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Kim, J.-M., Santure, A.W., Barton, H.J. et al. (7 more authors) (2018) A high-density SNP chip for genotyping great tit (Parus major) populations and its application to studying the genetic architecture of exploration behaviour. Molecular Ecology Resources, 18 (4). pp. 877-891. ISSN 1755-098X

https://doi.org/10.1111/1755-0998.12778

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- 1 A high density SNP chip for genotyping great tit (Parus major) populations and
- 2 its application to studying the genetic architecture of exploration behaviour

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#### 24 Abstract

High density SNP microarrays ('SNP chips') are a rapid, accurate and efficient method for 25 genotyping several hundred thousand polymorphisms in large numbers of individuals. While 26 SNP chips are routinely used in human genetics and in animal and plant breeding, they are 27 28 less widely used in evolutionary and ecological research. In this paper we describe the development and application of a high density Affymetrix Axiom chip with around 500 000 29 SNPs, designed to perform genomics studies of great tit (Parus major) populations. We 30 demonstrate that the per-SNP genotype error rate is well below 1% and that the chip can 31 also be used to identify structural or copy number variation (CNVs). The chip is used to 32 explore the genetic architecture of exploration behaviour (EB), a personality trait that has 33 been widely studied in great tits and other species. No SNPs reached genome-wide 34 35 significance, including at DRD4, a candidate gene. However, EB is heritable and appears to 36 have a polygenic architecture. Researchers developing similar SNP chips may note: (i) SNPs previously typed on alternative platforms are more likely to be converted to working assays, 37 (ii) detecting SNPs by more than one pipeline, and in independent datasets, ensures a high 38 proportion of working assays, (iii) allele frequency ascertainment bias is minimised by 39 performing SNP discovery in individuals from multiple populations and (iv) samples with the 40 lowest call rates tend to also have the greatest genotyping error rates. 41

#### 43 Introduction

44 It is now becoming commonplace to sequence and assemble the genomes of organisms that have been the focus of ecological research but are not classical genetic model organisms 45 (Brawand et al. 2014; Colbourne et al. 2011; Ellegren et al. 2012; Hu et al. 2011; Jones et al. 46 47 2012; Lamichhaney et al. 2015; Soria-Carrasco et al. 2014). While assembled genomes are undoubtedly essential tools for understanding topics in evolutionary and ecological genetics, 48 in taxa with moderate to large genomes the cost of sequencing the full genomes of hundreds 49 or thousands of individuals remains prohibitive for the majority of laboratories, and beyond 50 the budget of even very large grants. Thus, analytical techniques that require large sample 51 sizes, such as quantitative trait locus (QTL) linkage mapping / genome-wide association 52 studies (GWAS) (Visscher et al. 2017), molecular quantitative genetics (Gienapp et al. 2017a; 53 Jensen et al. 2014) and studies that utilise realised relatedness / inbreeding coefficients 54 55 (Powell et al. 2010) are reliant on alternative technologies. Broadly, these can be categorised 56 into two approaches; (i) genotyping-by-sequencing (GBS) methods (Davey et al. 2011) such as restriction-site associated sequencing (RAD-seq) (Hohenlohe et al. 2010) and double-digest 57 58 RAD-seq (ddRAD-seq) (Peterson et al. 2012) and (ii) SNP microarray ('SNP chip') methods (Spencer et al. 2009; Syvanen 2001), where a set of known SNPs are probed on chips 59 60 manufactured by providers such as Illumina (Shen et al. 2005) and Affymetrix (Matsuzaki et 61 al. 2004).

#### 62

GBS-approaches while perhaps cheaper, are more technically demanding, both in terms of 63 laboratory work, and in post-sequencing processing of NGS data (Bajgain et al. 2016; Miller et 64 al. 2012; Robledo et al. 2017). Furthermore, the sites that are typed are typically not known 65 in advance, and call rates can vary widely between different SNPs. SNP chips are more 66 expensive, but tend to have higher call rates per SNP, and specific target SNPs can be 67 68 included in chip design. In addition, the same SNPs are typed in every individual, which is not the case for GBS approaches (Bajgain et al. 2016). A disadvantage of SNP chips is 69 ascertainment bias (Bajgain et al. 2016; Miller et al. 2012). Because SNPs have to be 70 71 discovered before they are designed to be on a chip, there is usually bias towards the inclusion of SNPs with higher minor allele frequencies (MAF) on the chip. For some types of 72

analyses (e.g. GWAS) this is not necessarily a disadvantage, because statistical power is
greater for SNPs with higher MAF. However, ascertainment bias is clearly a problem for tests
that require an accurate description of the site frequency spectrum in different genomic
regions (Albrechtsen *et al.* 2010) e.g. tests that aim to detect signatures of selection such as
Tajima's D. Thus, the optimal method for genotyping many individuals can depend on the
question being addressed, the laboratory and bioinformatics experience of the user and the
laboratory budget.

The great tit (*Parus major*) is a model vertebrate system in evolutionary ecology because this 81 82 passerine bird readily breeds in nest boxes (making it possible to identify parents and 83 offspring and thus build pedigrees), it has a short generation time and large broods, and it is widely distributed across Europe, Western Asia and parts of the Middle East (Perrins 1979). 84 Longitudinal studies (Kluijver 1951; Lack 1964) of great tits have informed researchers about 85 classic topics in evolutionary and behavioural ecology (Lack 1968) including mating systems 86 and reproductive decisions (Smith et al. 1989), the frequency (Harvey et al. 1979) and 87 importance of dispersal (Garant et al. 2005; Postma & van Noordwijk 2005), adaptation to 88 climate change (Charmantier et al. 2008; Nussey et al. 2005; Visser et al. 1998), the study of 89 personality traits (Dingemanse et al. 2004; Groothuis & Carere 2005; Van Oers & Naguib 90 2013), innovativeness and cognition (Cole et al. 2012; Quinn et al. 2016; Titulaer et al. 2012), 91 92 social learning (Aplin et al. 2015; Aplin et al. 2012), and understanding how quantitative 93 genetic variation is maintained in natural populations (McCleery et al. 2004). In more recent 94 years, great tits have become the focus of molecular genetic studies exploring the genetic 95 architecture of quantitative traits (Gienapp et al. 2017b; Robinson et al. 2013; Santure et al. 96 2013; Santure et al. 2015), phylogeography (Kvist et al. 2003; Lemoine et al. 2016), fine-scale 97 genetic structure and dispersal (Garroway et al. 2013; Radersma et al. 2017), the efficacy, 98 nature and relative occurrence of positive and purifying selection (Corcoran et al. 2017; 99 Gossmann et al. 2014) and immunogenetics (Sepil et al. 2013; Sepil et al. 2012). Much of this 100 work has been facilitated by a SNP chip containing probes for around 10,000 SNPs, of which around 6,000 are polymorphic and reliably scoreable (Van Bers et al. 2012). This '10K chip' 101 102 has been used in QTL and GWAS mapping studies and to construct a great tit linkage map 103 (van Oers et al. 2014) which led to insights into the nature of sex-differences in

