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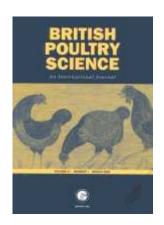
## ► To cite this version:

Pau Navarro, Peter Visscher, Alfons Koerhuis, Dimitrios Chatziplis, Chris Haley. Segregation Analysis of Blood Oxygen Saturation in Broilers Suggests a Major Gene Influence on Ascites. British Poultry Science, 2007, 47 (06), pp.671-684. 10.1080/00071660601077931. hal-00545306

## HAL Id: hal-00545306 https://hal.science/hal-00545306

Submitted on 10 Dec 2010

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## Segregation Analysis of Blood Oxygen Saturation in Broilers Suggests a Major Gene Influence on Ascites

Journal:	British Poultry Science
Manuscript ID:	CBPS-2005-020.R1
Manuscript Type:	Original Manuscript
Date Submitted by the Author:	15-Mar-2006
Complete List of Authors:	NAVARRO, PAU; University of Edinburgh, Institute of Evolutionary Biology; Roslin Institute, Division of Genetics and Genomics Visscher, Peter; University of Edinburgh, Institute of Evolutionary Biology Koerhuis, Alfons Chatziplis, Dimitrios Haley, Chris; Roslin Institute, Division of Genetics and Genomics
Keywords:	Ascites, Broilers, Genetics



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1	1	Segregation Analysis of Blood Oxygen Saturation in Broilers Suggests a Major
2 3	2	Gene Influence on Ascites
4 5	3	P. NAVARRO <sup>*,1,2</sup> , P. M. VISSCHER <sup>†</sup> , D. CHATZIPLIS <sup>‡</sup> , A. N. M. KOERHUIS <sup>‡</sup> AND
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27 28	16	SHORT TITLE: SEGREGATION ANALYSIS BLOOD OXYGEN SATURATION
29 30	17	
31 32	18	ABBREVIATION KEY: a = additive effect; d = dominance effect; Flesh = fleshing
33	19	score; MCMC = Markov Chain Monte Carlo; $p_b$ = frequency of the b allele; $p_B$ = frequency of
34 35	20	the B allele; $p_{bb}$ = frequency of the bb genotype; $p_{Bb}$ = frequency of the Bb genotype; $p_{BB}$ =
36 37	21	frequency of the BB genotype; REML = restricted maximum likelihood; RN = Napole yield;
38 39	22	SaO = blood oxygen saturation; Weight = body weight; $\sigma_e^2$ = residual variance; $\sigma_m^2$ = major
40 41	23	locus variance; $\sigma_p^2$ = phenotypic variance; $\sigma_u^2$ = polygenic variance
42	24	
43 44	25	SECTION: GENETICS
45 46	26	(Key words: ascites, blood oxygen saturation, broiler, major gene, production)
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Abstract 1. Blood oxygen saturation (SaO) is a potential indicator trait for resistance to ascites in chickens. 2. The objective of the study was to investigate the genetic architecture of SaO in a meat-type chicken line reared in commercial conditions. 3. Data were collected over 15 generations of selection and were divided into two data sets on the basis of a change in recording age from six to five weeks of age approximately halfway through the period. The resulting pedigrees comprised in excess of 90,000 birds each and, on average, 12% of these birds had SaO records. 4. Segregation analyses of SaO were carried out assuming a mixed inheritance model that included a major locus segregating in a polygenic background. 5. The analyses suggest that a major gene is involved in the genetic control of SaO in this line. The putative gene acts in a dominant fashion and has an additive effect of around 0.90  $\sigma_p$ , equivalent to a predicted difference in SaO between the two homozygous classes of more than 10%. The frequency of the allele that increases SaO changed from 0.53 to 0.65 from the first to the second set of data, consistent with selection on SaO scores. 6. Using estimated genotype probabilities at the putative major locus, we inferred that it acts in an overdominant fashion on body weight and fleshing score. If the low SaO allele leads to a susceptibility to ascites, its combined effects are consistent with it being maintained in the population by a balance of natural selection on fitness and artificial selection on growth and carcass traits. 7. Even with selection on both SaO and growth traits, the combined genotypic effects would make it difficult to remove the unfavourable low-SaO allele by means of traditional selection without the use of genetic markers.

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**INTRODUCTION** 

Blood oxygen saturation (SaO) is a potential indicator trait for resistance to ascites in chickens (Wideman et al., 1998). In a previous study (Navarro et al., 2006), we presented heritabilities of SaO, body weight (Weight) and fleshing score (Flesh, a measure of breast conformation), and genetic correlations between these traits for four meat-type chicken lines. We showed that SaO was moderately heritable (heritabilities for this trait ranged from 0.1 to 0.2) and that its genetic correlation with production traits was low, so that simultaneous selection for increased SaO and increased production should be possible. These genetic parameters were obtained assuming an infinitesimal model (Fisher, 1918), which assumes that the (quantitative) trait was influenced by an infinite number of unlinked loci (polygenes), each with an infinitely small additive effect on the trait. However, in recent years, several studies have shown that one or few genes, or quantitative trait loci (QTL), explain an important amount of the phenotypic or genetic variation for some quantitative traits. Today, examples of genes or QTL with large effect on quantitative traits of agricultural interest are numerous. For example, the RN-mutation in pigs (Milan et al., 2000) affecting meat quality, the Booroola gene (Piper and Bindon, 1982) in sheep affecting ovulation rate and the double muscling gene (Hanset and Michaux, 1985a; Hanset and Michaux, 1985b) in cattle. Several of the known major genes in livestock were first inferred from their effects on

segregation of phenotypes within pedigrees. Although simple metrics can provide evidence for major gene segregation, fullest use of available data is made in the context of an appropriate analytical model. Mixed inheritance models were first introduced in human genetics to discriminate between modes of inheritance and particularly to infer the presence of major genes (Elston and Stewart, 1971; Morton and Maclean, 1974). These methods were first used within a maximum likelihood framework, which restricted their practical use to the analysis of small pedigrees. Although a series of approximations of the mixed inheritance model likelihood are available for animal breeding populations with simple structures (see, for example, Knott et al. (1992)), analysis of large complex pedigrees (like the ones usually encountered in animal breeding) is only feasible when sampling based techniques are used either to estimate

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likelihoods (Guo and Thompson, 1991; Guo and Thompson, 1994) or to implement Bayesian 

analysis (Janss et al., 1995).

Markov Chain Monte Carlo (MCMC) sampling methods provide an efficient means to carry out these tasks. In particular the Gibbs Sampler, an MCMC method, is now widely used in genetic analyses. It is capable of generating samples from the joint distribution (usually complex) of several random variables by sampling from known and simple conditional distributions. From these samples, marginal distributions of each variable can be obtained and provide estimates of the posterior distributions of the model parameters.

Little is known about the genetics underlying ascites-related traits. Here, we investigate the genetic architecture of SaO using segregation analysis. Data come from the line for which we obtained the highest estimates of genetic variance and heritability for SaO in our previous analyses (Navarro et al., 2006). This line shows a slightly higher ascites-related mortality than other Aviagen Ltd. lines (A. Koerhuis, personal communication) and it is the heaviest of the lines studied. We study the possible existence of a major gene or quantitative trait locus (QTL) involved in the control of SaO. To this end, we have carried our analyses assuming a mixed inheritance model that includes a major locus as well as polygenes. In subsequent analyses, we have used the estimated genotype probabilities at the putative major locus to investigate its effect on body weight and fleshing score. The results obtained are consistent with the segregation of a major gene and help reconcile observations on the genetic correlations between traits, the incidence of ascites and its relationship with selection on growth and carcass traits.

## MATERIALS AND METHODS

Data

Two data sets (data sets 1 and 2) that each consisted of around eight overlapping generations of selection were available from a meat-type chicken population. The population studied is a male line that has been closed for between 30 to 40 generations and has a history of selection on wheat diets. Selection has been more focused on growth rate and efficiency and less emphasis has been placed on yield. In addition the population has been exposed to considerable 

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5 being best)

110	family selection against broiler mortality and leg defects. Both data sets contained records of
111	SaO, body weight (Weight) and fleshing score (Flesh, a measure of breast conformation) SaO
112	was directly measured using a pulse oximeter. A sensor was attached to a Criticare Pulse
113	Oximeter 504US <sup>1</sup> and positioned on the wing to illuminate the tissue between the radius and
114	ulna for measurement of percentage saturation of haemoglobin with oxygen (Julian and
115	Mirsalimi, 1992). When the bird was settled, two readings were taken, and the record for this
116	bird was taken to be an average of both readings. Fleshing is a conformation score with higher
117	scores relating to superior breast muscle development relative to the size of the whole bird.
118	Recording is carried out in handheld terminals grading the birds between 1 and 5, 1 being the
119	birds with the least breast meat and 5 the most. Feel of the breast breadth and depth and length
120	of the keel are also taken into account. SaO data were only available for male selection
121	candidates whereas Weight and Flesh were recorded on most birds. Records were taken at six
122	weeks of age for data set 1. Data set 2 consisted of data from the same line immediately
123	following a shift of the recording age from six to five weeks of age.
124	A description of the pedigree and data structure for the data sets used is presented in
125	Table 1. For both data sets, the mean number of birds with SaO record per full-sib family was
126	less than five (with a minimum value of one and a maximum value of 25) and the mean paternal
127	half-sib family size was less than 30 (with a minimum value of one and a maximum value of
128	106).
129	[TABLE 1].
130	Statistical Analyses
131	Segregation analyses to assess the possibility that a locus with large effect was involved
132	in the genetic control of SaO were performed on data sets 1 and 2. Since results from more
133	recent data are of greatest interest if follow up studies were to be carried out or our findings

