247 simpler Poisson model without zero inflation highlighted an over-representation of zeros, causing 248 the model to fit poorly to the data. The probability of observing a given number of offspring 249 recruited into the population in following years was modeled as a function of X_3 , which is similar 250 to X_2 with the addition of an intercept. Year δ_3 and nestbox γ_3 random effects were included as 251 well. Since offspring recruitment was analyzed at the level of the brood (one measure of 252 recruitment per brood), we did not have repeated measurements in a given year for mothers, 253 and therefore included a year-specific observation-level random effect $o_{3(\gamma)}$.

$$\log(\boldsymbol{\mu}_3) = \boldsymbol{X}_3\boldsymbol{\beta}_3 + \boldsymbol{\delta}_3 + \boldsymbol{\gamma}_3 + \boldsymbol{o}_{3(Y)}$$
(3)
$$p(\boldsymbol{N}_{recruits} \mid \boldsymbol{\psi}, \boldsymbol{\mu}_3) = \begin{cases} \boldsymbol{\psi} + (1 - \boldsymbol{\psi})Poisson(0 \mid \boldsymbol{\mu}_3), & \text{if } N_{recruits} = 0\\ (1 - \boldsymbol{\psi})Poisson(\boldsymbol{N}_{recruits} \mid \boldsymbol{\mu}_3), & \text{if } N_{recruits} > 0 \end{cases}$$

We also tried an alternative modeling approach by using a binomial distribution to estimate the probability of offspring recruiting in the population, but unfortunately this model suffered from convergence issues that could not be resolved.

To investigate context dependence of the phenotypic correlations between these three traits, the year-specific among-individual random effect $\alpha_{1(\gamma)}$ and observation-level random effects $o_{2(\gamma)}$ and $o_{3(\gamma)}$ were drawn from a multivariate normal distribution governed by yearspecific covariance matrices $P_{(Y)}$ (equation 4). The year-specific covariance matrices can then be decomposed in their primary elements, i.e., the year-specific phenotypic correlations between the three traits (r_{12} , r_{13} , r_{23}) and their variances ($\sigma_{\alpha 1}^2$, σ_{02}^2 , σ_{03}^2), given that a covariance is just the product of the correlation between traits and the square roots of the variances. We then model the year-specific phenotypic correlations ($r_{(Y)}$), as well as the year specific variances ($\sigma^2_{(Y)}$), as a function of a subset of the environmental covariates contained in X_4 (equation 4). The covariates are spring temperature, spring precipitation, population density, and beech mast index.

$$\begin{bmatrix} \alpha_{1(Y)}, \sigma_{2(Y)}, \sigma_{3(Y)} \end{bmatrix} \sim Multivariate Normal(\mathbf{0}, \mathbf{P}_{(Y)})$$
(4)
$$\mathbf{P}_{(Y)} = \begin{bmatrix} \sigma_{\alpha_{1(Y)}}^{2} & r_{12(Y)} \sigma_{\alpha_{1}(Y)} \sigma_{o_{2}(Y)} & r_{13(Y)} \sigma_{\alpha_{1}(Y)} \sigma_{o_{3}(Y)} \\ r_{12(Y)} \sigma_{\alpha_{1}(Y)} \sigma_{o_{2}(Y)} & \sigma_{o_{2}(Y)}^{2} & r_{23(Y)} \sigma_{o_{2}(Y)} \sigma_{o_{3}(Y)} \\ r_{13(Y)} \sigma_{\alpha_{1}(Y)} \sigma_{o_{3}(Y)} & r_{23(Y)} \sigma_{o_{2}(Y)} \sigma_{o_{3}(Y)} & \sigma_{o_{3}^{2}(Y)}^{2} \end{bmatrix}$$
$$\operatorname{atanh}(\mathbf{r}_{(Y)}) = \mathbf{X}_{4}\boldsymbol{\beta}_{4}$$
$$\exp(\sigma_{(Y)}) = \mathbf{X}_{4}\boldsymbol{\beta}_{5}$$