<sup>80</sup> 

recombination rate (heterochiasmy). The linkage map was in turn used to help assemble thegreat tit genome (Laine *et al.* 2016).

While the 10K SNP chip has helped provide insight into the architecture of some quantitative 106 traits, it also suffers from some important limitations (Santure et al. 2015). The most 107 important of these is that the marker density (~ 1 SNP per 20Kbp) is too low for most of the 108 109 genome to be adequately 'tagged' by typed SNPs that are in strong linkage disequilibrium 110 (LD) with untyped sites. Furthermore, molecular quantitative genetic approaches such as chromosome partitioning (Yang et al. 2011) or regional heritability mapping (Nagamine et al. 111 112 2012), where markers are used to measure between-individual relatedness in specific 113 genomic regions, typically require a much higher marker density than is afforded by the 10K 114 chip (Berenos et al. 2014).

115 To overcome the low power of the 10K chip, and to provide better resolution in association studies, outlier detection tests and molecular quantitative genetic analyses we have 116 117 developed a high density (HD) chip with probes for over 600 000 SNPs. In this paper we describe the development of this great tit HD SNP chip. The chip can also be used to detect 118 the presence of structural variation or copy number variants (McCarroll & Altshuler 2007) in 119 the great tit genome. We demonstrate an application of the HD chip, using a behavioural 120 trait, to showcase how the genetic architecture of phenotypic variation can be estimated. It is 121 hoped that the methods and lessons described in this paper will serve as a useful guide to 122 researchers developing high density SNP chips in other organisms. 123

#### 124 Methods

125

## 126 DNA sequencing

127 To identify SNPs to include on the chip, whole genome resequencing was performed on 30 birds. Ten of the birds were from the long term study population at Wytham Woods, Oxford, 128 UK (51°46' N, 1°20' W), and the remaining 20 were from locations across a wide area of 129 Europe (Fig. S1), collected as part of the Great Tit HapMap Project. The sequencing is 130 described elsewhere (Laine et al. 2016), but briefly, samples were sequenced on an Illumina 131 HiSeq 2000 platform at The Genome Institute, Washington University. Sequencing was 132 paired-end, with insert sizes 300 bp and a read length of 100 bp. Each bird was sequenced to 133 134 ~10x coverage. Note that one of the samples used in this paper, from near to Zurich in 135 Switzerland (population #27 in Fig. S1), was not used in the genome assembly paper (Laine et al. 2016), because coverage was lower than for other samples ( $\sim$ 5x). The Zurich sample is 136 included in the NCBI sequence read archive submission (SRP066678). 137

138

## 139 SNP Discovery

140 SNP discovery was performed in several steps, with the aim of identifying markers that are 141 polymorphic across multiple great tit populations, with minimal ascertainment bias towards 142 populations where the SNPs were initially discovered. Paired-end reads were filtered and trimmed with the FASTX-Toolkit (http://hannonlab.cshl.edu/fastx toolkit/) using a length of 143 80 bp and quality score of 20 as minimum cut-off scores to remove low-quality reads. The 144 145 remaining reads from each individual were mapped onto the great tit reference genome v1.03 with the MEM algorithm of the Burrows-Wheeler Aligner (Li & Durbin 2009). The 146 147 aligned sequence reads on the genome were stored as individual BAM files. Using VCFtools (Danecek et al. 2011), the BAM files were filtered to a minimum quality score of 20 and read 148 149 depth of 5.

Following alignment of reads to the great tit genome, a combination of different SNPdiscovery algorithms and different strata of the dataset were used, summarised in Figure 1.

SNPs were independently called using the ANGSD v0.549 (Korneliussen et al. 2014), 152 SAMTools v0.1.19 (Li 2011; Li et al. 2009) and GATK v2.4 (DePristo et al. 2011; McKenna et al. 153 2010) packages. Parameter settings are reported in Table S1. SNPs were called either from 154 155 the 10 UK birds, the 20 mainland European birds, or the combined dataset of 30 birds. SNPs 156 called from the different software/datasets were then compared (Figure 1) and a set of ~1.4M SNPs that were common to all SNP discovery softwares and all datasets were 157 considered for inclusion on the SNP chip. VCFtools was used to filter out SNPs with minor 158 allele frequency (MAF) less than 0.05 and call quality less than 50. SNPs that were predicted 159 160 to be within 30 bp of each other were filtered out because it was likely that the presence of 161 one SNP would adversely affect the ability to successfully genotype the other(s), due to 162 inefficient or biased hybridisation of allele-specific oligonucleotides. SNPs prone to this form of possible typing error are known as Off Target Variants (OTV) in the Affymetrix genotype 163 164 calling workflow (see below). A total of 1,213,160 SNPs passed all of these filtering criteria (Figure 1). 165

166

# 167 SNP selection

168 The SNP discovery phase of the work identified more SNPs than could be included on the169 chip. To prioritise which SNPs to use on the chip, the following criteria were used:

170 1) 'Top priority' SNPs were those that had been successfully typed on the lower density
171 10K chip described in earlier work (Van Bers *et al.* 2012) or had been discovered in
172 the SNP discovery pipeline described above *and* were discovered during the
173 construction of the earlier 10K chip but not included on it (Santure *et al.* 2011; van
174 Bers *et al.* 2010). 6,773 SNPs that were typed on the original chip and a further 9,713
175 SNPs that were discovered but not included on the 10K chip were included in the 'Top
176 priority' set.

