

Supplementary Information for

Comparative transcriptomics of 3 high-altitude passerine birds and their low-altitude relatives

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This PDF file includes:

Supplementary text Figs. S1 to S14 Tables S1 to S12 Caption for database S1 References for SI reference citations

Other supplementary materials for this manuscript include the following:

Dataset S1

Supplementary Information Text

Materials and Methods

Ethics Statement. All samples were collected and all experiments were conducted in accordance with the regulations of the ethics committee of the Institute of Zoology, Chinese Academy of Sciences, Beijing, China, with authorization from the local forestry authorities, and in compliance with the National Wildlife Conservation Law of China. Voucher specimens were cataloged in the ornithological collection of the National Zoological Museum, Institute of Zoology, Chinese Academy of Sciences, Beijing, China.

Specimen Collection, RNA Extraction, and Transcriptome Sequencing. All 6 species used in this study are resident passerines in 2 families within the order Passeriformes: the gray-crested tit (*Lophophanes dichrous*), the rufous-vented tit (*Periparus rubidiventris*), the marsh tit (*Poecile palustris*), and the yellow-bellied tit (*Pardaliparus venustulus*) in the family Paridae; and the rufous-fronted tit (*Aegithalos iouschistos*) and the black-throated tit (*A*. *concinnus*) in the family Aegithalidae (1–3). The high-altitude species, all native to the Qinghai-Tibet Plateau (QTP), were *L. dichrous* (2,300–4,600 m above sea level), *Pe. rubidiventris* (2,400–4,300 m), and *A. iouschistos* (2,700–4,300 m) (1–3). The closely related species, generally distributed in low altitudes in East Asia, were *Po. palustris* (0–2,100 m), *Pa. venustulus* (0–2,000 m), and *A*. *concinnus* $(0-2,500 \text{ m})$ $(1-3)$. High-altitude species were collected on the QTP, and low-altitude species were collected in eastern China (Fig. 1*A*; Table S1). We collected 4 to 5 adults of each of the 6 tit species using mist nets on autumn 2015 and autumn 2016 (Table S1). Birds were killed by thoracic compression and we collected 5 tissues (cardiac muscle, flight muscle, liver, lung, and kidney) known to be associated with metabolic performance and oxygen utilization (4, 5). These tissues were immediately placed in the RNA preservative RNAhold (TransGen, Beijing, China), and stored at −80°C. Total RNA was extracted using the EASYspin Fibrous Tissue RNA Mini Kit (Aidlab Biotech, Beijing, China), following the manufacturer's instructions. The quality of each RNA sample was examined with an Agilent 2100 Bioanalyzer (Agilent Technologies, Palo Alto, CA, USA). mRNA was isolated using Oligo (dT) magnetic beads, and fragmented for cDNA synthesis. After purification and end repair, nucleotide A (adenine) was added, the mRNA fragments were connected using adapters, and amplified with PCR. All sample libraries were quantified and qualified using an Agilent 2100 Bioanalyzer (Agilent Technologies, Palo Alto, CA, USA) and an ABI StepOnePlus Real-Time PCR System (Applied Biosystems, Foster City, CA, USA) by the Beijing Genomics Institute (Shenzhen, China). Paired-end 150 bp libraries were sequenced with the Illumina HiSeq 4000 and Illumina HiSeq X Ten sequencing platforms (Table S1). Raw data were cleaned by removing reads with >10 bases aligned to the adapter sequences (allowing \geq 10% mismatches), reads with \geq 10% ambiguous bases ("N") and reads with $>$ 40% bases having a quality score <20, using SOAPnuke (version 1.5.3) (6).

De Novo Assembly, Mapping, and Quantification. Cleaned reads were combined into tissue groups for individual species, and assembled into transcriptomes de novo with Trinity (version 2.4.0) (7). All Trinity options were set to default except the minimum kmer coverage, which was set to 2 instead of 1; a minimum kmer coverage of 2 has been shown to increase application speed, reduce memory usage, and improve assembly accuracy (7). All transcripts were then filtered to reduce the impact of redundant, erroneous, nonexpressed, and poorly expressed transcripts. First, we clustered the transcript sequences and removed redundant transcripts using CD-HIT (version 4.6.8), setting word length to 10 and the sequence identity threshold to 0.95 (8). We then computed ExN50 statistic, a statistic measuring assembly quality, following the Trinity manual [\(http://trinityrnaseq.github.io\)](http://trinityrnaseq.github.io/) (7). The ExN50 is defined as the minimum contig length required to cover 50% of the transcriptome, based only on the most highly expressed transcripts (7). We also used Bowtie2 (version 2.3.2) to assess transcript quality, by mapping reads back to their respective transcriptomes (9). We used BUSCO (version 3.0.2) to determine transcriptome assembly completeness based on conserved avian orthologs (downloaded from https://busco.ezlab.org/datasets/aves_odb9.tar.gz) (10). Second, we mapped all of the paired-end reads from each sample back to its own de novo transcriptome using RSEM (version 1.3.0) (11). We obtained the resulting fragments per kilobase of exon per million fragments mapped (FPKM). For each species, we retained only transcripts where FPKM was >1 in at least half of all samples from any one tissue.