<sup>1</sup> Criticare Systems Inc., Milwaukee, U.S.A, supplied by R.L. Dolby, Stirling, UK

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1	134	were to have an impact on breeding programme decisions, a more comprehensive set of	Deleted: Segregation Analysis. A
2	135	analyses was done on data set 2. Details of the analyses methods are presented as an annex.	Formatted: Font: Not Bold, Not
3 4			Italic           Deleted: The mixed model equation
5 6	136	In brief, a mixed inheritance model was used for the segregation analysis. Mixed $\neq''$	that describes the model fitted to the data is:¶ y = Xb + Zu + ZWm + e
0 7	137	inheritance models are a combination of infinitesimal and finite gene models. In our analyses, a	y = xb + 2u + 2v + n + e [1]] where y is the vector of phenotypic
8 9	138	single major locus was modelled in addition to a polygenic effect. The major locus was assumed	observations, <b>b</b> is the vector of fixed non- genetic effects and <b>X</b> is the design matrix relating fixed non-genetic effects to
10	139	to be autosomal and biallelic with Mendelian transmission probabilities and with an additive (a)	observations. <b>Z</b> is the incidence matrix for random polygenic effects ( $\mathbf{u} \sim N(0,$
11 12	140	and a dominance effect (d). The genotypic value for birds with genotype BB at the major locus	$\mathbf{A}\sigma_{u}^{2}$ ) -where <b>A</b> is the numerator relationship matrix and $\sigma_{u}^{2}$ is the polygenic variance)- and single locus
13 14	141	is a, -a for bb birds and d for Bb birds. The major locus was assumed to be in Hardy-Weinberg	effects. W is a three column matrix that contains information on the genotype of
15	142	equilibrium proportions in the "base generation" (i.e., the first generation of a data set).	each individual and <b>m</b> is the vector of major-genotype means ( <b>m</b> ' = [ -a, d, a ]), hence <b>Wm</b> is the vector of random effects
16 17	143	These analyses provide as output distributions of the parameters estimated and the mean	at the single locus. $\mathbf{e} (\sim N(0, \mathbf{I}\sigma_c^2))$ is a vector of random errors. Janss et al. (1995) proposed an efficient
18 19	144	and the standard deviation of these distributions can be used as estimates of the parameters and	scheme using the Gibbs sampler for the study of mixed inheritance models in
20 21	145	their standard error. In this case, we obtained estimates of major locus effects and allelic	animal populations. In our analyses, carried out with software developed at Roslin Institute by Ricardo Pong-Wong
22	146	frequencies, polygenic and residual variances, as well as genotypic probabilities for each bird.	(Walling et al., 2002), we used the sampling scheme they described (see Janss et al. (1995) and Janss et al. (1997)
23 24	147	Major locus effects and frequencies are used to estimate the variance explained by the major	for details) to obtain marginal posterior distributions for the major locus
25 26	148	locus, and this is then used to assess if it is likely that a major locus is indeed segregating for	parameters (frequency and additive and dominance effect), population mean and polygenic and residual variances. For
27 28	149	SaO.	each iteration of the Gibbs sampler, every bird was assigned a genotype. Averaging over all retained iterations provides major
29	150	We also carried out some exploratory analyses on genotype probabilities estimated for	locus genotype probabilities ( $p_{BB}$ , $p_{Bb}$ and $p_{bb}$ ) for each bird in the pedigree.¶ The variance explained by the major
30 31	151	sires and selection candidates from data set 2, and investigated the effect of the putative major	locus $(\sigma_m^2)$ is defined as: $[\sigma_m^2 = 2 p_B (1 - p_B) [a + d ((1 - p_B) - p_B)]^2 + $
32 33	152	locus on body weight and fleshing score.	$[2 p_B (1 - p_B) d]^2$ [2]¶ (Falconer and Mackay, 1996) and was computed from the major locus genotypic
34	153	RESULTS	effects and allele frequency sampled at each iteration. Likewise, we calculated
35 36			the degree of dominance as d/a.¶ We used non-informative prior distributions, uniform on $(-\infty; +\infty)$ for
37	154	Data	fixed non-genetic effects and d, on [0; + $\infty$ ) for a and on [0; 1] for major allele
38 39	155	Table 2 shows descriptive statistics of the distributions of SaO, Weight and Flesh.	B frequency. We used an inverse-gamma prior distribution on $(0; +\infty)$ for
40	156	Means and standard deviations were obtained with GENSTAT (GENSTAT 5 COMMITTEE,	variances with a flat prior for log(variance). This type of prior distribution for variances should cause
41 42	157	1993). Skewness and kurtosis coefficients were obtained with MINITAB 12 (MINITAB Inc.,	the mean of the marginal posterior distributions to tend towards zero if the
43 44	158	1998). Whilst mean body weight for data set 1 was 20% higher than mean data set 2 body	data available do not support varia [1] <b>Deleted:</b> A description of the pedigree and data structure for the data sets used is
45 46	159	weight, differences were smaller for mean SaO and Flesh (respectively, 2% lower and 2%	presented in Table 1. For both data sets, the mean number of birds with SaO
47	160	higher for data taken at six weeks in the less recent pedigree). Coefficients of variation were	record per full-sib family was less than five (with a minimum value of one and a maximum value of 25) and the mean
48 49	161	similar within traits across data sets. SaO distributions (adjusted for fixed effects or unadjusted)	paternal half-sib family size was less than 30 (with a minimum value of one and a maximum value of 106).
50		7	maximum value of 100).
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showed skewness coefficients that were more extreme than -0.70 for both data sets. Adjusting

raw data for fixed effects slightly decreased absolute skewness but increased kurtosis (making

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## Deleted: [TABLE 1],

**Deleted:** Table 4 shows estimates of  $\sigma_u^2$ ,  $\sigma_e^2$  and  $\sigma_p^2$  obtained from the REML analyses for blood oxygen saturation

### Deleted: , [TABLE 4]

Deleted: For all runs and parameters, chains seemed to have converged to their equilibrium distributions after a 5000 iteration burn-in period and sample autocorrelation was generally low (absolute values smaller than 0.1) for lags over 100 for all parameters (results not shown). Marginal posterior distributions of all parameters were symmetric and approximated normal distributions. Table 5 shows the marginal posterior means, posterior standard deviations, Monte Carlo standard deviation of marginal posterior means and the effective number of samples per chain for all sampled parameters. The difference between marginal posterior means from the six chains ran for data set 1 was not always strictly within the Monte Carlo sampling error estimated as proposed by Geyer (1992). Nonetheless, all chains seemed to have converged to the equilibrium distribution (using different starting values) and marginal posterior means were very close. The effective number of samples was variable within chains between parameters and within parameters between chains, with values ranging from nine to more than 600 independent samples. Generally  $\sigma_u^2$  and  $\sigma_e^2$  showed smaller effective numbers of samples, which reflects poorer mixing for these parameters.¶ [TABLE 5]¶

Samples were pooled across chains and the means of the pooled distributions and their standard deviations were used as point estimates of the sampled parameters and their standard errors. Since the total number of independent samples for any parameter was greater than 100, the mean and the standard deviation of the pooled posterior distribution were assumed to be good estimates of the parameter and its standard error.

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**Deleted:** shows point estimates of the parameters sampled and those derived and the standard deviation of their pooled posterior distributions. All distributions presented zero densities for parameter values equal to zero. Following Janss et al. (1995) we inferred that a locus with large effect on SaO was segregatif ... [2]

**Deleted:** Although the estimated d was slightly larger than a, estimated major locus effects were similar in size (the dominance deviance was estimated to be  $1.12 (\pm 0.06)$  and was indeed just different from one. W

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164	the distribution more leptokurtic), more markedly so for data set 1.
165	[TABLE 2]
166	Table 3 shows REML estimates of heritabilities and genetic correlations (and standard
167	errors) for SaO, Weight and Flesh obtained from trivariate analyses for data sets 1 and 2 when
168	fitting a purely polygenic model. The estimated heritability for SaO from data set 1 was higher
169	than that from data set 2. This was due to a 43% decrease in $\sigma_u^2$ (that changed from 14.37 to
170	<u>8.18)</u> accompanied by a smaller (16%) decrease in $\sigma_e^2$ (that changed from 54.06 to 45.18).
171	Genetic correlations between SaO and Weight and Flesh were negative but not significantly
172	different from 0 (P > 0.05) for either data set.
173	[TABLE 3]
174	Segregation Analyses
175	Figure 1 shows the pooled posterior distributions of $\sigma_{\underline{u}}^2$ , $\sigma_{\underline{m}}^2$ and $\sigma_{\underline{s}}^2$ for data sets 1 and
176	2. Following the criteria detailed in the annex (i.e. the major locus variance distributions
177	presented zero densities for values equal to zero) we inferred that a major locus involved in the
178	control of SaO was segregating in the population studied. Table 4 shows estimates and standard
179	deviations of the major locus additive and dominance effects, B allele frequency and residual,
180	polygenic and major locus variances as well as polygenic and major locus heritabilities and
181	dominance deviance, The dominance deviance was very close to 1 for both data sets (1.12±0.06
182	and 1.02±0.06 respectively) and therefore we will assume in the following that a and d can be
183	considered equal, so that the locus acts in a dominant fashion, For data set 1 a = d = $7.2 \%$ SaQ
184	which means that the difference between bb birds and BB or Bb birds in SaO would be around
185	14 %. The standardized locus additive effect was 0.80 $\sigma_p$ (or 1.12 $\sqrt{(\sigma_u^2 + \sigma_e^2)}$ or 1.21 $\sigma_e$ ). The
186	frequency of the major locus allele that increases SaO was estimated to be $p_B = 0.53$ . This locus
187	alone would explain 48% of the total variance and 87% of the total genetic variance in SaO. The
188	additive genetic variance accounted for by the major locus would be 79% of the total additive
189	genetic variance.