A list of candidate genes were identified that could potentially explain variation in ecologically relevant traits such as personality traits (Fidler *et al.* 2007; van Oers *et al.* 2004) and timing of breeding (Visser *et al.* 2003). A list of candidate genes and putatively associated traits is provided in Table S2. At the time the chip was being designed, the great tit genome was not annotated. Therefore, to identify the location

of the candidate genes on the great tit genome, the cDNA sequence of the candidate gene in zebra finch (*Taeniopygia guttata*), another passerine, chicken (*Gallus gallus*), or if none of those were available, human or mouse, was downloaded from NCBI and the location on the great tit genome was identified by BLAST search. The start and end point of the gene was identified and SNPs were considered for inclusion if they were within any part of the gene. 654 (of which 28 were also 'Top Priority' SNPs) from 110 genes were chosen for inclusion on the chip.

3) The remaining SNPs were selected based on how likely they were to be convertible to 189 190 a working and scoreable assay on the chip. The list of SNPs and their flanking 191 sequences were sent to the Affymetrix bioinformatics team who used their in silico 192 design tool to model the probability (termed the 'P convert design score') of the SNP converting to a working assay. The software uses the SNP bases and its flanking 193 sequence, and considers factors such as GC content and the predicted amount of 194 195 non-specific hybridisation to other (non-target) genomic regions. Following this process, SNPs with a P convert design score >0.69 were retained for inclusion on the 196 chip. This threshold compares favourably to those used in the design of HD chips for 197 198 chicken (Kranis et al. 2013), catfish (Liu et al. 2014), and water buffalo (Iamartino et al. 2017), where thresholds of 0.20, 0.50 and 0.60 were used respectively. 199

An Axiom myDesign high density chip was manufactured by Affymetrix. A total of 610 970 SNPs were included on the final design, of which 17 122 were from criteria 1 or 2 and the remainder were from criteria 3. The genomic distribution of attempted SNPs are described in Table S3 and Fig. S1.

204

## 205 Genotyping

Genotyping was performed on a Gene Titan platform at Edinburgh Genomics. A total of 21
plates, each with up to 96 samples, were typed (2016 available slots). Across the 21 plates, 9
negative controls were included. All plates contained at least one duplicate sample to aid
with estimation of error rate. 1073 typed samples were from the Wytham Woods population.
The remainder of the total 2007 birds came from a number of study sites (Table 1, Fig. S1)
from across the species range in Europe and Asia, and were provided by members of the

Great Tit HapMap Consortium, either as pre-extracted DNA, or more usually as blood 212 samples in Queen's storage buffer or ethanol. DNA was extracted using an ammonium 213 acetate precipitation method (Bruford et al. 1998) and DNA quality and quantity measured 214 215 using picogreen on a fluorometer. 1,696 samples were at a concentration exceeding 50ng/ul, 216 while 89 were at concentrations lower than 20ng/ul. All except 33 samples passed the 217 manufacturer's recommendation of 200ng of DNA. 13 Japanese tit (Parus minor) birds were genotyped, as well as 9 putative P. major / P. minor hybrids. Abel, the male used as the 218 reference bird for the great tit genome assembly (Laine et al. 2016), was typed four times 219 220 (two replicates on two different plates). SNP genotype calling was performed using the 221 Ps\_Metrics and Ps\_Classification functions within the Affymetrix Axiom Analysis Suite 222 1.1.0.616. Samples with dish QC < 0.82 or call rates < 0.95 were discarded, as were SNPs with call rates <0.97 or those identified as containing Off-Target Variants (OTVs). 223

#### 224 Quantifying Genotyping Error Rate

225 Genotyping errors were estimated in two ways. First, the replicated samples meant that the proportion of inconsistent genotypes between different typing attempts of the same bird 226 could be estimated. The error rate was obtained from the Z2 score - the proportion of SNPs 227 at which two individuals (replicates) share both alleles identically-by-descent - reported by 228 the --genome command in Plink 1.9 (Chang et al. 2015). Second, genotypes from the SNP 229 chip were compared with the whole genome resequencing SNP calls for 28 birds that were 230 successfully genotyped and sequenced to ~10x coverage (Laine et al. 2016). Note that 231 232 discrepancies between chip and resequencing SNP genotypes can arise either because the 233 SNP chip genotype is wrong, or because the SNP call from the resequencing is wrong. 234 Therefore, comparison between the resequencing and the SNP chip genotyping provides an upper limit on the genotyping error on the SNP chip. Concordance between the chip and the 235 236 resequencing data was determined using the GenotypeConcordance tool implemented 237 within GATK, after SNPs with Genotype Quality Scores <30 were filtered from the 238 resequencing dataset.

239

240 Copy number variant (CNV) detection

CNVs were detected using the PennCNV software (Wang et al. 2007). PennCNV input files of 241 the 996 birds from the Wytham Woods population were prepared using the Axiom Analysis 242 Suite's CNVTool and probe intensities from all SNPs. PennCNV uses two parameters from the 243 244 SNP genotyping, the logR ratio and the B allele frequency, to identify genomic segments 245 containing SNPs indicative of copy number variation. The logR ratio is a measure of signal 246 intensity. SNP assays in individuals with extra copies of a genomic region (duplications) should generate higher intensity signals, while SNPs in individuals with fewer than two copies 247 248 of a genomic segment (deletions) should generate lower intensity signals. The B allele 249 frequency measures the relative signal intensity of the two possible alleles at each SNP. 250 Ratios that are inconsistent with allele call ratios of 2:0 (i.e. A allele homozygote), 1:1 (i.e. 251 heterozygote) or 0:2 (i.e. B allele homozygote) are indicative of departures from two copies of that nucleotide (i.e. the normal diploid state) being present in the sample. For example, an 252 individual with a duplication at a CNV site on one chromosome, would have three copies in 253 254 total, meaning the ratios of alleles A:B could be 1:2 or 2:1, which is impossible when two copies are present. CNVs called by PennCNV were retained and converted to Plink format 255 256 using the perl script penncnv\_to\_plink (www.openbioinformatics.org/penncnv/download/penncnv to plink.pl). 257 The plink 258 commands --cfile --cnv-overlap and --cnv-seglist were used to generate a list of all CNVs, identify overlapping CNVs, estimate CNV frequencies and summarise the CNVs present in 259 each individual (.cnv.indiv file). 260