Ortholog Identification and Functional Annotation. We selected the zebra finch (*Taeniopygia guttata*) as an outgroup (12). This species belongs to the Estrildidae, a family more primitive than the Paridae and the Aegithalidae in avian phylogenetic tree (13). The coding sequences (CDSs) and protein sequences of the zebra finch were downloaded from Ensembl (http://ftp.ensembl.org/pub/release-91/fasta/taeniopygia_guttata/) (14). For each unique gene, only the longest transcript and protein sequence were retained. One-to-one orthologs among all 6 tit species and the zebra finch were identified using the reciprocal best-hit method in BLASTn (version $2.6.0+$), with an E value cutoff of 1e-10 and a minimum percentage identity of 30%. When best-hit values were equivalent for more than one result, we chose the longest transcript. Orthologous protein sequences of the zebra finch were used as proxies for searches against protein databases [NCBI nonredundant (NR) and Swiss-Prot] with BLASTp (version 2.6.0+; setting the E value cutoff to 1e-5 and the maximum number of blast hits to 20). The best hit was considered the final annotation. The NR results were used as input for Blast2GO PRO (version 4.1.9) (15) to determine Gene Ontology (GO) terms and InterPro IDs. The Kyoto Encyclopedia of Genes and Genomes (KEGG) orthology of each protein was determined with the KAAS-KEGG Automatic Annotation Server (http://www.genome.jp/tools/kaas/), using the Bi-directional Best Hit (BBH) method (16).

Sequence Alignment. We identified the CDSs in each of the 6 tits by aligning the orthologous protein sequences of the zebra finch to the orthologous gene sequences of each tit, using

Exonerate (version 2.2.0) with the model protein2genome (17). All orthologous CDSs were aligned by codon using Prank (version 170427) (18); branch-site likelihood ratio tests for positive selection in Prank have been shown to be more accurate than those of ClustalW, MAFFT, and Muscle (18, 19). We used Gblocks (version 0.91b) (20) in codon mode to eliminate poorly aligned codons, gaps, ambiguous bases ("N"), and sequences <75 bp long, so as to avoid overestimating the rate of nonsynonymous substitutions. The remaining high-confidence alignments were used for all downstream analyses: the phylogenetic analysis was based on both mitochondrial and nuclear genes, whereas tests of positive selection, genomic convergence were only based on nuclear genes.

Phylogenetic Analysis. The nucleotide sequence alignments of all orthologous genes were concatenated to form a super-alignment. Because 4-fold-degenerate (4D) sites are regarded as neutral and free from selective constraints (21, 22), we extracted the 4D sites from the superalignment using a custom script. We used jModeltest (version 2.1.10) (23) to determine the bestfit model of the nucleotide substitution for the concatenated 4D sites, based on the Akaike information criterion (AIC). RAxML (version 8.2.10) (24) was used to reconstruct a maximum likelihood (ML) phylogeny with 1,000 bootstrap replicates, and FigTree (version 1.4.2) (http://tree.bio.ed.ac.uk/software/figtree/) was used to visualize the topology.

Identification of Positive Selection. Using our ML topology as a guide, we ran 7 different branch-site likelihood ratio tests (LRTs) to identify positively selected genes, setting 1 to 3 highaltitude lineages as the foreground branches (the branches of interest were specified a priori) (Table S5). The branch-site model (null model: model = 2, NSsites = 2, ω = 1; alternative model: model = 2, NSsites = 2, ω = 1.4) was implemented in the CODEML module of the PAML package (version 4.9) (25). We used Chi-square tests with 1 degree of freedom to evaluate differences in LRT results; $P < 0.05$ was considered significant. Genes shown to be under positive selection were combined and considered candidates. The ratio of nonsynonymous substitutions per nonsynonymous site to synonymous substitutions per synonymous site (dN/dS) represents the rate at which a particular protein-coding sequence has evolved, indicating selective force of the gene (26). We used a one-ratio model (model = 0, NSsites = 0, ω = 1.4) to estimate the overall dN/dS ratio for each ortholog to determine whether specific gene sets exhibited significant shifts in evolutionary rates, and whether altitude, ortholog expression, or connectivity (i.e., number of direct connections from one gene to other genes) correlated with evolutionary rate.