[TABLE 4]

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Figures 2 and 3 show respectively the distributions of a and d and of p<sub>B</sub> for data sets 1 and 2. The estimated locus effects obtained from the analysis of data set 2 were roughly the same, although slightly smaller, than the estimates obtained from the analysis of data set 1: the estimate of a from data set 2 was proportionately 0.89 the estimate from data set 1 and the estimated d was 0.82 the estimate from data set 1. Despite this, the standardized locus additive effect increased from 0.80 to 0.87  $\sigma_p$ . The estimated  $p_B$  was 0.65 that is 0.12 higher than the estimate obtained from data set 1. This major locus would explain 33% of the total variance observed for SaO in data set 2 and 82% of the total genetic variance. The additive genetic variance accounted for by the major locus was estimated to be 70% of the total additive genetic variance.

[FIGURE 1], [FIGURE 2], [FIGURE 3]

202 Sampled Genotype Probabilities and Allele Frequencies. The correlation between
203 chains of estimated probabilities for each genotype for individual birds was higher than 0.96,
204 and the mean standard error (averaging over all birds with data and ancestors) of each genotype
205 probability was smaller than 0.01.

Sire genotype probabilities obtained from data set 2 show that approximately 1.8% of the sires were assigned a bb genotype, 32.9% a Bb genotype and 11.1% a BB genotype with a probability higher than 0.8. If the inferred mode of action of the putative gene is dominant, information from relatives is necessary to discriminate heterozygotes from the dominant homozygotes. In our case, more than 40% of sires were identified as being either BB or Bb with high probability (>0.8) but around a further 15% of sires had similar (and close to 0.5) probabilities of being BB or Bb, although they had very low probabilities of being bb.

Figure 4 shows how major allele frequencies vary over time for data set 2. Estimates of allele frequencies were obtained from sires alone and from all birds with records. For sires, each point in the graph was obtained from 29 birds whereas in the case of selection candidates each point was obtained from 1000 birds. For selection candidates, regression of allele frequencies over time has a negative slope for  $p_b$  and a positive one for  $p_B$ , showing how within the period Deleted: Table 6 also shows the means and standard deviations of the pooled distributions for the sampled and derived parameters for data set 2. The visual inspection of the six chains did not show convergence problems. Figure 1 shows the pooled posterior distributions of  $\sigma_u^2$ ,  $\sigma_m^2$  and  $\sigma_e^2$  for data set 2. Pooled posterior distributions for all parameters presented zero densities for parameter values equal to zero. Since the density at zero for  $\sigma_m^2$  was zero, presence of a locus with large effect on SaO segregating in the population was inferred. The estimated dominance deviance was not different from one, so the putative locus was assumed to act in a dominant fashion

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**Deleted:** Analyses were repeated for data set 2, using raw phenotypes (records not adjusted for fixed effects) and sampling fixed effects (age of dam and hatch). These analyses yielded estimates of the parameters presented in table 6 that were similar to the ones obtained from adjusted phenotypes (results not shown), showing that, in this case, preadjustement of phenotypes did not have a significant effect on parameter estimates.<sup>¶</sup>

218 corresponding to data set 2 the frequency of the major allele that increases SaO increased over

time. [FIGURE 4] Deleted: 7 Estimation of the Putative Locus Effect on Weight and Fleshing Score. Table 5 shows the estimates of the putative locus additive and dominance effect on SaO, Weight and Flesh obtained from the regression of trait values on genotype probabilities at the major locus using data set 2. The estimated additive effect was not different from zero for Weight and Flesh, but the estimated dominance effect was large for both. This suggests that birds heterozygous at this putative locus would have substantially higher body weight and fleshing score at five weeks than either of the homozygotes. The estimated effects for SaO were significantly larger than the estimates obtained from the segregation analysis. Deleted: 7 [TABLE 5] DISCUSSION Overall, the segregation analyses of SaO data indicate that a locus with large effect is involved in the genetic control of SaO in this line. Results obtained from the two sets of data provide a consistent picture: a dominant major locus with an additive effect of around 0.90  $\sigma_p$ that is responsible for a predicted difference in SaO between the two homozygotes of more than 10% is segregating in this line. The frequency of the allele that increases SaO increased with selection on SaO from  $p_B = 0.53$  to around 0.65. It is difficult to assess if the observed difference in estimated p<sub>B</sub> from data sets 1 and 2 really reflects a change in allele frequencies over time or is a consequence of phenotypes recorded at different ages (six and five weeks

respectively). Nonetheless, Figure 4 shows that, within a time period (data set 2), the estimated
frequency of the allele that increases SaO increases slightly over time, which is consistent with
the between data set trend.

For data set 1, the predicted proportion of heterozygous individuals would be around 50%. Because the gene is dominant, around 25% of the population would show low SaO values. Despite this, this locus alone would explain 48% of the total variance and around 87% of the genetic variance in the "base population". For data set 2, the predicted proportion of 

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heterozygous individuals would be around 45% and only around 12% of the population would show low SaO values. The proportion of the total variance observed in the data set 2 "base population" explained by this putative locus has decreased to 33% and that of the genetic variance to 80%. From data set 1 to data set 2, the estimate of the major locus variance has more than halved. Changes in the major locus allele frequency alone account for 71% of this difference compared to 46% accounted for by changes in estimated effects alone. The polygenic variance estimated from data set 2 was roughly two thirds of the estimate obtained from data set 1. This, together with an increase in the frequency of the allele that increases SaO, is consistent with the fact that increasing SaO has been one of the breeding goals in the population studied. As a result of decreases in major gene and polygenic variances, the total and the major locus heritabilities have decreased, since the residual variance has remained approximately constant. Note that the frequencies of birds with low SaO values in the two data sets do not necessarily provide a direct prediction of the expected frequency of ascites as the correlation between ascites and SaO in this population is unknown. In fact we might predict that a low SaO value predisposes a bird to ascites, but the actual development of ascites is also dependent on other environmental factors. For example, Julian and Mirsalimi (1992) showed that there was a significant mean difference in SaO between ascitic and non-ascitic birds from a heavy meat-type chicken, but not all birds with low SaO developed ascites during their trial.

Selection experiments carried out in other broiler populations to study ascites
susceptibility tend to suggest that this trait is influenced by a single biallelic major locus that
would act in a recessive fashion (see for example, Druyan et al. (2001), Druyan et al. (2002),
Wideman and French (1999) and Wideman and French (2000)) and this would support our
findings.

The mean skewness coefficient of our data sets (after adjustment for fixed effects) was around -0.77. In an outbred situation, where one expects only a proportion of families to be segregating at a putative major locus, the trait distribution within full and/or half sib families would depend on the sire and dam major genotypes, and families that do not segregate at the major locus would only show "background skewness" (i.e., skewness not caused by the major **Deleted:** When a major locus is segregating, the population distribution of phenotypes can be skewed. MacLean et al. (1975) showed that skewness of the phenotypic distributions, when not caused by segregation of loci with large effect, could lead to detection of a spurious major locus.

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**Deleted:** MacLean et al. (1976) suggested applying a transformation to

Using data set 2, we applied a

the phenotypic data to remove skewness prior to analysis, but showed that this

could considerably reduce the power to

detect major genes when present, as well

as posing problems for the interpretation of the results (Demenais et al., 1986).

locus segregation). Figure 5 shows the distribution of adjusted SaO phenotypes within two sire families with over 100 offspring each. Sire 1 was assigned a Bb genotype with a probability greater than 0.99 in the segregation analysis whereas sire 2 was assigned a BB genotype with a probability greater than 0.98 and a bb genotype with a probability smaller than 0.02. It can be seen that dispersion within sire family 1 is larger than dispersion within sire family 2, which is consistent with the predicted genotype status of the two sires.

[FIGURE 5]

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We observed that, for the analyses carried out, the total additive variance estimated using a mixed inheritance model was greater than the additive variance estimated using a polygenic model. We carried out a simulation study, presented in the annex, that supports the hypothesis that changes in allele frequencies caused by selection are the source of the observed discrepancies.