268

Regarding the choice of priors, we used a standard flat prior for the zero-inflation coefficient ψ (equation 5), which is a default prior for this parameter in most statistical software.

$$\psi \sim Beta(1,1) \tag{5}$$

271

We specified regularizing priors for all the β slope coefficients (equation 6) to reduce our risk of false positive and increase the robustness and generalizability of our findings (see Lemoine, 2019 for discussion). Narrower priors were used for β_4 to avoid putting to much weight on extreme correlations.

$$\boldsymbol{\beta}_{1}, \boldsymbol{\beta}_{2}, \boldsymbol{\beta}_{3}, \boldsymbol{\beta}_{5} \sim Normal(0, 1) \tag{6}$$
$$\boldsymbol{\beta}_{4} \sim Normal(0, 0.5)$$

276

For the year-specific among-individual σ_{α} and year-specific observation-level σ_{o} standard deviations, as well as for the within-brood variance σ , we used exponential priors (equation 7).

$$\sigma_{\mu_1} \sim Exponential(2) \tag{7}$$

279

We specified the year random effects $\boldsymbol{\delta}$ on the three traits studied by drawing them from univariate (i.e. non-correlated) normal distributions, also using exponential distributions for the variance terms λ (equation 8).

$$\delta_{1} \sim Normal(0, \lambda_{1})$$
(8)
$$\delta_{2} \sim Normal(0, \lambda_{2})$$

$$\delta_{3} \sim Normal(0, \lambda_{3})$$

$$\lambda_{1}, \lambda_{2}, \lambda_{3} \sim Exponential(2)$$

283

284 Finally, since breeding individuals sample nest boxes non-randomly, the nextbox random effects 285 **y** were specified as multivariate, thus estimating the among-nestbox covariances, as not 286 accounting for this correlation could potentially lead to biasing the estimation of the context-287 dependent among-individual correlations we aimed to detect. We therefore drew the y vectors 288 from a multivariate normal distribution with covariance matrix $\boldsymbol{\Sigma}$. The covariance matrix $\boldsymbol{\Sigma}$ is 289 decomposed into its standard deviation matrix S, with exponential priors for each standard 290 deviation parameter ω , and its correlation matrix **R**, which is specified with a Lewandowski-291 Kurowicka-Joe prior distribution (equation 9; see Martin 2023 for further details on the LKJ prior).

| | Σ = | SRS | | |
|--------------------------------|--|---|--|-----|
| S = | $\begin{bmatrix} \omega_1 \\ 0 \\ 0 \end{bmatrix}$ | $\begin{array}{c} 0 \\ \omega_2 \\ 0 \end{array}$ | $\begin{bmatrix} 0\\ 0\\ \omega_3 \end{bmatrix}$ | |
| $\omega_1, \omega_2, \omega_3$ | $_{3} \sim E$ | xpon | ential | (2) |
| F | ₹ ~ L | KJ (2) |) | |

293 Model implementation

294 The multivariate CRN model (Martin, 2023; Bliard et al., 2024) described above was implemented 295 in a Bayesian framework using the statistical programming language Stan (Carpenter et al., 2017), 296 which uses an extended and cutting-edge Hamiltonian Monte Carlo algorithm (Hoffman & 297 Gelman, 2014). We ran the model through R version 4.3 (R Core Team, 2023), using the R package 298 CmdStanR version 0.8.1 (Gabry & Češnovar, 2020). As detailed in the previous methods section, 299 weakly informative regularizing priors were used for all parameters. We performed 20 alternative 300 models, one for each of the imputed dataset, to ensure that imputation uncertainty was 301 propagated through the analysis. Each model ran on 3 chains with a warm-up period of 1000 302 iterations, and sampled for 1000 iterations per chain, keeping all the iterations (Link & Eaton, 303 2012), thus totalling 3000 saved posterior samples per alternative model. We ensured that 304 convergence was reached for each model by obtaining R-hat values below 1.01 for all parameters 305 (Gelman & Rubin, 1992), and by visually inspecting trace plots. We then merged the posterior 306 distributions of all the 20 alternative models, thus obtaining a single posterior distribution made 307 of 60000 posterior samples (3000 x 20) for the combined model accounting for imputation 308 uncertainty. Throughout the results, we report the posterior median effect sizes, alongside 309 credible intervals. We provide the Stan code GitHub on

(9)

310 (https://github.com/lbiard/tradeoffs_parus_major) and will archive it on Zenodo upon311 acceptance of the manuscript.