Additional CNV analyses included (i) an examination of two replicates of the reference genome bird, Abel, and (ii) CNV calling using nine father-mother-offspring trios from the Wytham Woods population. As with the analysis of all Wytham Woods birds, the PennCNV command detect\_cnv\_pl was used, only with the -trio argument included. In principle, detected CNVs are more likely to be reliable calls if they are observed to be inherited in a Mendelian fashion.

267

#### 268 Genetic architecture of a personality trait

269 The chip was used to explore the genetic architecture of Exploration Behaviour in a novel270 environment (EB), a personality trait linked to aggression, risk-taking and dispersal in great

tits (Quinn et al. 2009). EB is known to be heritable (Dingemanse et al. 2004; Drent et al. 271 2003; Quinn et al. 2009; Santure et al. 2015) and it has also been the focus of candidate gene 272 studies, especially at the Dopamine D4 receptor (DRD4) gene (Fidler et al. 2007; Korsten et al. 273 274 2010), following the first report that DRD4 could affect novelty-seeking behaviour in humans 275 (Ebstein *et al.* 1996). The protocol for measuring EB is described in detail elsewhere (Cole & 276 Quinn 2014; Quinn et al. 2009). Briefly, wild birds were captured during February-March (2005) or September-March (2006-2009) and assayed in a novel environment room at 277 Wytham Woods field station. For the purposes of the downstream genetic analyses we used 278 279 the same measure of EB as that used in previous studies. Briefly, the first principal 280 component (PC1) of 12 behavioural measures was treated as the EB score. PC1 was square-281 root transformed prior to genetic analysis and a single value for each individual was obtained by fitting a linear mixed model with the terms ID, year, days after September 1<sup>st</sup>, and assay 282 number of that individual all included as predictors. Details are described elsewhere (Quinn 283 284 et al. 2009). Several aspects of EB genetics were explored. First, we performed a genomewide association study (GWAS) using the Grammar method (Aulchenko et al. 2007a), 285 implemented in GenABEL (Aulchenko et al. 2007b). Grammar accounts for the possibility of 286 test statistic inflation caused by relatives in the dataset by fitting a realised genome-wide 287 relationship matrix estimated from the SNP data as a random effect. The residual from the 288 random model was used as the phenotype. In addition, genomic correction was performed 289 by estimating lambda, the slope of observed chi square values on expected chi square values, 290 291 and dividing all tests statistics by lambda before estimating nominal P-value. Genome-wide statistical significance was estimated by permutation test, using the GenABEL mmscore 292 command and 1000 permutations of the data. The GWAS was performed on a total of 415 293 birds from Wytham Woods. All Z-linked SNPs and any autosomal SNPs with MAF < 0.05 or 294 295 significant departures from Hardy-Weinberg Equilibrium ( $P < 1x10^{-5}$ ) were filtered from the dataset leaving a total of 459 502 autosomal SNPs. 296

In addition to the GWAS, an additional analysis of the same dataset fitted all SNPs simultaneously, in one model. Here, the objective was to estimate the proportion of phenotypic variation explained by each SNP, in order to understand aspects of the trait architecture such as the heritability, the number of SNPs in linkage disequilibrium with causal variants and the distribution of effect sizes of those SNPs. The BayesR method (Erbe *et al.* 

2012), whereby it is assumed that the SNPs causing phenotypic variance are drawn from a 302 mixture of different effect size distributions, was used to model the genetic architecture of 303 304 EB. The BayesR package (Moser et al. 2015) was used to run the analyses, with default 305 settings of 4 distributions, with mean effect sizes of 0.01, 0.001, 0.0001 or 0 of the phenotypic variation. The program was run for 50 000 iterations of an MCMC chain, with the 306 first 20 000 iterations treated as burn-in, and every 10<sup>th</sup> chain after that being sampled, 307 giving a total of 3000 samples of the chain. Priors for  $V_A$  and  $V_E$  were specified using an 308 inverted chi-squared distribution with scale parameters of 0.033 and 0.117 respectively, each 309 310 with 4 degrees of freedom. These values give a prior heritability of around 0.20 which is 311 consistent with pedigree-based estimates of EB in the Wytham Woods population (Quinn et 312 al. 2009; Santure et al. 2015). Note that setting the priors so that V<sub>A</sub> and V<sub>E</sub> were identical (i.e. the heritability was 0.5) gave almost identical posterior estimates, so the genetic 313 314 architecture does not appear to be sensitive to the priors.

#### 316 Results

#### 317 Summary Statistics

Following genotype calling and quality control steps, a total of 1 846 samples typed at 502 318 685 SNPs were retained for analysis. A summary of the different types of SNP category is 319 provided in Table 2. Samples that contained less than the recommended 200ng of DNA were 320 321 more likely to fail than those with >200ng of DNA; 9/33 failures versus 140/1962 failures 322 (Fisher's Exact Test: Odds ratio = 4.87, 95% CI 1.95-11.12, P = 0.0005). However, among samples that passed quality control, there was no relationship between the call rate and the 323 amount of DNA present in the sample ( $F_{1,1844} = 0.942$ , P = 0.33). SNPs that had been 324 previously typed on the 10K chip were more likely to be converted to a successfully typed 325 SNP, and to pass QC checks. For previously typed SNPs the conversion rate was 5924/6773 326 (0.87) compared to 496 826 / 604 197 (0.82) for unvalidated SNPs; Fisher's Exact Test odds 327 ratio 1.51, 95% CI = 1.40-1.62, P = 0.0006. However, SNPs that were discovered during both 328 329 the construction of the 10K chip and of the HD chip but were not typed on the 10K chip actually had a lower conversion success rate, 7807/9713 (0.80), than SNPs that were only 330 discovered during HD chip construction, 489 019 / 594 484 (0.82); Fisher's Exact Test: Odds 331 ratio = 0.88, 95% CI = 0.84-0.93, P = 2.0 x  $10^{-6}$ . Thus, the untyped SNPs from the low density 332 chip were less reliable than the newly discovered SNPs. 333