286 By regressing Weight and Flesh phenotypes on functions of major locus genotype 287 probabilities we obtained estimates of the effects of the putative locus on these traits. The locus 288 that has an effect on SaO seems to act in an overdominant fashion for weight and fleshing score. 289 This would be consistent with the estimate of zero for the genetic correlation between these 290 traits and oxygen saturation from the analysis done assuming a purely polygenic model with 291 additive genetic effects and would also explain the intermediate frequency of the high SaO 292 allele estimated from data set 1, which increases after selection to increase oxygen saturation. In 293 an experiment involving the hypobaric exposure of birds, Pavlidis et al. (2003) observed 294 significant heterosis for body weight at 14, 18 and 42 days in the reciprocal crosses of an 295 ascites-resistant and an ascites-susceptible line, but observed no differences in body weight 296 between the ascites-resistant and ascites-susceptible lines. These observations fit well with our 297 results. Estimates of the putative gene effects for SaO obtained from this analysis were 298 approximately two-fold the ones obtained from the segregation analysis. Genotype probabilities were estimated from segregation analysis and only birds with phenotypes from the tails of the 299 300 SaO trait distribution (and/or strong family information) are likely to have extreme (i.e., close to 301 0 or 1) estimates of genotype probabilities. This would cause these individuals to have a high

transformation to SaO data, in order to obtain a trait distribution closer to a Normal. The transformation applied was Ln (100 - SaO), and the transformed trait distribution had a skewness coefficient of -0.29 and a kurtosis coefficient of -0.17. The heritability of Ln (100 - SaO) was 0.14, which is almost identical to that obtained for untransformed data. The outcome of the analysis of transformed data was that a dominant locus with large effect on Ln(100-SaO) (a = d =  $0.58 \sigma_p$ ) was segregating in this line, but neither the frequency nor the mode of action of this putative locus were in agreement with the results obtained from untransformed data. Indeed, an allele that increases Ln(100-SaO) would decrease SaO, so the estimated  $p_B = 0.69$  from this analysis needs to be compared to (1 (0.65) = 0.35. In the same way, if the locus that increases Ln(100-SaO) were dominant, the proportion of birds showing low SaO values would be around 81% compared with the predicted 12% from the untransformed data analysis. Moreover, the correlation between the probability of a bird being heterozygote estimated from transformed and untransformed data was -0.17 (P < 0.001) for birds with SaO data and -0.11(P = 0.03) for sires with SaO data. The fact that the estimates of  $p_{Bb} \mbox{ are not }$ similar from transformed and untransformed data suggests that these analyses are describing different phenomena. Selection experiments carried out in other broiler populations to study ascites susceptibility tend to suggest that this trait is influenced by a single biallelic major locus that would act in a recessive fashion (see for example, Druvan et al. (2001). Druvan et al. (2002), Wideman and French (1999) and Wideman and French (2000)). This would support the mode of action suggested for SaO by the analysis of untransformed data.¶ We observed that, for the analyses carried out, the total additive variance estimated using a mixed inheritance model was greater than the additive variance estimated using a polygenic model. In order to assess whether this would be expected in the presence of a segregating major gene in a population under selection a simulation study was performed, 125 five-generation pedigrees (base population and four generations of random or phenotypic selection) were simulated with a structure chosen to resemble the (real) pedigree analyzed. In each generation, 40 males were mated to eight (different) females that produced three male and three female offspring each (i.e., population size was maintained

constant). In the case of phenotypi ... [3]



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influence in the regression and hence could lead to an overestimation of the locus effect for
SaO. The extent to which this would affect estimates of effects for Weight and Flesh would be a
function of the true genetic correlation amongst these traits and SaO.

305 Conclusions and further research

Our study indicates that a QTL or gene with large effect on SaO is segregating in the population studied. It must be borne in mind that, although segregation analysis is the most powerful marker-free method for major gene or QTL detection, it is sensitive to deviations from normality, and the distribution of the data analyzed was skewed. Nevertheless, the majority of the different analyses performed here are consistent with the presence of a major gene. Only the result from the analysis of transformed data (presented in the annex) provides a cautionary note, but previous studies suggest this may be expected even in the presence of a genuine major gene. Accepting the presence of a major gene, the mode of action of the putative locus on SaO and on weight and fleshing score, the fixation of the favourable allele (i.e., the one that increases SaO) by means of traditional selection would be a difficult task. Under selection only for growth and carcass characteristics, the low SaO allele would be maintained in the population by the advantage of the heterozygous bird. The combined effects of selection to increase both SaO and weight and fleshing score will reduce the fitness of the low SaO homozygote, but will still result in the heterozygote being the favoured genotype and hence the low SaO allele will be retained in the population. Nonetheless, elimination of carriers of the allele that decreases SaO is of interest since it would lead to greatly improved broiler health, would reduce the broiler industry ascites-related economic losses and remove the need for continual SaO testing. However, given the estimated effects of the locus, this would be most effectively achieved using genetic markers to identify and select against the low SaO allele. A QTL mapping study in a suitable population is a necessary further step that would confirm or refute our findings and identify potential markers to manipulate the low SaO allele.

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327	ACKNOWEDGEMENTS
328	We acknowledge support from the Biotechnology and Biological Sciences Resear
329	Council. PN is also grateful to Aviagen Ltd. for funding and to Ricardo Pong-Wong
330	providing data analysis software.
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418	Table 2. Means and standard deviations (in brackets) for blood oxygen saturation
419	(SaO, in % units), body weight (Weight, in kg) and fleshing score (Flesh, a measure of
420	breast conformation, in arbitrary units, measured in a scale of 1 to 5) for raw phenotypes
421	(RAW) and for SaO phenotypes adjusted for fixed effects (ADJ) for data sets 1 and 2.
422	Skewness (Sk) and kurtosis (Ku) coefficients of the distributions of raw SaO phenotypes
423	and analyzed data are also presented

Data set		SaO (%)	Weight (kg)	Flesh (units)	Sk	Ku
1	RAW	80.02 (9.15)	2.72 (0.34)	3.17 (0.92)	-0.78	0.46
	ADJ	0.64 (8.08)	-	-	-0.75	1.06
2	RAW	81.81 (7.98)	2.16 (0.28)	3.10 (0.90)	-0.85	0.88
	ADJ	-0.42 (7.23)	-	-	-0.74	0.93

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Table 3. Heritabilities (on diagonal) and genetic correlations (below diagonal) and

their standard errors (in brackets), obtained for body weight (Weight), fleshing score

	five weeks)	using full pedigrees	1	
ata set		SaO	Weight	Flesh
	SaO	0.21 (0.02)		
	Weight	-0.02 (0.06)	0.26 (0.01)	
	Flesh	-0.10 (0.05)	0.53 (0.03)	0.22 (0.01)
	SaO	0.15 (0.02)		
	Weight	-0.10 (0.06)	0.32 (0.01)	
	Flesh	-0.10 (0.06)	0.62 (0.02)	0.19 (0.01)
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430 431	¥	<b>Deleted:</b> Table 5. Descriptive statistics of chains obtained from the analysis of data set 1. Marginal posterior means (MPM), posterior standard deviations (MCSD) of MPMs and effective number of independent samples (ENS) per chain for the major locus additive (a) and dominance (d) effect, B allele frequency (p <sub>B</sub> ), population mean (Mean) and residual ( $\sigma_c^2$ ) and polygenic ( $\sigma_u^2$ ) variances. A mean ENS is also shown for each sampled parameter [] Parameter[4] <b>Deleted:</b> Table 4. REML estimates of genetic ( $\sigma_u^2$ ), residual ( $\sigma_c^2$ ) and phenotypic ( $\sigma_a^2$ ) variances obtained for blood oxygen saturation for both data sets studied[] Data set[5]

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Table 4. Point estimates and standard deviations (in brackets) of the major locus additive (a) and dominance (d) effect, B allele frequency (p <sub>B</sub> ),
population mean (Mean) and residual ( $\sigma_e^2$ ) and polygenic ( $\sigma_u^2$ ) variances obtained from the segregation analysis of SaO for data sets 1 and 2. Estimates are
also presented for the major locus variance $(\sigma_m^2 = 2 p_B (1 - p_B) [a + d ((1 - p_B) - p_B)]^2 + [2 p_B (1 - p_B) d]^2)$ , total phenotypic variance $(\sigma_p^2 = \sigma_m^2 + \sigma_u^2 + \sigma_e^2)$ ,

variance ratios  $(h_T = (\sigma_m^2 + \sigma_u^2)/\sigma_p^2, h_m = \sigma_m^2/\sigma_p^2, h_{am} = (2 p_B (1 - p_B) [a + d ((1 - p_B) - p_B)]^2)/\sigma_p^2$  and  $h = \sigma_u^2/(\sigma_u^2 + \sigma_e^2))$  and dominance deviance (d/a)

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Dat	ta set	а	d	p <sub>B</sub>	Mean	$\sigma_e^2$	$\sigma_{u}^{2}$	$\sigma_m^2$	$\sigma_{\rm p}^{2}$	h <sub>T</sub>	h <sub>m</sub>	h <sub>am</sub>	h	d/a
Dut				÷					P					
1		7.22	8.05	0.53	-5.60	35.58	6.06	39.19	80.83	0.56	0.48	0.36	0.14	1.12
		(0.20)	(0.32)	(0.03)	(0.33)	(1.14)	(1.00)	(3.10)	(3.07)	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)
2		6.46	6.60	0.65	-4.84	32.67	3.93	18.25	54.85	0.40	0.33	0.17	0.11	1.02
2		(0.21)	(0.32)	(0.02)	(0.26)	(0.85)	(0.62)	(1.82)	(1.84)	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)