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Results

314 Our results reveal that the offspring quantity-quality trade-off remains expressed across all 315 environmental contexts, with slight relaxation under favourable conditions. In contrast, the 316 phenotypic correlation between offspring mass and recruitment is strongly context-dependent, 317 becoming null under favourable conditions such as low density but persisting in harsher years. 318 Contrary to our hypothesis, we found no correlation between brood size and recruitment. 319 We expected the offspring quantity-quality trade-off to be highly constrained, whereby 320 mothers producing larger broods would also produce smaller offspring. The results of our model 321 confirm this expectation, as the among-mother correlation between brood size and offspring 322 mass was found to be negative across all environmental contexts (Figure 1). The negative 323 correlation between brood size and offspring mass was slightly relaxed in years of high 324 precipitation, and, to a lesser extent, in years of low population density, although these effects 325 were small and are associated with high uncertainties (Figure 1).

The among-mother correlation between the mass of offspring produced and their recruitment in subsequent years tended to be positive overall (Figure 2), such that mothers producing larger offspring tend to have higher offspring recruitment. This follows expectations that larger offspring are more likely to survive, thus being more likely to be present as breeders in following years. However, we found rather strong effects of the environmental context on this correlation. Following our expectations, under favorable conditions such as low population density, high spring temperature, or high spring precipitation, this correlation tended to be null,
such that the mass of offspring was not clearly associated with their recruitment (Figure 2). While
we expected the same for beech mast index, we found the opposite result, with the correlation
becoming null in years of low beech mast (Figure 2).

Contrary to our hypothesis, we found no correlation between brood size and recruitment, and this correlation was invariant across environmental contexts (Figure 3). We discuss below whether this null correlation could be the result of either biological or statistical constraints.

The among-nestbox correlations between brood size and offspring mass (median = 0.033 [10-90% intervals = -0.519; 0.563]) and between brood size and recruitment (0.032 [-0.525; 0.575]) were found to be close to zero. However, we found an overall positive correlation among nest boxes between offspring mass and recruitment (0.387 [-0.249; 0.776]), which could reflect some degree of spatial variation in nestbox or overall territory quality.

Estimated effects of all the covariates on the three among-individual correlations highlight that the uncertainty around the median estimated effects is fairly large despite the high sample size used (Figure 4). Environmental covariates are also found to influence trait variances in various ways (Figure S3, S4, S5, S6). Overall, covariate effects on the primary traits (Figure S1, S2) align with previous studies: population density negatively affected reproductive traits, while beech mast index and maternal breeding age had positive effects across all traits. In addition, posterior predictive checks highlight a good fit of the model to the data (Figure S7).

351

352

Discussion

353 We used individual-based data from one of the longest individual-based monitoring of a great tit 354 population, together with a newly developed hierarchical "covariance reaction norm" model 355 (Martin, 2023) tailored for demographic data lacking repeated measurements within years for 356 some traits (Bliard et al., 2024). Despite some uncertainty in the results, we found evidence that 357 the phenotypic correlations between brood size and offspring mass, and especially between 358 offspring mass and offspring recruitment, are temporally variable and dependent on the 359 environmental conditions experienced during the breeding season. Overall, harsher conditions 360 lead females who lay larger broods to have smaller offspring, and the propensity for these smaller 361 offspring to recruit is lower. Interestingly, these relationships are weakened during favorable 362 breeding seasons. Yet, regardless of the environment, the fitness outcome for mothers does not 363 seem to be influenced by the size of their brood, as it is not ultimately associated with offspring 364 recruitment, though offspring recruitment is not always a reliable fitness proxy for mothers (Wolf 365 & Wade, 2001). We discuss these findings and potential limitations of our modeling approach 366 that could blur some of the biological associations studied here.