#### 334 Genotyping Error Rate

Among 30 individuals (resulting in 65 pairwise comparisons, due to some birds being typed 335 336 >2 times) that were repeat genotyped on the SNP chip, there was a per SNP genotyping error rate of 0.004. If comparisons were restricted to the 56 comparisons where both samples had 337 338 call rates >0.98, the error rate was 0.002, indicating that individuals with lower call rates 339 tended to be more error prone. The discordance in SNP calls between the chip and the resequenced data was ~0.01, although this was apparently mostly driven by errors in the 340 sequencing data, because the degree of discordance is negatively correlated with the depth 341 342 of the genome coverage, which varies between 4.5x and 13.8x (see Fig. S3).

343

#### 344 Resequencing data predict SNP chip allele frequencies

The minor allele frequencies (MAFs) of each SNP estimated from the 30 resequenced birds 345 were compared to the MAFs estimated from the 996 birds genotyped in the Wytham Woods 346 population. Notably, there was a very strong positive relationship between the minor allele 347 348 frequencies in the two datasets (Fig. S4A; HD Chip MAF = 0.016 + 0.918\*ReSeq MAF, F<sub>1,480756</sub> =  $1.65*10^6$ ,  $r^2 = 0.77$ , P <  $2.2x10^{-16}$ ). Thus, the MAFs estimated from the resequencing data 349 350 from 30 birds sampled across Europe are a reliable predictor of the MAFs obtained by typing a much larger sample from a single population on the HD chip. Similar analyses using 351 genotyped birds from two randomly selected mainland European populations showed the 352 353 same pattern (Fig. S4B, S4C); Montpellier, HD Chip MAF = 0.023 + 0.867\*ReSeq MAF, F<sub>1,480756</sub> =  $8.16*10^5$ ,  $r^2$  = 0.63, P <  $2.2x10^{-16}$ , 50 individuals; Gotland, HD Chip MAF = 0.022 + 354  $0.874^{*}$ ReSeq MAF,  $F_{1,480756} = 8.69^{*}10^{5}$ ,  $r^{2} = 0.64$ , P <  $2.2 \times 10^{-16}$ , 47 individuals. The relationship 355 was stronger for the Wytham Woods birds than the two other populations, but this is largely 356 because the HD chip MAFs were estimated from more birds in the Wytham Woods dataset, 357 358 and are therefore presumably estimated more accurately. A similar analysis conducted on 50 randomly chosen birds from Wytham Woods produced a relationship that was only slightly 359 stronger than that seen in the Montpellier and Gotland populations (Fig. S4D; HD Chip MAF = 360 0.023 + 0.879\*ReSeq MAF,  $F_{1,480756} = 9.76$ \* $10^5$ ,  $r^2 = 0.67$ , P <  $2.2 \times 10^{-16}$ ). Thus, the strong 361 relationship between SNP chip MAF and resequencing is not simply an artefact of 10 of the 362 30 resequenced birds being from Wytham Woods. The mean minor allele frequencies were 363 very similar in the three populations (Wytham 0.280, Montpellier 0.273, Gotland 0.274). 364

#### 365 CNV analysis

366 A total of 41 526 putative CNVs (34,947 with PennCNV confidence scores >5) were 367 discovered in 996 birds from Wytham Woods. The great majority (37 419 or 90.1%) of CNVs were single copy duplications. Birds had a mean (SD) of 41.9 (160.9) CNVs each, spanning a 368 369 mean (SD) distance of 3.19 (16.22) Mbp. However, there was a strong positive relationship 370 between the amount of CNV in a bird's genome and the Axiom Analysis Suite parameter 371 cluster\_distance\_SD (Figure 2). Cluster\_distance\_SD is a per-sample measure, defined as the 372 standard deviation of the distance to the cluster centre, estimated from all of the individual's called genotypes. Samples with high values of cluster distance SD are typically indicative of 373 374 individuals whose genotypes are difficult to call, perhaps because the sample was of low quality or quantity. Restricting the analysis to those individuals with cluster\_distance\_SD 375

<0.65 (n = 701), resulted in far fewer CNVs. In total there were 8139 CNVs observed, of which 376 1523 (18.7%) were a deletion of two copies (i.e. the segment was missing from both 377 chromosomes), 1 424 (17.5%) were single copy deletions, 5,176 were single copy 378 379 duplications (63.6%) and 16 (0.2%) were double copy duplications. The retained birds had a 380 mean (SD) of 11.6 (6.8) CNVs spanning a mean (SD) total distance of 0.34 (0.40) Mbp. The 381 distributions of the number and total distance spanned of CNVs in the full dataset were far more skewed (Fig. 3A, 3B) than in the restricted dataset (Fig. 3C, 3D). The skewedness of the 382 number and total distance of CNVs in the full dataset was 10.98 and 10.93 respectively, while 383 384 equivalent values in the restricted dataset were 2.71 and 5.14. Plink estimated there were 385 1397 distinct non-overlapping CNVs, of which 1204 were at a frequency < 0.01. However, a 386 small number of CNVs were at a frequency approaching 0.15. For an example of a large CNV identified in multiple individuals see Fig. S5. 387

388 PennCNV analysis of two replicates of the reference genome bird, Abel, revealed there were 389 fewer CNVs than in the Wytham Woods population. For one replicate, the 390 cluster\_distance\_SD score was sufficiently low (0.59) to retain the sample in the filtered 391 dataset. No CNVs were detected, which is perhaps not surprising as CNV regions may not 392 have been possible to assemble when the genome was being assembled. The other replicate 393 had a cluster\_distance\_SD score of 0.69, and contained a total of six possible CNVs (although 394 four of them had confidence scores <5), with a total length of 104 Kbp. Some, perhaps all, of these CNVs are likely to be false positives, but even with their inclusion, the reference bird 395 396 contains less CNV regions than the mean of the Wytham Woods dataset (mean summed 397 CNVs = 3.19 Mbp in the unfiltered dataset, 0.34 Mbp in the filtered dataset).