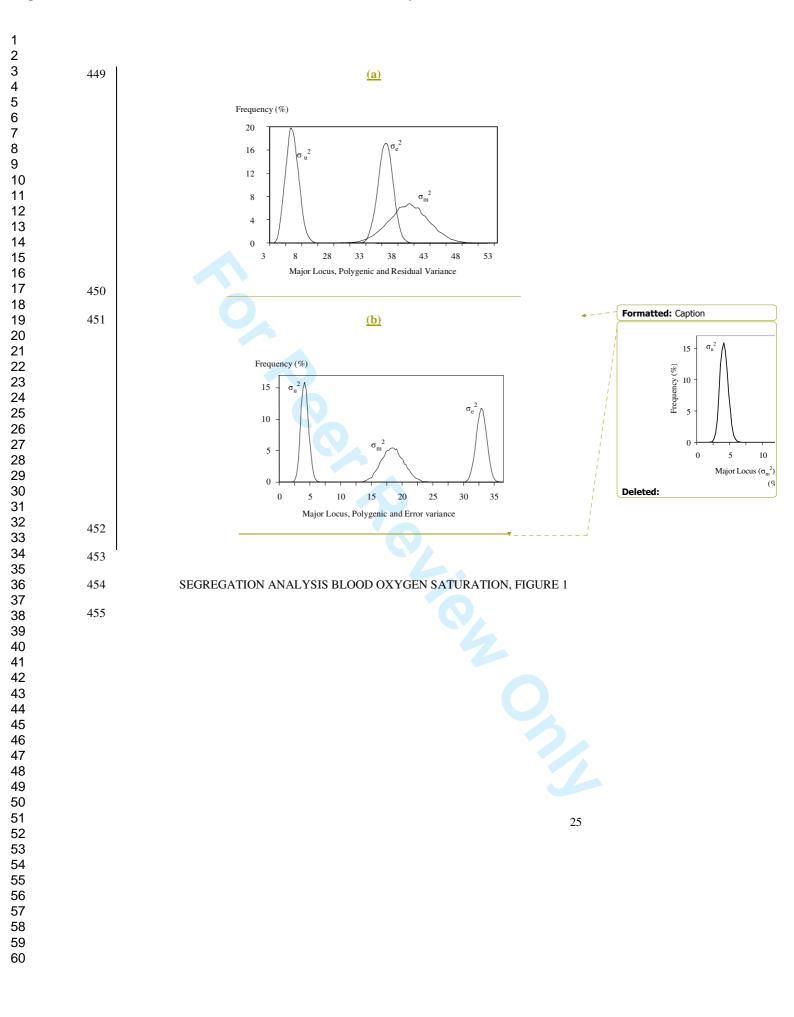
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438	Table 5. Estimates and standard errors (in brackets) of the putative locus additive (a)	Del
439	and dominance (d) effect for blood oxygen saturation (SaO), body weight (Weight) and fleshing	
440	score (Flesh, a measure of breast conformation) obtained from the regression of trait values on	
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	438 439 440 441 442 443 444	438Table 5. Estimates and standard errors (in brackets) of the putative locus additive (a)439and dominance (d) effect for blood oxygen saturation (SaO), body weight (Weight) and fleshing440score (Flesh, a measure of breast conformation) obtained from the regression of trait values on441genotype probabilities at the major locus. Data recorded at five weeks of age (data set 2) were442used to obtain these estimates443 $\frac{1}{SaO (\%)}$ $\frac{11,96 (0.14)^{**}}{0.022}$ $16.61 (0.27)^{**}$ Weight (kg) $-0.71 \times 10^2 (0.55 \times 10^2)$ $5.84 \times 10^2 (0.88 \times 10^2)^{+*}$ Flesh (units) $-0.03 (0.02)$ $0.24 (0.04)^*$ * Significantly different from $0 (P \le 0.01)$ .445.

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3	447	Figure 1. Pooled posterior distributions of the polygenic $(\sigma_u^2)$ , major locus $(\sigma_m^2)$	Deleted: Table 8. Simulated
4 5 6 7 8 9 10 11 12 13 14	448	and residual (g, <sup>2</sup> ) variances obtained from data set 2	parameters (in brackets at table heading) and estimates (with standard deviations) obtained assuming either a purely polygenic model (POL and POLF) or a mixed inheritance model (MIX). Estimates were obtained by averaging estimates from 125 replicated populations. a and d are the major locus additive and dominance effect and p <sub>B</sub> is the B allele frequency. Residual ( $\sigma_c^2$ ) and polygenic ( $\sigma_a^2$ ) variances are shown, as are major locus additive, dominance and total variances ( $\sigma_{am}^2 = 2 p_B (1 - p_B) [a + d ((1 - p_B) - p_B)]^2, \sigma_{am}^2 = (2 p_B (1 - p_B) [a + d ((1 - p_B) - p_B)]^2, \sigma_{am}^2 = (2 p_B (1 - p_B) d_2)$ and $\sigma_m^2 = \sigma_{am}^2 + \sigma_{am}^2$ , total phenotypic variance ( $\sigma_a^2 = \sigma_m^2 + \sigma_a^2$ ), total
15 16			additive variance $(\sigma_a^2 = \sigma_{am}^2 + \sigma_u^2)$ and variance ratios $(h_T = (\sigma_m^2 + \sigma_u^2)/\sigma_p^2, h = \sigma_u^2/(\sigma_u^2 + \sigma_e^2)$ and $h_a = (\sigma_{am}^2 + \sigma_u^2)/(\sigma_u^2 + \sigma_e^2)$
17			$\sigma_p^2$ ). POLF and POL show estimates of
18			parameters obtained from polygenic analyses before and after censoring
19 20			female phenotypes. Results are presented for populations under phenotypic (PHE) or random (RAN)
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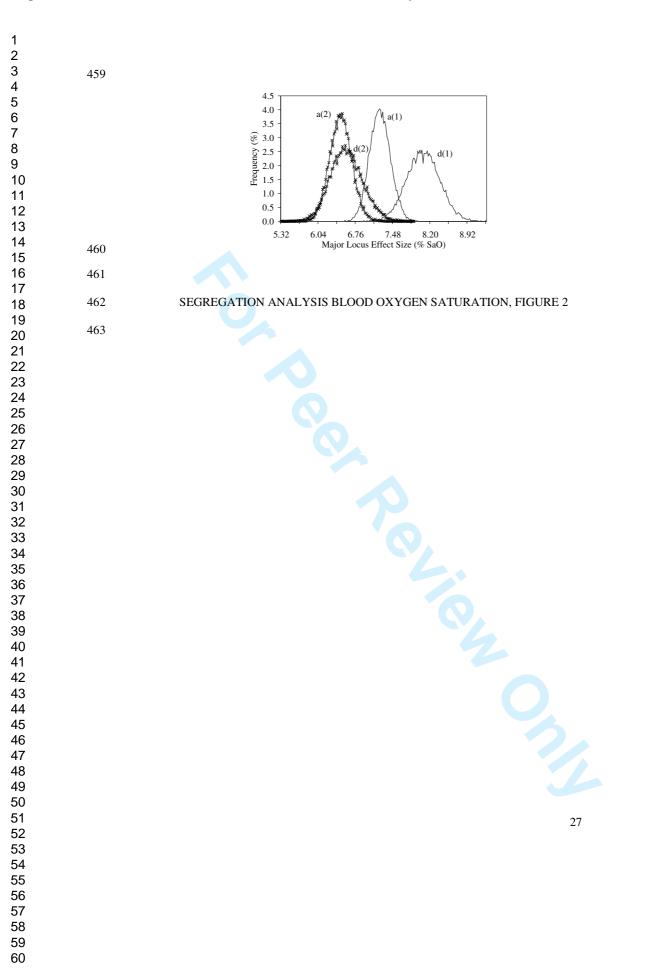
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456 Figure 2. Pooled posterior distributions of the major locus additive and

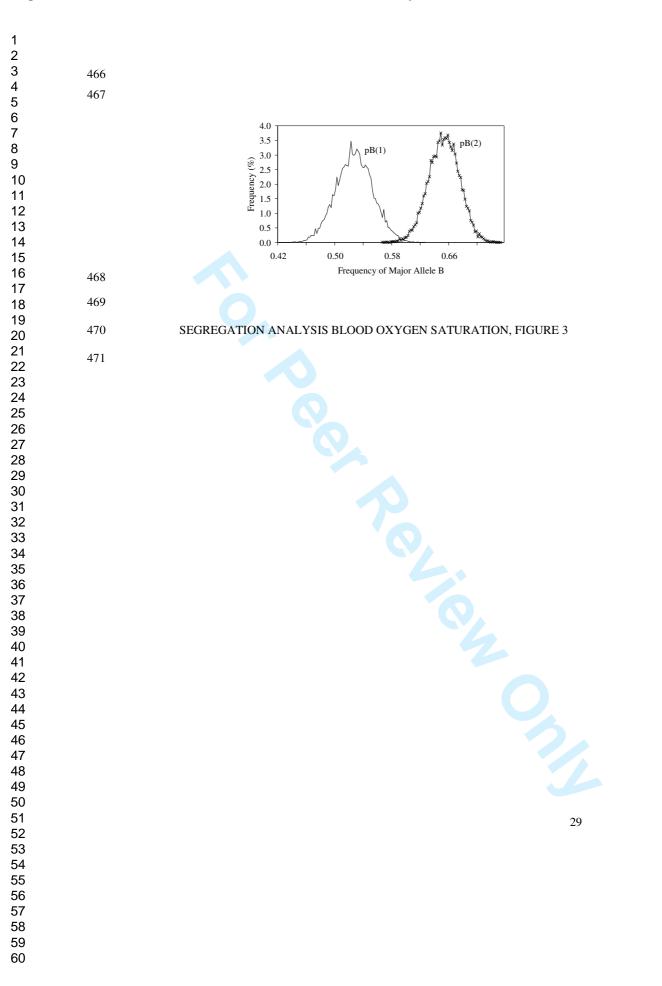
dominance effects obtained from data set 1 (a(1) and d(1)) and from data set 2 (a(2) and

d(2))