Detection of Genomic Convergence. Based on the amino acid sequences translated from all orthologous alignments and the ML tree topology, we reconstructed ancestral character states with CODEML (25), using the Empirical $+$ F model, the Jones, Taylor, and Thorton (JTT) matrix, and a discrete gamma model for forty rate categories. We identified genes under convergence as those meeting 2 criteria: (*i*) identical amino acid residues in any 2 of the 3 highaltitude lineages, and (*ii*) for each of those 2 lineages, the identical amino acid residues differed from the homologous positions in the most recent common ancestor of each high- and lowaltitude species pair. If the amino acid residues of the 2 most recent common ancestors of the high-altitude species were identical, they were considered "parallel" and if they were different, they were considered "converged". Both cases were considered to represent convergent evolution (27). The positions of convergent nonsynonymous amino acid substitutions were determined by comparison with the orthologous sequences of the zebra finch. To minimize the impact of random convergence, we used JTT-f_{gene} amino acid substitution models. First, the node sequences, branch lengths, relative evolutionary rates, and average amino acid frequencies across all sites were used to estimate the expected number of convergent sites in each ortholog, following Zou and Zhang (28). Second, a Poisson test was used to detect differences between the observed and expected number of convergent sites in each ortholog (where $P < 0.05$ was considered significant). Genes were considered adaptively convergent genes if they not only had a nonrandom convergent change, but also if they had been subject to positive selection.

Normalization of Transcriptomic Data. To minimize the impact that gene expression differences were falsely detected due to artifacts, such as different number of transcripts and transcript lengths in 6 de novo transcriptome assemblies, we focused gene expression analyses on the one-to-one orthologs which had high-confidence alignments across the 6 species. We first trimmed these orthologs to the same lengths and calculated gene expression values by mapping all of the paired-end reads from each sample back to the trimmed orthologs of each species using RSEM (version 1.3.0) (3). We normalized gene expression data to allow the comparison of these data among biological replicates, tissues, and species. To compare gene expression values among replicates from the same tissue in the same species, we used the trimmed mean of M-value normalization (TMM), as implemented in the R package edgeR (version 3.16.5) (29). For comparisons among species and among tissues, we used scaling factors to normalize the expression levels of all orthologs across all samples (30, 31). That is, we first determined the median expression levels of the top 1,000 most conserved genes (i.e., lower coefficient of variance) in the interquartile range for each sample. Second, we identified the scaling factors that adjusted the median expression values to a common value. Third, we used these scaling factors to scale the gene expression levels of all sample. Our gene expression analyses were based on normalized expression data for the trimmed orthologs.

Expression Profile Analysis. We constructed a gene expression matrix with 128 columns, each representing a sample, and 7,048 lines, each corresponding to the expression of an ortholog. We used this matrix to calculate the Spearman's correlation coefficients between all pairs of samples. We used a nonparametric correlation because this method is less sensitive to outliers and inaccuracies caused in expression normalization. Hierarchical clustering of Spearman's correlation coefficients between all pairs of samples across all genes was performed using the complete-linkage agglomerative method and the correlation distance metric. The symmetrical heat map of all samples was generated using the R package pheatmap (version 1.0.10).

Principal Component Analysis (PCA). Normalized gene expression data were log transformed. We performed a PCA on these transformed data using the R package gmodels (version 2.18.1). We performed 2 sets of PCAs: one PCA of the overall dataset, including samples from all 5 tissues across all 6 species and 5 separate PCAs on each of 5 tissues. For the first PCA, a one-way [analysis](javascript:void(0);) [of](javascript:void(0);) variance (ANOVA) was applied to each PC axis to detect the effects of tissue and species on the samples, using the R package stats (version 3.5.1). All *P* values were corrected for the effects of multiple tests using FDR (FDR < 0.05 was considered statistically significant) (32, 33).

Gene Expression Phylogeny Analysis. Pairwise distance between samples was calculated by 1 − Spearman's correlation coefficient. Gene expression tree for each tissue was reconstructed using neighbor joining approach in R package ape (version 5.1) according to the pairwise distance matrix (34). These neighbor-joining expression-based trees were visualized using FigTree (version 1.4.2).