367 The trade-off between offspring quantity and offspring quality was found to be strong 368 and highly constrained in this population of great tit. Regardless of the environmental conditions 369 experienced during the breeding seasons, the among-females correlation between brood size 370 and the size of their offspring was close to -1, thus highlighting a strong trade-off. We only found 371 a weak influence of the environmental context, with the expression of the trade-off being slightly 372 stronger under harsh conditions (e.g. high population density). Convincing evidence of context-373 dependence between offspring number and size has been found in studies on human fertility, 374 whereby such trade-off is absent in favorable socio-economic classes while being found under 375 poorer socio-economic conditions (Gillespie et al., 2008; Meij et al., 2009; Lawson & Mulder, 376 2016). Similarly, laboratory studies on invertebrates found phenotypic and genetic correlations 377 between offspring number and size to depend on the degree of food availability (Messina & 378 Slade, 1999; Czesak & Fox, 2003; Messina & Fry, 2003). However, we found that the trade-off is 379 expressed across all environments in great tits, and a potential explanation could be that little 380 variance in quality or resource acquisition remains among females once accounting for primary 381 predictors such as mother's mass and age. For instance, the study of Ebert (1993) on Daphnia 382 has shown that the offspring number and size trade-off is initially found to be influenced by food 383 availability, but the genetic correlations all became negative once accounting for mother's 384 condition. Similarly, negative phenotypic correlations between offspring quantity and quality 385 were found after adjusting for maternal size in a meta-analysis across animal species (Lim et al., 386 2014). Therefore, if our primary covariates accounted well for maternal heterogeneity in this 387 great tit population, it could result in such a strongly negative correlation.

388 We found that the correlation between offspring mass and recruitment is overall positive 389 (Figure 2), such that larger offspring are better quality offspring, thus being more likely to recruit 390 in the population in following years. This is in line with numerous other past results in great tits, 391 wherein offspring mass or size are usually found to be associated with future outcomes, from 392 survival to recruitment (Both et al., 1999; Monrós et al., 2002; Garant et al., 2004; Wilkin et al., 393 2006; Bouwhuis et al., 2015; Rodríguez et al., 2016), while being independent of their laying date 394 (Wilkin et al., 2006). However, our study also explores the dependence of this association on 395 environmental conditions experienced during the breeding season. Interestingly, we found that 396 this association was stronger under harsh conditions, whereby producing small offspring might 397 be particularly detrimental as they would not fare well due to poor climatic conditions (e.g., dry 398 and cold springs; Figure 2) or stronger competition from a higher population density (Both et al., 399 1999). However, during favorable breeding seasons, the correlation between offspring mass and 400 recruitment becomes null, with mild conditions and low competition allowing even frail offspring 401 to survive and recruit in following seasons, thus highlighting that phenotypic selection for 402 offspring body mass is likely variable and its temporal dynamics are potentially mediated by 403 environmental conditions (Braby, 1994; Grant & Grant, 2002; Siepielski et al., 2009). This echoes 404 findings from Bouwhuis et al. (2015), where broods with heavier offspring experienced a better 405 recruitment probability, with this relationship being stronger during warmer springs. Such 406 fluctuating selection is expected to promote the evolution of adaptive plasticity in reproductive 407 behavior (de Jong, 1995). Despite most results following our expectations, the estimated effect 408 for the beech mast index goes opposite to our predictions, with theoretically better years (i.e., 409 higher beech mast index) associated with a stronger, more positive correlation. Although 410 speculative, one possible explanation could be that females do an anticipatory adjustment of 411 brood size based on future resource availability, whereby they would adjust brood size based on 412 some external cues that correlate with beech seed production in the autumn following the 413 breeding season. For instance, these anticipatory effects in relation to masting events have been 414 found in red squirrels Tamiasciurus hudsonicus and Sciurus vulgaris (Boutin et al., 2006). In great 415 tits, this might lead to increased brood size at the population level during years of high beech 416 mast (Figure S1), which in turn is likely to increase nestling and fledgling abundance in the 417 population. This increase in the abundance of great tits and potentially other bird species might 418 lead to a decrease in individual perceived predation risk (e.g., through dilution effects), thus

making it less detrimental for nestlings to put on weight (Gentle & Gosler, 2001; Macleod *et al.*,
2005). Though the estimated effect is rather modest in size and somewhat uncertain (Figure 4),
warranting caution with biological interpretation, this highlights the need for further exploration
of the indirect effects of environmental variables on reproductive trade-offs.