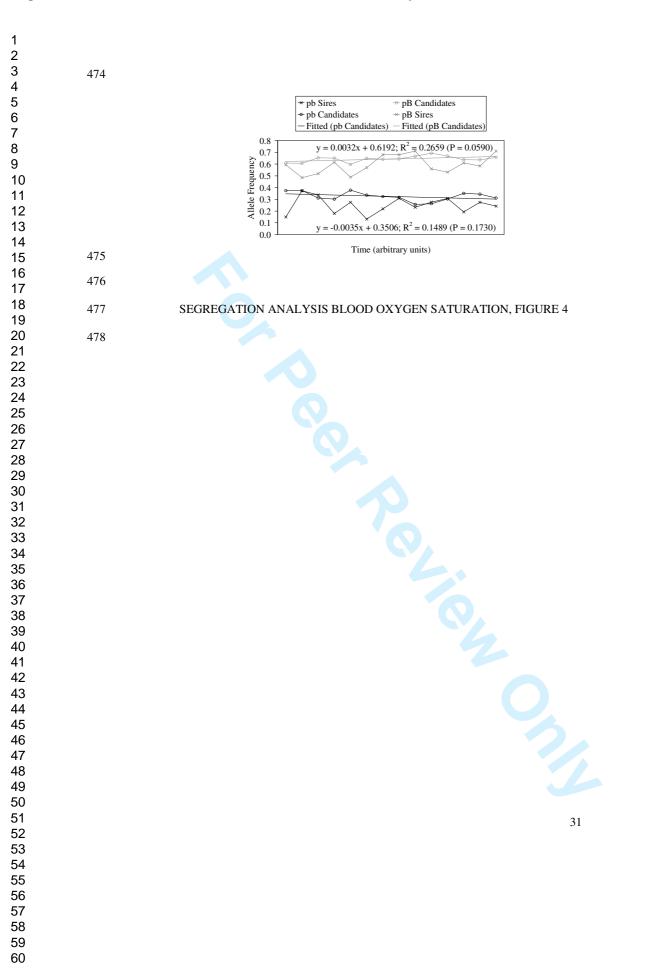
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464	Figure 3. Pooled posterior distributions of the major allele B frequency
465	obtained from data set 1 $\left(p_B(1)\right.)$ and from data set 2 $\left(p_B(2)\right)$

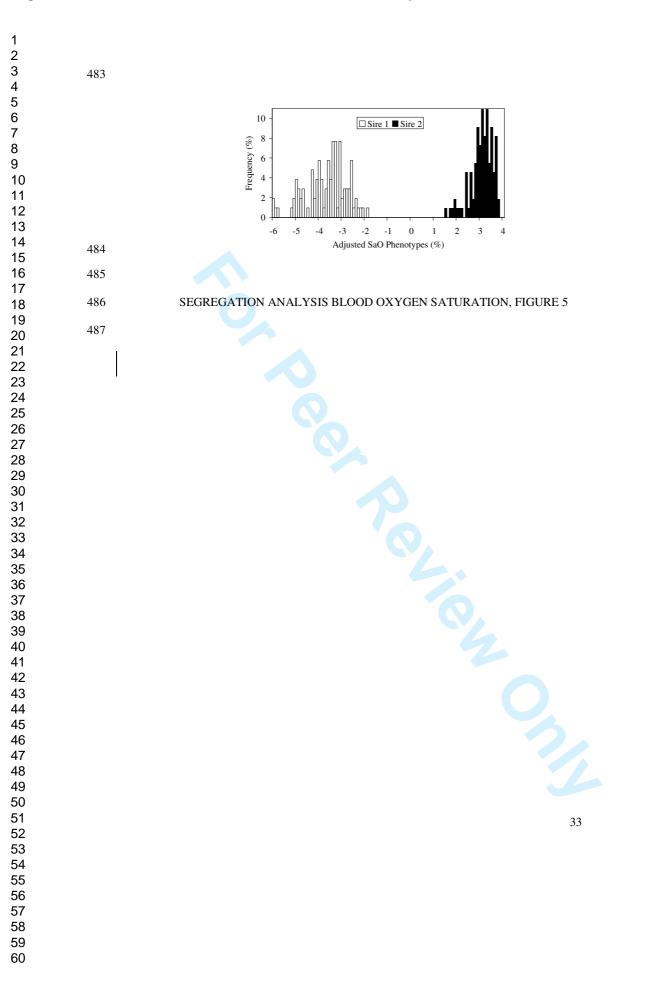


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- 3 4	472	Figure 4. Major allele frequencies plotted over time. Estimates of allele
5	473	frequencies were obtained from sires alone and from all birds with records
6 7 8 9 10 11 2 13 14 15 16 7 18 9 20 21 22 32 45 26 7 8 9 30 12 33 45 36 7 8 9 0 11 21 22 34 25 67 89 30 12 23 45 26 7 89 30 12 33 45 36 37 89 0 41 2 34 45 46 7 89 0 11 22 34 55 67 89 0 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 78 90 11 22 34 56 77 89 0 12 23 45 56 77 89 0 12 23 24 56 77 89 0 12 23 34 56 77 89 0 14 23 34 56 77 89 0 14 23 34 56 77 89 0 12 23 34 56 77 89 0 12 23 34 56 77 89 0 12 23 34 56 77 89 0 12 23 34 56 77 89 0 12 33 45 56 77 89 0 12 23 34 56 77 89 0 12 23 24 55 55 55 55 55 55 55 55 55 55 55 55 55		



479	Figure 5. Distribution of adjusted SaO phenotypes within two sire families with
480	over 100 offspring each. The genotypes of sire 1 and sire 2 were estimated to be
481	heterozygous Bb and homozygous BB, with probabilities higher than 0.99 and 0.98
482	respectively.