Differentially Expressed Genes. We obtained differentially expressed genes using 4 methods to compare gene expression values between each of the 3 high- and low-altitude species pairs: R packages DESeq2 (version 1.14.1) (35), edgeR (version 3.16.5) (29), reproducibility-optimized test statistic (ROTS, version 1.2.0) (36), and limma (version 3.30.13) (37). For DESeq2 (35), we used DESeqDataSetFromMatrix to construct an object and DESeq to conduct differential expression analysis based on the negative binominal distribution. For edgeR (29), we used calcNormFactors to calculate normalization factors, estimateDisp to estimate common dispersion

and tagwise dispersion, and exactTest to determine expression differentiation. For ROTS (36), we used calcNormFactors in edgeR (29) to calculate normalization factors, voom in limma (37) to transform data, and ROTS to perform differential expression analysis (500 bootstrap permutations). For limma (37), we used calcNormFactors in edgeR (29) to calculate normalization factors, voom to transform data, lmFit to fit a linear model, and eBayes to compute moderated t-statistics for differential expression. Genes with a count-per-million >1, a 2-fold (or greater) change in relative expression between the high- and low-altitude species, and an FDRadjusted $P < 0.05$ were deemed differentially expressed (32, 33). Only genes identified by all the 4 methods were considered to be differentially expressed genes. Genes with similar expression shifts (e.g., either up- or down-regulated in the same tissue of the high-altitude species) were selected and then combined. We then performed expression profile analysis of all differentially expressed genes, as described above.

Weighted Gene Coexpression Network Analysis (WGCNA). The gene expression matrix for each tissue was log transformed and used to build a weighted coexpression network using the R package WGCNA (version 1.61) (38) following the guidelines. Briefly, we set different soft thresholds (powers) to fit the scale-free topology and calculate the mean connectivity among genes. We determined a suitable minimum power value to approximate the best scale-free topology using the model fitting index \mathbb{R}^2 cut-off. We used 18, 12, 30, 18, and 14 as the best available powers to transform the similarity matrices into adjacency matrices for the lung, cardiac muscle, kidney, liver, and flight muscle, respectively (Fig. S11). We determined a topological overlap measure (TOM) for each pair of genes based on the adjacency matrices. We then performed average linkage hierarchical clustering with TOM-based dissimilarity to construct a dendrogram, setting 0.25 as the height cutoff and 30 as the minimum module size (Fig. S12). We calculated the first principal components as measure of module expressions. We tested the Pearson's correlation between module expression and altitude. We then calculated the Student

asymptotic *P* values for these correlations, correcting for the effects of multiple tests using FDR (32, 33). The modules of highly coexpressed genes with |correlation coefficients| >0.6 and FDR <0.05 were considered altitude-related modules, and genes in these modules were considered to be altitude-associated genes. We then performed expression profile analysis of all altitudeassociated genes across all tissues, as described above. We also tested the relationships between module expression and phenotypic traits (body length, body weight, wing length, tail length, tarsus length, and culmen length).

Comparisons of Evolutionary Rates and Detection of Explanatory Variables. We compared the evolutionary rates between differentially expressed genes and nondifferentially expressed genes, and between altitude-associated genes and non-altitude-associated genes. We tested differences in evolutionary rates between complementary gene sets using Mann–Whitney *U* tests. The connectivity of each ortholog was extracted from the WGCNA results for each tissue and then took the average. We then used linear models to determine the effect of altitude, gene expression, and gene connectivity, as well as altitude plus gene expression and altitude plus gene connectivity, on evolutionary rate (dN/dS ratio), using the R package stats (version 3.5.1). Ortholog expression, connectivity, and dN/dS values were log-transformed.

% of the top most highly expressed transcripts

Fig. S1. ExN50 plot of contig N50 length in regard to percentage of the top most highly expressed transcripts.

Fig. S2. Venn diagram of (*A*) shared and unique orthologs across the 6 tit species based on the Blast results between these species and *Taeniopygia guttata*, and (*B*) overlapping annotation results of 7,915 orthologs using NR, Swiss-prot, Interpro, GO, and KEGG, produced using TBtools (https://github.com/CJ-Chen/TBtools). Lodi, *Lophophanes dichrous*; Peru, *Periparus rubidiventris*; Aeio, *Aegithalos iouschistos*; Popa, *Poecile palustris*; Pave, *Pardaliparus venustulus*; Aeco, *A*. *concinnus*; Tagu, *T*. *guttata*.

Fig. S3. Venn diagram indicating shared and unique positively selected genes across the 3 high-altitude species. The number and percentage of positively selected genes are shown in the figure.

Fig. S4. Distributions of coefficient of variance of gene expression levels among all samples before and after normalization, for all genes, conserved genes, and nonconserved gene.

Fig. S5. Comparison of the Spearman's correlation coefficients between all pairs of samples for each tissue based on the gene expression estimations using the trimmed and raw orthologs.