423 Overall, we found a lack of correlation between brood size and subsequent successful 424 recruitment, together with no evidence of a dependence on the environmental context. Several 425 non-mutually exclusive reasons, both biological and statistical, could explain this invariant and 426 null correlation. First, the lack of association could just reflect that after accounting for primary 427 predictors on both traits, there is just no biological association between residual brood size and 428 recruitment and no environmental effects, which would mean that regardless of environmental 429 conditions, producing a small brood of big nestlings or a large brood of small nestlings is likely 430 leading to the same fitness outcome for females. Second, brood size and recruitment are both 431 non-repeated measures within a given year (i.e., context). Thus, even though we are interested 432 in the among-individual correlation between the traits, by not having several measures per 433 individual in a given year, within- and among-individual covariances cannot be properly 434 disentangled. Such observation-level correlation reflects the among-individual correlation only if 435 traits repeatabilities are high (Bliard et al., 2024). The repeatability of clutch size in great tit is 436 usually medium to high (e.g., 0.51 in Perrins and Jones (1974)). However, if the repeatability of 437 females' offspring recruitment is low, our estimate may mostly reflect the within-individual 438 correlation between both traits (Searle, 1961; Dingemanse & Dochtermann, 2013; Bliard et al., 439 2024). Given that brood size is in part optimized following Lack's principle (Williams, 1966), such 440 that any large deviation is likely leading to reduced recruitment (Gustafsson & Sutherland, 1988;

441 Pettifor et al., 1988; but see Westneat et al., under review), the within-individual correlation 442 could be expected to be close to null, which might explain our results. Third, recruitment of 443 offspring into the population in following years is an imperfect measure of fitness. As previously 444 noted, because offspring effects on recruitment may be independent of maternal traits, it might 445 thus be a poor proxy of females' fitness per se (Wolf & Wade, 2001). It is necessarily an 446 underestimate due to imperfect detection, being confounded with long distance (i.e., outside the 447 study area) natal dispersal (Gimenez et al., 2008). Dispersal events could themselves be linked to 448 the environmental context experienced by the nestlings (McCaslin et al., 2020). For instance, it 449 had been argued that social dominance, which could hypothetically be related to the size of the 450 brood an offspring was reared in, could in turn influence the natal dispersal distance of offspring 451 (Nilsson & Smith, 1985; Smith & Nilsson, 1987; Smith et al., 1989). Such a limitation could 452 potentially obscure any association between brood size and recruitment (Gimenez et al., 2008). 453 Finally, it could also be possible that the lack of association and lack of environmental effects 454 result from interaction effects between environmental variables that were not accounted for, 455 even though we did not have specific biologically motivated interaction to include.

Altogether, we found that, although the brood size – offspring mass trade-off was highly constrained, the among-individual correlation between offspring mass and recruitment was strongly dependent on changes in population density and harshness of the environment during the breeding season, with females producing larger offspring experiencing higher recruitment only during harsh breeding seasons. This study demonstrates that in this great tit population, among-individual covariances respond to continuous environmental change and temporal variation in population density, a phenomenon that has mostly been neglected up to now, which 463 highlights that knowledge about life-history theory and trade-offs can be improved through the 464 incorporation of context dependence. Future studies could extend this approach to other 465 populations or species (Culina et al., 2021), to further understand how environmental variation 466 shapes trade-offs and life-history evolution (Chantepie et al., 2024). Overall, such a framework 467 allows us to revisit old ecological questions related to patterns of selection in fluctuating density-468 dependent environments through the lens of new multivariate statistical methods, and therefore 469 expand from an often univariate view on the topic to studying multivariate patterns of trait 470 (co)expression (Wright et al., 2019; Martin, 2023).