398

An analysis of nine father-mother-offspring trios from Wytham Woods (Table S4) identified 103 possible CNVs, of which 98 showed Mendelian inheritance, suggesting they were likely to be correct calls. 71 CNVs involved insertions, 27 involved deletions and 5 had both insertions and deletions segregating at the same location. The ratio of insertions: deletions is similar to that described in the analyses of all Wytham Woods samples.

#### 405 Genetic architecture of Exploration Behaviour

406 The GWAS of EB did not identify any SNPs that were significant at the genome-wide level (Figure 4A). The QQ plots indicated that the distribution of p values was very close to that 407 expected under the null distribution if none of the SNPs explain variation in EB (Figure 4B), 408 and lambda was estimated as 1.018 (SE 1.7x10<sup>-5</sup>). Thus the effects of population genetic 409 410 structure seem to be adequately accounted for. However, one SNP approached genomewide significance (P = 0.136; Table S5), and is worthy of mention. SNP AX-100303447 at 411 49.67Mbp on Chromosome 3 is located approximately 3.5 Kbp downstream of interleukin 22 412 413 receptor subunit alpha 2 IL22RA2 (Figure 4C). This gene is notable for being implicated in the 414 regulation of alcohol drinking in alcohol-preferring laboratory rats; experimental interference 415 of IL22RA2 expression results in reduced alcohol intake (Franklin et al. 2015). There is no evidence that the DRD4 gene explains variation in exploration behaviour in the Wytham 416 Woods population (Figure 4D). 417

The BayesR analysis of EB was consistent with a highly polygenic genetic architecture. The heritability estimate was modest and had a very large 95% credible interval (Table 3), although it was very similar to previous estimates from pedigree-based quantitative genetic analyses. It was estimated that a large number of SNPs contributed to trait variation, and that much of the additive genetic variance (V<sub>A</sub>) was caused by SNPs in the smaller effect size distributions (Table 3).

#### 425 Discussion

426 In this study, we generated a high density SNP chip and showed that the majority of target SNPs could be genotyped reliably and accurately and across multiple great tit populations. A 427 total of approximately 900 million SNP genotypes were generated with considerably less than 428 429 1% typing error. Similar chips are routinely used in studies of humans (Frazer et al. 2007; 430 Simonson et al. 2010), model organisms (Yang et al. 2009), companion animals (Hayward et 431 al. 2016) and agriculturally important species (Rincon et al. 2011; Winfield et al. 2016), but their application in wild vertebrate populations remains rare – although there are some 432 433 examples using 40-50K SNP chips, e.g. in Soay sheep (Johnston et al. 2013), collared flycatchers (Kawakami et al. 2014; Silva et al. 2017) and house sparrows (Silva et al. 2017). 434 435 We found the cost of genotyping to be relatively low (approximately £0.0003 per SNP genotype per individual). 436

Several lessons were learned that may be useful to researchers considering designing their 437 438 own HD chips. First, we attempted to type some samples that were of marginal quality relative to the manufacturer's recommendations. Although many of them were successfully 439 typed, the pass rate was lower than the remaining samples. Second, our chip included some 440 SNPs that had already been successfully typed on a smaller 10K Illumina SNP chip. These SNPs 441 did perform better than those which were unproven prior to the HD chip manufacture. Thus, 442 we recommend using SNPs that have been previously validated, even if prior testing was 443 performed on an alternative platform. Third, in addition to sequencing 10 birds from Wytham 444 445 Woods, we sequenced 20 birds from multiple other populations during the SNP discovery 446 and there is little evidence that the chip is biased towards SNPs that are more polymorphic in 447 the Wytham Woods population. If the discovery had relied on sequencing a single population it is likely that there would have been a greater ascertainment bias towards SNPs that have 448 449 high minor allele frequencies in that population. Perhaps, most importantly, our relatively 450 high success rate (~82% of attempted assays were converted to QC-passed, polymorphic 451 SNPs) is at least partially attributable to performing SNP calling with different datasets and 452 different callers and then using consensus SNPs for the chip design.

There was a strong positive correlation between the SNP MAFs predicted from the 30resequenced birds during the discovery phase, and the chip MAFs estimated from almost

1000 genotyped birds from the Wytham Woods population. During SNP discovery there will 455 be a tendency to assign higher confidence scores to SNPs with higher MAFs, because the rare 456 457 allele will be identified in multiple individuals. Thus, the site frequency spectrum of the SNP 458 chip cannot be expected to be representative of the whole genome, but for many 459 applications, a chip with relatively high MAFs can be beneficial. This is most obviously the 460 case in GWAS or linkage mapping studies where the power to detect linkage is partially a 461 function of MAF. The chip has already been used to detect regions of the genome responsible for adaptive evolution of bill length in European great tits (Bosse et al. 2017). 462

463

464 We used the chip to examine the genetic architecture of Exploration Behaviour, a widelystudied behavioural trait in great tits (Fidler et al. 2007; Korsten et al. 2010; Mueller et al. 465 2013) and other bird species (Edwards et al. 2015). No SNP reached genome-wide 466 significance, although this is perhaps unsurprising given that the sample size was fairly 467 modest (~400) and the trait was shown to have a reasonably low heritability in this dataset. 468 These findings are similar to a previous study using the lower density 10K chip, where 469 heritability of EB was also modest ( $h^2 = 0.26$ , SE = 0.08) and no SNPs were significant at the 470 genome-wide level in a GWAS (Santure *et al.* 2015). 471

472 Previous candidate gene studies of personality traits in great tits and other birds have 473 focused mainly on dopamine receptor D4 (DRD4), and there is convincing evidence that it explains a small but significant amount of variation in great tit EB in a population in the 474 Netherlands (Fidler et al. 2007). With this in mind, DRD4 was chosen as a candidate gene 475 during the SNP construction and the region was over-represented on the chip. However, 476 there was very little evidence that DRD4 explained significant variation in the Wytham Woods 477 478 population. This is consistent with earlier studies (Korsten et al. 2010; Mueller et al. 2013) 479 that failed to find an association in Wytham Woods and elsewhere. It is probably prudent to 480 be cautious about most associations between DRD4 and exploration behaviour in bird species, unless genome-wide data are available. This is because single locus studies are 481 unable to reveal the extent to which test statistic inflation due to population structure or 482 covariance between environmental and additive genetic variance is driving false positive 483 results; see for example Knowler et al. (1988), discussed in Lynch & Walsh (1998). Of course, 484

this potential form of bias applies to any candidate gene study that lacks comparable datafrom numerous non-candidate genomic regions.