Fig. S6. Neighbour-joining expression trees based on pairwise distance matrices for (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle.

Fig. S7. PCA plot across all species in (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle. High-altitude species are represented by close symbols, and low-altitude species are represented by open symbols.

log2FC

18

Fig. S8. Volcano plot indicating the results of differential expression analyses using DESeq2, edgeR, ROTS, and limma for genes in (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle, for the 3 high- and low-altitude pairs. A gene was considered to be a differentially expressed gene if a 2-fold (or greater) expression change between the high- and low-altitude species, and an adjusted *P* value by FDR < 0.05 were observed. Each dot represents one gene. Red dots represent differentially expressed genes. Black dots represent no significantly biased gene.

Fig. S9. Venn diagram illustrating differentially expressed genes that were detected by DESeq2, edgeR, ROTS, and limma in (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle, for the 3 high-and low-altitude pairs. Numbers in red and blue indicate genes up- and down-regulated in the high-altitude species relative to their respective low-altitude species.

Fig. S10. Venn diagram indicating differentially expressed genes that were shared among the 3 highand low-altitude pairs in (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle, and *(F)*. Numbers in red and blue indicate genes up- and down-regulated in the highaltitude species relative to their respective low-altitude species.

Fig. S11. Plot of scale free topology and mean connectivity in regard to soft-thresholding power for samples from (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle. Red line indicates an \mathbb{R}^2 cut-off of 0.9. Asterisk indicates the soft threshold power chosen for module detection.

Fig. S12. Clustering dendrogram showing ortholog expression pattern for samples from (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle. Each colored bar below represents each module.

Fig. S13. Pearson's correlation coefficient (Cor) and corresponding significance level (*P* and FDR value) between the expression of each module and the altitude of samples from(*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle. "#" indicates the number of genes in this module. The color bar indicates the correlation coefficient. Asterisk indicates altitude-related module.

Fig. S14. Graphs showing the significant associations between module expression and altitude for (*A*) lung, (*B*) cardiac muscle, (*C*) kidney, (*D*) liver, and (*E*) flight muscle. Species are represented by point shape.

Table S1. Basic information of the 6 tit species.

"√" indicates that this tissue was sequenced. Cm, Cardiac muscle; Fm, Flight muscle; Lv, Liver; Ln, Lung; Kd, Kidney; M, Male; F, Female.

Species	Sample name	Clean bases (bp)	Clean Reads	Q20	Q30	GC	Overall mapping rate
L. dichrous	HeguF1 Ln	9,432,901,200	62,886,008	98.73%	95.39%	54.79%	89.80%
L. dichrous	HeguF1_Cm	13,433,093,700	89,553,958	97.16%	92.10%	53.46%	86.07%
L. dichrous	HeguF1 Kd	9,047,755,200	60,318,368	98.40%	94.03%	55.38%	85.71%
L. dichrous	HeguF1 Lv	13,598,628,600	90,657,524	96.59%	91.41%	55.17%	83.33%
L. dichrous	HeguF1_Fm	13,697,594,700	91,317,298	96.25%	90.68%	53.26%	83.04%
L. dichrous	HeguF ₂ Ln	9,442,329,000	62,948,860	98.71%	95.26%	52.22%	90.81%
L. dichrous	HeguF ₂ Cm	14,539,201,500	96,928,010	97.23%	92.27%	53.65%	86.07%
L. dichrous	HeguF2_Kd	12,803,231,700	85,354,878	97.77%	93.12%	55.27%	84.46%
L. dichrous	HeguF2 Lv	11,893,043,400	79,286,956	97.65%	92.78%	55.30%	82.38%
L. dichrous	HeguF ₂ Fm	13,255,542,000	88,370,280	96.35%	90.94%	53.20%	83.05%
L. dichrous	HeguM0_Cm	11,104,946,100	74,032,974	95.18%	88.72%	53.23%	87.01%
L. dichrous	HeguM0 Lv	9,431,719,500	62,878,130	94.95%	88.39%	53.34%	85.11%
L. dichrous	HeguM0 Fm	11,583,836,100	77,225,574	98.12%	94.13%	50.80%	86.37%
L. dichrous	HeguM1 Ln	9,219,009,900	61,460,066	98.66%	95.16%	54.56%	89.43%
L. dichrous	HeguM1_Cm	9,069,689,100	60,464,594	98.50%	94.28%	54.54%	83.88%
L. dichrous	HeguM1 Kd	9,116,568,300	60,777,122	98.41%	94.08%	54.20%	85.90%
L. dichrous	HeguM1 Lv	14,881,887,000	99,212,580	96.39%	90.98%	54.52%	84.49%
L. dichrous	HeguM1 Fm	14,274,740,700	95,164,938	96.22%	90.65%	53.30%	82.55%
Pe. rubidiventris	HeigF1_Ln	9,369,666,000	62,464,440	98.68%	95.17%	53.53%	88.17%
Pe. rubidiventris	HeigF1_Cm	9,711,568,500	64,743,790	96.17%	90.57%	52.44%	87.36%
Pe. rubidiventris	HeigF1_Kd	11,050,219,200	73,668,128	97.90%	93.30%	53.35%	86.33%
Pe. rubidiventris	HeigF1 Lv	13,486,945,800	89,912,972	96.29%	90.80%	55.19%	84.14%
Pe. rubidiventris	HeigF1 Fm	13,071,523,200	87,143,488	97.76%	93.04%	55.00%	82.22%
Pe. rubidiventris	HeigM0 Cm	9,739,182,900	64,927,886	94.95%	88.31%	52.84%	86.21%
Pe. rubidiventris	HeigM0 Lv	9,617,238,600	64,114,924	95.26%	88.99%	54.36%	83.27%
Pe. rubidiventris	HeigM0_Fm	9,490,467,900	63,269,786	95.44%	89.18%	55.14%	82.95%
Pe. rubidiventris	HeigM1_Ln	9,301,864,500	62,012,430	98.64%	95.07%	56.10%	86.86%
Pe. rubidiventris	HeigM1_Cm	10,622,726,400	70,818,176	96.19%	90.58%	53.17%	85.66%
Pe. rubidiventris	HeigM1_Kd	9,138,825,000	60,925,500	98.42%	94.05%	54.63%	86.06%