471

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480 Authors contributions

481 LB conceived the study and analyzed the data, using an initial modeling framework developed by

482 JSM. EC and BS collected and curated the data. LB wrote the first draft. All authors contributed

483 to the editing of the manuscript.

484 Data and code availability

| 485 | The formatted data, as well as the R and Stan code necessary to reproduce the results are |
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| 486 | available on GitHub https://github.com/lbiard/tradeoffs_parus_major and will be archived on |
| 487 | Zenodo. The raw datasets analyzed in the current study are available in the SPI-Birds Database |
| 488 | (study name: Wytham Woods, study ID: WYT, version: 1.0.0, data custodian: Ben Sheldon). |
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Figures





Figure 1: Estimated phenotypic correlations between offspring mass and brood size as a function
of population size (top left panel), spring temperature (top right panel), spring precipitation
(bottom left panel), and beech mast index (bottom right panel). Posterior median effect sizes are
represented by the darker lines, and 10% to 90% credible intervals are represented by the shaded
bands.

Offpring mass - Recruitment



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519 Figure 2: Estimated phenotypic correlations between offspring mass and recruitment as a 520 function of population size (top left panel), spring temperature (top right panel), spring 521 precipitation (bottom left panel), and beech mast index (bottom right panel). Posterior median 522 effect sizes are represented by the darker lines, and 10% to 90% credible intervals are 523 represented by the shaded bands.

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Brood size - Recruitment



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Figure 3: Estimated phenotypic correlations between brood size and recruitment as a function of
population size (top left panel), spring temperature (top right panel), spring precipitation (bottom
left panel), and beech mast index (bottom right panel). Posterior median effect sizes are
represented by the darker lines, and 10% to 90% credible intervals are represented by the shaded
bands.

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Figure 4: Estimated effects of standardized predictors on the phenotypic correlations between
offspring mass and brood size (blue), offspring mass and recruitment (red), and brood size and
recruitment (green).



Figure S1: Associations estimated by the model between spring temperature, spring precipitation, population density, beech mast index, breeding age, parental mass, and laying date synchrony (panels from left to right) with offspring mass (top row), brood size (middle row), and recruitment (bottom row). Posterior median effect sizes are represented by the darker lines, and 10% to 90% credible intervals are represented by the shaded bands.





560 Figure S2: Estimated effects of standardized predictors on primary traits: offspring mass (blue),

- 561 brood size (red), and recruitment (green).

Offpring mass variance



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Figure S3: Estimated among-mother variance in offspring mass as a function of population size (top left panel), spring temperature (top right panel), spring precipitation (bottom left panel), and beech mast index (bottom right panel). Posterior median effect sizes are represented by the darker lines, and 10% to 90% credible intervals are represented by the shaded bands.

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Brood size variance



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578 Figure S4: Estimated observation-level variance in brood size as a function of population size (top 579 left panel), spring temperature (top right panel), spring precipitation (bottom left panel), and 580 beech mast index (bottom right panel). Posterior median effect sizes are represented by the 581 darker lines, and 10% to 90% credible intervals are represented by the shaded bands.

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Recruitment variance



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Figure S5: Estimated observation-level variance in offspring recruitment as a function of population size (top left panel), spring temperature (top right panel), spring precipitation (bottom left panel), and beech mast index (bottom right panel). Posterior median effect sizes are represented by the darker lines, and 10% to 90% credible intervals are represented by the shaded bands.

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598 Figure S6: Estimated effects of standardized predictors on the among-mother variance in 599 offspring mass (blue), observation-level variance in brood size (red), and observation-level 600 variance in offspring recruitment (green).

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Figure S7: Posterior predictive checks showing the concordance between the distribution of the data (y) and the distribution of data generated under the statistical model (y_{rep}), for brood size (top panel), offspring mass (middle panel), and offspring recruitment (bottom panel). This highlights a decent fit of the models, but a small overestimation of zeros in recruitment.

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