487

High density SNP chips have been used to identify structural or copy-number variation (CNVs) 488 in other organisms (Wang et al. 2013; Wu et al. 2015; Zhang et al. 2014). We used the 489 490 PennCNV software to identify putative CNVs in the great tit genome. CNVs tended to be at 491 low frequency, which made validation hard because relatively few cases of each putative CNV are present. Furthermore, it was clear that lower quality samples were prone to false positive 492 CNV calls. An additional complexity is that identifying the exact start and end points of each 493 494 CNV is non-trivial, so when CNVs in different birds partially overlap, it is not straightforward to determine whether they are the same CNV or not. That CNVs have lower minor allele 495 496 frequencies than SNPs is not surprising because (i) they may be under stronger purifying selection if they have bigger phenotypic effects and (ii) the chip was biased in favour of the 497 498 inclusion of SNPs with moderately high minor allele frequencies and designed completely blind to the existence of CNVs. While CNVs are not a main focus of this study, it is clear that 499 some CNV calls were repeatable across different birds, and that the extent and effects on 500 phenotypic variation of CNVs are legitimate follow-up questions. Future CNV analyses should 501 ideally include replication from different methodologies (e.g. qPCR or sequencing-based 502 methods). 503

504

High density chips provide a straightforward method for typing several hundred thousand 505 506 SNPs. It is also the case that HD chips are relatively robust to low yield or highly degraded DNA, whereas the DNA requirements for sequencing, especially long-read sequencing 507 508 technologies, tend to be more demanding. Whole genome sequencing remains more expensive than SNP typing on a per individual basis, but that will not be the case for much 509 longer. Indeed, the HD chip era may be relatively short. Sequencing strategies that involve 510 sequencing a few individuals' genomes at high coverage, which are then used to impute the 511 512 genomes of many more individuals sequenced at ~1x coverage or lower, may already be as cheap an alternative, and will yield more data (Gorjanc et al. 2015; Li et al. 2011; Pasaniuc et 513 514 al. 2012). At present low coverage whole genome sequencing results in data that are harder

to process, although the challenges of low coverage assembly, SNP calling and imputation are
becoming more straightforward. Ecological genomics studies that use low-coverage
sequencing of many individuals are not yet common, but there are a few notable examples
e.g. a population genomic analysis of walking-stick insects *Timema* genomes (Soria-Carrasco *et al.* 2014) and a phylogeography study of *Menidia menidia,* the Atlantic silverside fish,
(Therkildsen & Palumbi 2017)

In summary, high density SNP chips are a relatively straightforward approach for investigating 521 a diverse range of evolutionary genomics topics such as genetic architecture, adaptive 522 523 evolution, phylogeography, and inbreeding depression. Ultimately HD chips will be replaced by whole genome sequencing, but they are likely to be used for a few more years, especially 524 525 in population genetic studies of organisms with very large genome sizes such as pines (Neale et al. 2014; Nystedt et al. 2013) or salamanders (Nowoshilow et al. 2018), where sequencing 526 527 remains a relatively expensive option. We hope that the methodologies, lessons learned and 528 downstream applications described in this paper will be useful to other researchers considering developing a similar chip to address evolutionary or ecological questions in their 529 530 favourite study organism. The chip described in this paper is available to other users from 531 Thermo Fisher Scientific (the company that acquired Affymetrix in 2016). In great tits, the 532 chip has already been used to detect signatures of selection (Bosse et al. 2017), to perform 533 genomewide association studies on morphological (Bosse et al. 2017) and phenological (Gienapp et al. 2017b) traits, and to carry out detailed analysis of the role of CNVs on 534 535 genomic architecture (da Silva *et al.* In Press).

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# 796 Author Contributions

Designed the chip (J-MK, AS, KvO, MAMG, JS), performed the CNV analysis (HB, JS), designed
and performed the exploration behaviour assays (JQ, EC), coordinated the long term data and
blood sample collection (MV, BS), performed the genetic architecture analyses (JS), collected
field and DNA sample data (Great Tit HapMap consortium), wrote the paper (JS, with
contributions from all authors), conceived the study (JS, BS, MAMG, KvO, MV).

# 802 Acknowledgements

This work was supported by grants from the European Research Council (grants 339092 to 803 M.E.V., 250164 to B.C.S., and 202487 to J.S.) and Natural Environment Research Council 804 (grant NE/J012599/1 to J.S.). We thank Claire Bloor, Geoff Scopes and Alessandro Davassi of 805 806 Affymetrix for their help during the chip design and genotyping calling processes. Richard Talbot and Alison Downing of Edinburgh Genomics provided the genotyping service. Padraic 807 Corcoran, Kai Zeng, Veronika Laine, Lewis Spurgin and Mirte Bosse provided useful 808 discussions and or advice on SNP calling from Illumina reads or SNP chip quality control. We 809 810 thank Dany Garant and two anonymous reviewers for their insightful comments on, and 811 suggested improvements to, an earlier draft of the manuscript.

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# 813 Data deposition

Genotype and phenotype data are deposited as Plink files on Dryad under the provisional record doi:10.5061/dryad.7d467b6. All SNPs included on the chip are reported on the European Variation Archive (<u>https://www.ebi.ac.uk/eva/</u>) under accession number PRJEB24964. SNP discovery was performed on 30 resequenced birds, whose genomes are reported on the NCBI sequence read archive under project ID SRP066678.