Table S2. Basic information of transcriptome sequencing and alignment rates.

Cm, Cardiac muscle; Fm, Flight muscle; Lv, Liver; Ln, Lung; Kd, Kidney.

Species	Contig ExN50 peak length	Number of transcripts
L. dichrous	3,790	27,581
Po. palustris	3,418	28,909
Pe rubidiventris	3,183	31,493
Pa venustulus	2,223	30,074
A. <i>iouschistos</i>	3,303	36,505
A. concinnus	2,351	28,412

Table S3. Basic information of de novo transcriptome assembly using Trinity and CD-HIT.

	L.	Pe.	\mathcal{A}_{\cdot}	\bm{A} .	Pa.	$P_{O.}$
	dichrous	rubidiventris	iouschistos	concinnus	venustulus	palustris
	3,958	3,795	3,760	3,691	3,572	3,917
Complete BUSCOs	(80.5%)	(77.2%)	(76.5%)	(75.1%)	(72.7%)	(79.7%)
Fragmented BUSCOs	509	608	629	702	772	510
	(10.4%)	(12.4%)	(12.8%)	(14.3%)	(15.7%)	(10.4%)
Missing BUSCOs	448	512	526	522	571	488
	(9.1%)	(10.4%)	(10.7%)	(10.6%)	(11.6%)	(9.9%)
Total BUSCO groups	4,915	4,915	4,915	4,915	4,915	4,915
searched	(100%)	(100%)	(100%)	(100%)	(100%)	(100%)

Table S4. Statistics of BUSCO for the transcriptome assembly quality assessment of the 6 tit species.

Note that complete BUSCOs include single-copy and duplicate BUSCOs. Percentages of the total number of BUSCO groups searched are shown in parentheses (bottom).

Test No.	High-altitude species as foreground branch	No. of positively selected genes
	L. dichrous	81
$\mathcal{D}_{\mathcal{L}}$	L. dichrous and Pe. rubidiventris	151
3	L. dichrous, Pe. Rubidiventris, and A. iouschistos	203
$\overline{4}$	L. dichrous and A. <i>iouschistos</i>	154
5	Pe rubidiventris	77
6	<i>Pe. rubidiventris</i> and A. <i>iouschistos</i>	149
7	A. <i>iouschistos</i>	99
Total	$\widetilde{}$	379

Table S5. Branch-site likelihood ratio tests and the corresponding number of positively selected genes.

	Strategy No. Convergence in high-altitude species No. of convergent genes	
	L. dichrous and Pe. rubidiventris	143
	L. dichrous and A. <i>iouschistos</i>	86
	<i>Pe. rubidiventris</i> and A. <i>iouschistos</i>	68
Total	\sim	280

Table S6. Three different strategies used in convergence analysis of the high-altitude species and the corresponding number of convergent genes.