<text>



1488ANNEX489METHODSformatted: Font: Bold Formatted: abstract490Segregation Analysis. The mixed model equation that describes the model fitted to491the data is:492 $\mathbf{y} = \mathbf{Xb} + \mathbf{Zu} + \mathbf{ZWm} + \mathbf{e}$ 493 $\mathbf{y} = \mathbf{Xb} + \mathbf{Zu} + \mathbf{ZWm} + \mathbf{e}$ 494effects and X is the vector of phenotypic observations, b is the vector of fixed non-genetic495effects and X is the design matrix relating fixed non-genetic effects to observations. Z is the494incidence matrix for random polygenic effects (u - N(0, Ac_n^2) - where A is the numerator495relationship matrix and $c_n^2$ is the polygenic variance)- and single locus effects. W is a three496column matrix that contains information on the genotype of each individual and m is the497vector of major-genotype means (m' = 1 - a, d, a), hence Wm is the vector of random effects498the single locus. $\mathbf{e} (-N(0, Ic_n^2))$ is a vector of random errors.499Jans et al. (1995) proposed an efficient scheme using the Gibbs sampler for the490study of mixed inheritance models in animal populations. In our analyses, carried out with
3488ANNEX5489METHODS6490Segregation Analysis. The mixed model equation that describes the model fitted to7490Segregation Analysis. The mixed model equation that describes the model fitted to8491the data is:10492 $\mathbf{y} = \mathbf{X} \mathbf{b} + \mathbf{Z} \mathbf{u} + \mathbf{Z} \mathbf{W} \mathbf{m} + \mathbf{e}$ 11493where y is the vector of phenotypic observations, b is the vector of fixed non-genetic16494effects and X is the design matrix relating fixed non-genetic effects to observations. Z is the16495incidence matrix for random polygenic effects ( $\mathbf{u} \sim N(0, A\sigma_u^2)$ -where A is the numerator17496relationship matrix and $\sigma_u^2$ is the polygenic variance)- and single locus effects. W is a three19497column matrix that contains information on the genotype of each individual and m is the22498vector of major-genotype means ( $\mathbf{m}^* = [-a, d, a]$ ), hence Wm is the vector of random effects23499Ianss et al. (1995) proposed an efficient scheme using the Gibbs sampler for the26500Ianss et al. (1995) proposed an efficient scheme using the Gibbs sampler for the
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6490Segregation Analysis. The mixed model equation that describes the model fitted to8491the data is:10492 $\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{u} + \mathbf{Z}\mathbf{W}\mathbf{m} + \mathbf{c}$ [1]12493where $\mathbf{y}$ is the vector of phenotypic observations, $\mathbf{b}$ is the vector of fixed non-genetic14494effects and $\mathbf{X}$ is the design matrix relating fixed non-genetic effects to observations. $\mathbf{Z}$ is the16495incidence matrix for random polygenic effects ( $\mathbf{u} \sim N(0, A\sigma_n^2)$ ) -where $\mathbf{A}$ is the numerator17496relationship matrix and $\sigma_n^2$ is the polygenic variance)- and single locus effects. $\mathbf{W}$ is a three19497column matrix that contains information on the genotype of each individual and $\mathbf{m}$ is the21498vector of major-genotype means ( $\mathbf{m}^2 = [-a, d, a]$ ), hence $\mathbf{W}\mathbf{m}$ is the vector of random effects23499I the single locus. $\mathbf{e} (\sim N(0, 1\sigma_n^2))$ is a vector of random errors.2425500Janss et al. (1995) proposed an efficient scheme using the Gibbs sampler for the26501rund inherities an order incident scheme using the Gibbs sampler for the
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17 18496relationship matrix and $\sigma_u^2$ is the polygenic variance)- and single locus effects. W is a three19 20497column matrix that contains information on the genotype of each individual and m is the21 22498vector of major-genotype means (m' = [ -a, d, a ]), hence Wm is the vector of random effects23 23 24499at the single locus. e (~ N(0, $I\sigma_e^2)$ ) is a vector of random errors.24 25 26500Janss et al. (1995) proposed an efficient scheme using the Gibbs sampler for the26501study of mined inheritance models in grained neurolations. In our organize, corried out with
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25 500 Janss et al. (1995) proposed an efficient scheme using the Gibbs sampler for the 26 501 study of mixed inhoritonea models in emired perputations. In our englance corried out with
26 501 study of mixed inharitance models in animal nonvestigations. In our analyzes, carried out with
28 502 software developed at Roslin Institute by Ricardo Pong-Wong (Walling et al. 2002) we
29 30 503 used the sampling scheme they described (see Janss et al. (1995) and Janss et al. (1997) for
3132504details) to obtain marginal posterior distributions for the major locus parameters (frequency
<ul> <li>33</li> <li>34 505 and additive and dominance effect), population mean and polygenic and residual variances.</li> </ul>
35 36506For each iteration of the Gibbs sampler, every bird was assigned a genotype. Averaging over
37 38 507 <u>all retained iterations provides major locus genotype probabilities (p<sub>BB</sub>, p<sub>Bb</sub> and p<sub>bb</sub>) for each</u>
39 508 bird in the pedigree.
4041509The variance explained by the major locus $(\sigma_m^2)$ is defined as:
42 43 510 $\sigma_{m}^{2} = 2 p_{B} (1 - p_{B}) [a + d ((1 - p_{B}) - p_{B})]^{2} + [2 p_{B} (1 - p_{B}) d]^{2} $ [2]
44 45511(Falconer and Mackay, 1996) and was computed from the major locus genotypic
46 47 512 effects and allele frequency sampled at each iteration. Likewise, we calculated the degree of
48 513 dominance as d/a.
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514	We used non-informative prior distributions, uniform on ( $-\infty$ ; $+\infty$ ) for fixed non-
515	genetic effects and d, on [0; $+\infty$ ) for a and on [0; 1] for major allele B frequency. We
516	used an inverse-gamma prior distribution on ( $0$ ; + $\infty$ ) for variances with a flat prior for
517	log(variance). This type of prior distribution for variances should cause the mean of the
518	marginal posterior distributions to tend towards zero if the data available do not support
519	variation of the random effects. All genotypes were initialized as Bb.
520	Six runs of the Gibbs sampler were carried out for the analysis of each data set, with
521	different starting values. Differences in parameter estimates obtained from different chains
522	may reflect problems of mixing. Individual chains were composed by 255000 iterations that
523	were collected after allowing for a burn-in period of 5000 iterations, keeping each 100 <sup>th</sup>
524	iteration from this point onwards. In order to assess if the burn-in period and thinning
525	parameter we used were adequate, we studied the marginal posterior distributions of the
526	sampled parameters obtained from each run of the Gibbs sampler. For data set 1 analyses,
527	the marginal posterior means, that is the parameter's a-posteriori expectation, the posterior
528	standard deviations and the Monte Carlo standard deviations are reported. The Monte Carlo
529	standard deviation of the marginal posterior mean was computed following Geyer (1992) as
530	suggested by Sorensen et al. (1995) and the effective number of samples per chain, i.e. the
531	number of independent samples per chain for each parameter, was estimated. Following the
532	results obtained when studying the behaviour of the individual chains for data set 1, no
533	formal assessment of convergence was carried out for data set 2 analyses, but a visual
534	inspection of individual chains was carried out for each of the analyses. After studying
535	individual chains, the samples were pooled across chains and the mean of the pooled
536	distribution and its standard deviation were used as summary statistics. Janss et al. (1995)
537	suggested the use of the ratio of the density at $\sigma_m^2 = 0$ of the marginal posterior distribution
538	of $\sigma_m^2$ and the density at the global mode as a criterion to test the significance of the single
539	locus component. They inferred the presence of a single locus (0.05 significance level) if the
	<ul> <li>515</li> <li>516</li> <li>517</li> <li>518</li> <li>519</li> <li>520</li> <li>521</li> <li>522</li> <li>523</li> <li>524</li> <li>525</li> <li>526</li> <li>527</li> <li>528</li> <li>529</li> <li>530</li> <li>531</li> <li>532</li> <li>533</li> <li>534</li> <li>535</li> <li>536</li> <li>537</li> <li>538</li> </ul>

density at the global mode was 20 times larger than that at  $\sigma_m^2 = 0$ . We used the same criterion.

542	In order to ease computation, the segregation analyses were carried out using SaO
543	phenotypes adjusted for the fixed effects of hatch week (210 and 133 levels respectively for
544	data sets 1 and 2) and age of the dam at laying (10 and 9 levels respectively for data sets 1
545	and 2). Adjusted SaO phenotypes were obtained from trivariate analyses of SaO, Weight and
546	Flesh data, performed fitting an animal model within a Restricted Maximum Likelihood
547	(REML) framework using ASREML (Gilmour et al., 2000). These analyses assumed that all
548	three traits are under the genetic control of an infinite number of loci with small additive
549	effects. If a major locus was involved in the genetic control of a trait, its segregation variance
550	would contribute to the estimated $\sigma_{u}^{2}$ with the remainder included in the estimated $\sigma_{e}^{2}$ .
551	together with polygenic non-additive variance, since the infinitesimal model does not
552	accommodate non-additive genetic variation (although it can be extended to do so) or
553	changes in variance caused by changes in major locus allele frequency (Turelli and Barton,
554	1994). Only adjusted phenotypes from birds that originally had SaO records were used, but
555	the pedigree included contemporary unrecorded birds. This allowed us to obtain genotype
556	probabilities for all birds in the pedigree.
557	Analyses of Genotype Probabilities and Allele Frequencies. Some exploratory
558	analyses were carried out on genotype probabilities obtained from data set 2 analyses. From
559	each iteration of the Gibbs sampler, genotype configurations were obtained for all birds in
560	the pedigree. Averaging over all retained iterations, probabilities of each bird being BB, Bb
561	or bb could be obtained. For each bird, as many sets of genotype probabilities as chains were
562	produced and an overall estimate of each genotype probability was obtained by averaging the

results from each chain. Genotypic frequencies at a given moment in time could be obtained

by averaging the frequencies of birds in the chosen period and estimates of major allele

frequencies can be obtained as  $p_B = p_{BB} + 0.5 p_{Bb}$  and  $p_b = p_{bb} + 0.5 p_{Bb}$ . Since genotype

probability estimates are a function of the individual's phenotypic record and information