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820 The Authors have no conflicts of interest.

822 Figure 1: The pipeline for SNP discovery. The top right part of the figure identifies SNPs that were found in the UK birds (n= 10), the mainland Europe birds

- 823 (n=20) and in all birds (n=30) with the software GATK. The bottom left part of the figure identified SNPs that were found when all 30 birds were analysed with
- 824 three software packages GATK, SAMtools and ANGSD. The intersection of these discovery pipelines, i.e. SNPs that were detected in all populations by all
- 825 software packages, were considered for inclusion on the chip. After filtering for MAF > 0.05 and removal of SNPs located within 30bp of each other, a final list
- 826 of 1 213 160 SNPs remained.



- 828 Figure 2: Individuals with higher standard deviation (SD) in their cluster distance, indicating samples
- 829 whose genotypes are difficult to call, tend to have a greater proportion of their genomes called as
- 830 CNVs. The assembled great tit genome is approximately 1020Mbp long.



834

- 835 Figure 3: Distribution of the number and total distance spanned of CNVs in 996 Wytham Woods birds
- 836 (top panels) and the remaining 701 Wytham Woods birds after filtering on cluster\_distance\_SD <0.65
- 837 (bottom panels); i.e. after removing samples whose genotypes are difficult to call.
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**851** Table 1: Great tit populations where genotyping was attempted (see also Fig. S1).

Population	Population	Coordinates (N, E)	Birds typed	Birds passing QC
	Code	in decimal degrees		
Amur, Russia <sup>1</sup>	1	50.62, 131.37	72	63
Antwerp, Belgium <sup>3</sup>	2	51.13, 4.53	36	30
Cambridge, UK <sup>3</sup>	3	52.40, -0.23	35	34
Font Roja, Spain <sup>3</sup>	4	38.66, -0.54	30	29
Gotland, Sweden <sup>3</sup>	5	57.14, 18.33	50	47
Groblas, Poland <sup>3</sup>	6	52.28, 17.90	4	4
Harjavalta, Finland	7	61.33, 22.17	44	44
Hoge Veluwe, Netherlands	8	52.07, 5.84	38	36
Israel	9	32.62, 35.24	1	1
La Rouviere, France <sup>3</sup>	10	43.66, 3.67	31	27
Loch Lomond, Scotland <sup>3</sup>	11	56.13, -4.62	43	41
Mariola, Spain <sup>3</sup>	12	38.73, -0.55	33	33
Montpellier, France <sup>3</sup>	13	43.61, 3.87	50	50
Oulu, Finland <sup>3</sup>	14	65.13, 25.88	50	45
Pilis Mountains, Hungary <sup>3</sup>	15	47.72, 19.02	36	34
Pirio and Muro, Corsica <sup>3</sup>	16	42.37, 8.75	30	27
Radolfzell, Germany	17	47.74, 8.98	30	27
Sakhalin Island, Russia <sup>2</sup>	18	50.52, 143.11	13	13
Seewisen, Germany <sup>3</sup>	19	47.97, 8.98	50	46
Tartu, Estonia <sup>3</sup>	20	58.17, 25.08	43	42
Tomakomai, Japan <sup>2</sup>	21	42.67, 141.60	10	9
Velky Kosir, Czech Republic <sup>3</sup>	22	49.53, 17.07	36	33
Vienna, Austria <sup>3</sup>	23	48.21, 16.26	38	31
Vlieland, Netherlands	24	53.28, 5.01	30	21
Westerheide, Netherlands	25	52.00, 5.83	39	35
Wytham Woods, UK <sup>3</sup>	26	51.77, -1.33	1073	996
Zurich, Switzerland <sup>3</sup>	27	47.39, 8.57	30	29
Zvenigorod, Russia	28	55.73, 36.85	20	19
Total			2007	1846

852 <sup>1</sup> Sample contains 63 *Parus* major and 9 putative *P. major/P. minor* hybrids

853 <sup>2</sup> *Parus minor* populations

854 <sup>3</sup> Population included in the 30 resequenced genomes dataset

856 Table 2: Summary of SNP genotype calling, by Affymetrix Axiom Analysis Suite category. The 857 Conversion Type columns uses the Affymetrix terminology but can be summarised as follows: PolyHighResolution = SNP that is polymorphic and can be reliably scored due to the different 858 genotypes forming resolvable, discrete clusters; NoMinorHom = similar to a PolyHighResolution, but 859 860 where the minor allele homozygote is not observed, presumably due to a low genotype frequency; MonoHighResolution = a monomorphic SNP that can be reliably scored because it forms a single 861 cluster; CallRateBelowThreshold = a SNP with the expected number of clusters (usually 3, one for 862 863 each possible genotype), but where the proportion of samples scored at the SNP falls below a user-864 defined threshold. Here the threshold was 0.97; Off-target variant = SNPs, where additional (i.e. more than 3) clusters are observed, making genotype calling ambiguous; Other = all other unresolvable 865 866 SNPs.

### 867

Conversion Type	Count	Percentage	Retained for analysis
PolyHighResolution	498 036	81.5	497 972
NoMinorHom	4048	0.7	4047
MonoHighResolution	666	0.1	666
CallRateBelowThreshold	40 499	6.6	0
Off Target Variant (OTV)	9545	1.6	0
Other	58 176	9.5	0
Sum	610 970		502 685

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869

871 Table 3: Genetic architecture of exploration behaviour

Parameter	Estimate (95% credible interval)
Heritability	0.161 (<0.001-0.671)
Number of SNPs	3,253 (315-8,499)
PGE_0.0001	0.41 (0.01-0.89)
PGE_0.001	0.26 (<0.01-0.80)
PGE_0.01	0.33 (<0.01-0.90)

872 Heritability is the total heritability captured by the genotyped SNPs (often termed "SNP heritability" or

873 "chip heritability"). Number of SNPs is the number of SNPs inferred as explaining some (non-zero)

trait variation. PGE is the proportion of SNP heritability explained by SNPs in the 0.001, 0.001 and 0.01

**875** effect size distributions.