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Table S7. Adaptively convergent genes identified under positive selection with nonsynonymous convergent amino acid changes.

guttata. Lodi, *L*. *dichrous*; Peru, *Pe*. *rubidiventris*; Aeio, *A*. *iouschistos*.

Gene	Full gene name	Convergent amino acid substitution	Gene function
CYP2RI	Cytochrome P450 family 2 subfamily R member 1	1315V	Synthesis of cholesterol, steroids and other lipids
<i>L2HGDH</i>	L-2-hydroxyglutarate dehydrogenase	A402S	A FAD-dependent enzyme
HN1L	Hematological and neurological expressed 1 like	Q183R	Apoptosis modulation and signaling
<i>IFNAR2</i>	Interferon alpha and beta receptor subunit 2	R114Q	Phosphorylation of several proteins

Table S8. Adaptively convergent genes under positive selection with the same amino acid substitutions across all 3 high-altitude tit species.

The position of convergent amino acid substitution was determined based on the coding sequence of *T. guttata*. Gene function was identified through GeneCards database (www.genecards.org).

Table S9. Comparisons of coefficient of variance based on gene expression levels among all samples before and after normalization, for all genes, conserved genes, and nonconserved gene.

Gene set	Mann–Whitney U test (W)	P value
All genes	25,817,000	2.5e-5
Conserved genes	688,610	< 2 2e-16
Nonconserved genes	18,971,000	19e-4

Table S10. One-way ANOVAs for the PCA axes for all samples across the 5 tissues across the 6 tit species, and showing the first 2 axes.

	Tissue		Species			
	$F_{4,128}$	P value	FDR	$F_{5,128}$	P value	FDR
PC1	3,558.318	$< 2e-16$ ***	$<$ 2e-16 ***	0.023		
PC ₂	1,934.679	$< 2e-16$ ***	$<$ 2e-16 ***	0.098	0.992	

Significance levels, ****P* value (FDR) < 0.001 , ***P* value (FDR) < 0.01 , and **P* value (FDR) < 0.05 .

		Body	Body	Culmen	Tail	Tarsus	Wing
Tissue	Module	length	weight	length	length	length	length
	$\overline{2}$	-0.44	0.22	0.16	-0.46	-0.58	-0.19
		$(4.19e-2)$	$(3.16e-1)$	$(4.76e-1)$	$(3.30e-2)$	$(4.31e-3)$	$(3.85e-1)$
	5	0.76	0.31	0.38	0.37	0.51	0.56
		$(4.85e-5)$	$(1.63e-1)$	$(8.10e-2)$	$(8.70e-2)$	$(1.49e-2)$	$(7.27e-3)$
Lung	6	0.79	0.13	0.20	0.47	0.83	0.62
		$(1.02e-5)$	$(5.73e-1)$	$(3.65e-1)$	$(2.55e-2)$	$(1.44e-6)$	$(2.25e-3)$
	9	0.30	0.46	0.56	-0.23	0.54	0.70
		$(1.70e-1)$	$(3.30e-2)$	$(6.57e-3)$	$(3.07e-1)$	$(9.17e-3)$	$(2.99e-4)$
	25	-0.68	0.07	-0.11	-0.59	-0.44	-0.22
		$(4.93e-4)$	$(7.58e-1)$	$(6.17e-1)$	$(3.87e-3)$	$(3.92e-2)$	$(3.31e-1)$
	3	0.83	0.27	0.32	0.57	0.55	0.54
		$(6.32e-8)$	$(1.72e-1)$	$(1.02e-1)$	$(1.69e-3)$	$(2.25e-3)$	$(2.78e-3)$
Cardiac	20	-0.43	0.10	0.13	-0.45	-0.49	-0.22
muscle		$(2.10e-2)$	$(6.12e-1)$	$(5.07e-1)$	$(1.53e-2)$	$(7.68e-3)$	$(2.51e-1)$
	21	-0.77	-0.09	-0.07	-0.60	-0.84	-0.54
		$(1.61e-6)$	$(6.64e-1)$	$(7.36e-1)$	$(6.97e-4)$	$(2.63e-8)$	$(2.79e-3)$
	$\overline{2}$	-0.62	0.15	-0.02	-0.57	-0.49	-0.19
		$(2.30e-3)$	$(5.06e-1)$	$(9.26e-1)$	$(5.54e-3)$	$(1.99e-2)$	$(3.99e-1)$
	3	-0.83	-0.13	-0.19	-0.49	-0.87	-0.63
		$(2.09e-6)$	$(5.70e-1)$	$(4.06e-1)$	$(1.99e-2)$	$(1.37e-7)$	$(1.53e-3)$
Kidney	9	0.38	0.44	0.53	-0.17	0.62	0.72
		$(7.87e-2)$	$(3.92e-2)$	$(1.10e-2)$	$(4.42e-1)$	$(2.23e-3)$	$(1.37e-4)$
	12	0.82	0.31	0.40	0.47	0.50	0.55
	17	$(2.51e-6)$ 0.46	$(1.60e-1)$ -0.60	$(6.69e-2)$ -0.59	$(2.55e-2)$ 0.78	$(1.69e-2)$ 0.55	$(7.55e-3)$ -0.14
		$(3.15e-2)$	$(3.18e-3)$	$(3.83e-3)$	$(1.70e-5)$	$(8.02e-3)$	$(5.42e-1)$
		0.25	0.32	0.43	-0.17	0.50	0.55
	6	$(2.05e-1)$	$(9.74e-2)$	$(2.29e-2)$	$(3.98e-1)$	$(7.13e-3)$	$(2.32e-3)$
		-0.77	-0.32	-0.39	-0.47	-0.55	-0.59
	$8\,$	$(1.64e-6)$	$(1.00e-1)$	$(4.24e-2)$	$(1.16e-2)$	$(2.28e-3)$	$(9.54e-4)$
		-0.51	0.15	0.18	-0.54	-0.57	-0.24
	10	$(5.50e-3)$	$(4.33e-1)$	$(3.60e-1)$	$(2.85e-3)$	$(1.43e-3)$	$(2.09e-1)$
Liver		-0.66	-0.50	-0.45	-0.18	-0.80	-0.83
	17	$(1.47e-4)$	$(6.22e-3)$	$(1.74e-2)$	$(3.66e-1)$	$(3.77e-7)$	$(6.58e-8)$
	21	-0.53	0.24	0.06	-0.58	-0.43	-0.12
		$(4.00e-3)$	$(2.09e-1)$	$(7.43e-1)$	$(1.15e-3)$	$(2.15e-2)$	$(5.29e-1)$
	22	-0.53	0.47	0.51	-0.82	-0.58	0.01
		$(3.52e-3)$	$(1.12e-2)$	$(5.95e-3)$	$(9.90e-8)$	$(1.28e-3)$	$(9.71e-1)$
	\overline{c}	0.36	0.37	0.47	-0.13	0.61	0.67
		$(6.08e-2)$	$(5.31e-2)$	$(1.15e-2)$	$(4.96e-1)$	$(6.37e-4)$	$(8.94e-5)$
Flight	14	0.49	-0.52	-0.57	0.80	0.59	-0.04
muscle		$(8.49e-3)$	$(4.30e-3)$	$(1.49e-3)$	$(3.79e-7)$	$(8.84e-4)$	$(8.31e-1)$
	15	-0.80	-0.27	-0.36	-0.53	-0.53	-0.54
		$(4.21e-7)$	$(1.72e-1)$	$(5.85e-2)$	$(3.98e-3)$	$(3.94e-3)$	$(3.29e-3)$
	16	-0.50	0.18	-0.02	-0.49	-0.41	-0.17

Table S11. Pearson's correlation coefficients between module expression and phenotypic traits.

Note that the corresponding *P* value of Pearson's correlation coefficient is shown in the bottom parenthesis.

Formula	Explanatory variables	Coefficients	P value
$log(dNdS) \sim$ Altitude	Altitude	0.0396	$2.11e-1$
$log(dNdS) \sim log(Expression)$	log(Expression)	-0.1069	\leq 2e-16 ***
$log(dNdS) \sim log(Connectivity)$	log(Connectivity)	-0.0538	7.75e-6 ***
	Altitude	-0.0614	$5.49e-1$
	log(Expression)	-0.1422	$1.45e-8$ ***
$log(dNdS)$ ~	log(Connectivity)	0.0481	$1.10e-1$
$log(Expression)*$ Altitude + log(Connectivity)*Altitude	$log(Expression) +$ Altitude	0.0578	4.74e-2 $*$
	$log(Connectivity) +$ Altitude	-0.0865	$9.31e-3$ **

Table S12. Effects of altitude, ortholog expression, and connectivity on the dN/dS ratio using linear models.

Significance levels, ****P* value < 0.001, ***P* value < 0.01, and **P* value < 0.05.

Additional data table S1 (separate file)

List of differentially expressed genes shared among the 3 high- and low-altitude species pairs in lung, cardiac muscle, kidney, liver, and flight muscle. Genes with significantly higher or lower expression values in the high-altitude species compared to their respective low-altitude species were up-regulated or down-regulated. Gene function was identified through GeneCards database (www.genecards.org).

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