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567	from its relatives, we divided the population on the basis of the amount of information
568	available for each individual in birds with no record, selection candidates and sires. Most of
569	the results presented will be for the two last categories since accuracy of estimates should be
570	highest for sires but using estimates from selection candidates as well one can attain a
571	compromise between accuracy of estimates and sample size.
572	Estimation of the Putative Locus Effect on Weight and Fleshing Score. In order to
573	investigate the effect of the putative major locus on body weight and fleshing score
574	measured at five weeks of age, the phenotypic values for these traits were regressed on
575	functions of the genotype probabilities estimated from the segregation analysis of data set 2.
576	The model used was:
577	$\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{u} + \mathbf{S}\mathbf{c} + \mathbf{R}\mathbf{g} + \mathbf{e} $ [3]
578	with elements defined as in [1] and c, S, g and R are respectively the vector of
579	random maternal environmental effects for Weight and Flesh and the design matrix relating
580	maternal environmental effects to observations ( $\mathbf{c} \sim N(0, \mathbf{I}\sigma_{em}^{2})$ ) and the vector of random
581	maternal genetic effects for Weight and Flesh and the design matrix relating maternal
582	environmental effects to observations ( $\mathbf{g} \sim N(0, \mathbf{A}\sigma_{gm}^2)$ ). X now includes $c_a = (p_{BB} - p_{bb})$ and
583	$\underline{c_d} = \underline{p_{Bb}}$ , allowing one to estimate respectively the additive and the dominance effect of the
584	putative locus on the traits. A trivariate analysis was carried out within a REML framework,
585	fitting an animal model using ASREML (Gilmour et al., 2000).
586	RESULTS
587	Segregation Analyses
588	For all runs and parameters, chains seemed to have converged to their equilibrium
589	distributions after a 5000 iteration burn-in period and sample autocorrelation was generally
590	low (absolute values smaller than 0.1) for lags over 100 for all parameters (results not
591	shown). Marginal posterior distributions of all parameters were symmetric and approximated
592	normal distributions. Table A1 shows the marginal posterior means, posterior standard
593	deviations, Monte Carlo standard deviation of marginal posterior means and the effective
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		British Poultry Science Page 38
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2 3	594	number of samples per chain for all sampled parameters. The difference between marginal
4 5	595	posterior means from the six chains ran for data set 1 was not always strictly within the
6 7	596	Monte Carlo sampling error estimated as proposed by Geyer (1992). Nonetheless, all chains
8 9	597	seemed to have converged to the equilibrium distribution (using different starting values)
10 11	598	and marginal posterior means were very close. The effective number of samples was variable
12	599	within chains between parameters and within parameters between chains, with values
13 14	600	ranging from nine to more than 600 independent samples. Generally $\sigma_{\underline{u}}^2$ and $\sigma_{\underline{e}}^2$ showed
15 16	601	smaller effective numbers of samples, which reflects poorer mixing for these parameters.
17 18	602	The visual inspection of the six chains did not show convergence problems.
19 20	603	[TABLE A1]
21 22	604	Samples were pooled across chains and the means of the pooled distributions and spacing: single
23	605	their standard deviations were used as point estimates of the sampled parameters and their
24 25	606	standard errors. Since the total number of independent samples for any parameter was
26 27	607	greater than 100, the mean and the standard deviation of the pooled posterior distribution
28 29	608	were assumed to be good estimates of the parameter and its standard error. Table 4 shows
30 31	609	point estimates of the parameters sampled and those derived and the standard deviation of
32	610	their pooled posterior distributions. All distributions presented zero densities for parameter
33 34	611	values equal to zero. Following Janss et al. (1995) we inferred that a locus with large effect
35 36	612	on SaO was segregating in the population studied. Although the estimated d was slightly
37 38	613	larger than a, estimated major locus effects were similar in size (the dominance deviance was
39 40	614	estimated to be 1.12 (±0.06) and was indeed just different from one. We will assume in the
41 42	615	following that a and d can be considered equal,
43	616	Analyses were repeated for data set 2, using raw phenotypes (records not adjusted
44 45	617	for fixed effects) and sampling fixed effects (age of dam and hatch). These analyses yielded
46 47	618	estimates of the parameters presented in table 4 that were similar to the ones obtained from
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619	adjusted phenotypes (results not shown), showing that, in this case, preadjustement of
620	phenotypes did not have a significant effect on parameter estimates.
621	DISCUSSION
622	<u>On Skewness</u>
623	When a major locus is segregating, the population distribution of phenotypes can be
624	skewed. MacLean et al. (1975) showed that skewness of the phenotypic distributions, when
625	not caused by segregation of loci with large effect, could lead to detection of a spurious
626	major locus. MacLean et al. (1976) suggested applying a transformation to the phenotypic
627	data to remove skewness prior to analysis, but showed that this could considerably reduce
628	the power to detect major genes when present, as well as posing problems for the
629	interpretation of the results (Demenais et al., 1986). Using data set 2, we applied a
630	transformation to SaO data, in order to obtain a trait distribution closer to a Normal. The
631	transformation applied was Ln (100 - SaO), and the transformed trait distribution had a
632	skewness coefficient of -0.29 and a kurtosis coefficient of -0.17. The heritability of Ln (100
633	- SaO) was 0.14, which is almost identical to that obtained for untransformed data. The
634	outcome of the analysis of transformed data was that a dominant locus with large effect on
635	<u>Ln(100-SaO) (a = d = 0.58 <math>\sigma_{n}</math>) was segregating in this line, but neither the frequency nor the</u>
636	mode of action of this putative locus were in agreement with the results obtained from
637	untransformed data. Indeed, an allele that increases Ln(100-SaO) would decrease SaO, so the
638	estimated $p_{\rm B} = 0.69$ from this analysis needs to be compared to $(1 - 0.65) = 0.35$ . In the same
639	way, if the locus that increases Ln(100-SaO) were dominant, the proportion of birds showing
640	low SaO values would be around 81% compared with the predicted 12% from the
641	untransformed data analysis. Moreover, the correlation between the probability of a bird
642	being heterozygote estimated from transformed and untransformed data was $-0.17$ (P <
643	<u>0.001) for birds with SaO data and <math>-0.11</math> (P = 0.03) for sires with SaO data. The fact that the</u>
644	estimates of p <sub>Bb</sub> are not similar from transformed and untransformed data suggests that these
645	analyses are describing different phenomena. Selection experiments carried out in other
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broiler populations to study ascites susceptibility tend to suggest that this trait is influenced
by a single biallelic major locus that would act in a recessive fashion (see for example,
Druyan et al. (2001), Druyan et al. (2002), Wideman and French (1999) and Wideman and
French (2000)). This would support the mode of action suggested for SaO by the analysis of
untransformed data.

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#### **On Variance Components Estimates (Simulation)**

652 We observed that, for the analyses carried out, the total additive variance estimated 653 using a mixed inheritance model was greater than the additive variance estimated using a 654 polygenic model. In order to assess whether this would be expected in the presence of a 655 segregating major gene in a population under selection a simulation study was performed. 656 125 five-generation pedigrees (base population and four generations of random or 657 phenotypic selection) were simulated with a structure chosen to resemble the (real) pedigree 658 analyzed. In each generation, 40 males were mated to eight (different) females that produced 659 three male and three female offspring each (i.e., population size was maintained constant). In 660 the case of phenotypic selection, the 40 males and 320 females with highest phenotypes were 661 selected to produce the next generation. The simulated pedigrees consisted in 9600 662 individuals. Phenotypes were assumed to be under the control of a gene with large effect and 663 a large number of polygenes with small additive effect, as well as partially determined by the 664 environment. The parameters used for the simulation were the ones presented in Table 4 for 665 data set 2. Data from all animals or from males alone (to mimic our data structure) were 666 analyzed assuming an infinitesimal model, within a REML framework, using ASREML 667 (Gilmour et al., 2000). In a second stage, the pedigrees were analyzed assuming a mixed 668 inheritance model (as described in the materials and methods section) and only data from 669 males were used. Table A2 shows the means and standard deviations of the parameters 670 estimated. In brief, the simulation study showed that, in a population in which both a major 671 gene and polygenic variation are actually present and which is under phenotypic selection, 672 the estimate of the total additive variance is severely biased downward if a purely polygenic 40

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model is assumed. Estimates from REML of additive variances obtained by simulation are in close agreement with results obtained when analyzing real data. Assuming a change in major allele frequencies like the one shown in Figure 4 for selection candidates, we estimated that total additive variance would be underestimated by around 22% when assuming a purely polygenic model. Results from simulation show that this underestimation is around 31%. This, together with the fact that total additive variance seems to be well estimated (only <text> slightly overestimated) under random selection, both assuming purely polygenic or mixed inheritance, would support the hypothesis that changes in allele frequencies caused by selection are the source of the observed discrepancies. [TABLE A2]

	ances. A me	an ENS is	also show				$(\sigma_{\underline{u}}^{2})$
Parameter	<u>Chain</u>	<u>a</u>	d	<u>p</u> <sub>B</sub>	Mean	<u><math>\sigma_e^2</math></u>	<u>σ</u> ι
MPM		<u>7.236</u>	<u>=</u> 8.089	0.528	-5.642	<u>35.679</u>	<u>5.9</u>
	$\frac{1}{2}$	7.201	8.049	0.524	-5.585	35.320	6.1
	<u>3</u>	7.241	8.034	0.524	-5.587	<u>35.584</u>	6.2
	<u>4</u>	7.158	<u>8.113</u>	0.526	<u>-5.594</u>	<u>35.553</u>	<u>6.0</u>
	5	7.265	8.011	0.527	-5.597	<u>35.817</u>	<u>5.7</u>
	<u>6</u>	<u>7.214</u>	<u>8.025</u>	<u>0.525</u>	<u>-5.597</u>	<u>35.550</u>	<u>6.0</u>
<u>PSD</u>	<u>1</u>	<u>0.205</u>	<u>0.321</u>	<u>0.026</u>	<u>0.339</u>	<u>1.213</u>	<u>1.0</u>
	<u>2</u>	0.192	<u>0.315</u>	0.026	<u>0.338</u>	1.029	<u>0.9</u>
	<u>3</u>	<u>0.201</u>	<u>0.318</u>	0.026	<u>0.345</u>	<u>1.181</u>	0.9
	<u>4</u>	0.187	<u>0.323</u>	0.026	0.322	1.080	<u>0.9</u>
	<u>5</u>	<u>0.203</u>	<u>0.313</u>	<u>0.026</u>	<u>0.331</u>	<u>1.139</u>	<u>0.9</u>
	<u>6</u>	<u>0.194</u>	0.321	<u>0.026</u>	0.327	<u>1.142</u>	1.0
MCSD	<u>1</u>	<u>0.053</u>	<u>0.032</u>	<u>0.002</u>	<u>0.045</u>	<u>0.409</u>	0.2
	<u>2</u>	<u>0.011</u>	<u>0.037</u>	<u>0.001</u>	<u>0.038</u>	<u>0.110</u>	<u>0.1</u>
	<u>3</u>	0.042	0.027	<u>0.001</u>	<u>0.033</u>	<u>0.241</u>	0.2
	<u>4</u>	<u>0.013</u>	0.046	<u>0.001</u>	<u>0.035</u>	<u>0.162</u>	0.2
	<u>5</u>	0.040	0.024	<u>0.001</u>	<u>0.028</u>	0.321	0.1
	<u>6</u>	<u>0.016</u>	<u>0.023</u>	<u>0.001</u>	<u>0.026</u>	<u>0.213</u>	<u>0.1</u>
<u>ENS</u>	<u>1</u>	<u>15</u>	<u>102</u>	<u>138</u>	<u>56</u>	<u>9</u>	<u>2</u> ′
	<u>2</u>	<u>310</u>	<u>72</u>	<u>421</u>	<u>81</u>	<u>87</u>	4
	<u>3</u>	<u>23</u>	<u>143</u>	<u>410</u>	<u>109</u>	<u>24</u>	2
	<u>4</u>	<u>205</u>	<u>49</u>	<u>607</u>	<u>83</u>	<u>45</u>	1
	<u>5</u>	<u>25</u>	<u>174</u>	<u>516</u>	<u>137</u>	<u>13</u>	<u>29</u>
	<u>6</u>	<u>143</u>	<u>194</u>	<u>583</u>	<u>163</u>	<u>29</u>	<u>3</u>
Mean ENS	_	<u>120</u>	<u>122</u>	<u>446</u>	<u>105</u>	<u>34</u>	2

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The mixed model equation that describes	the model fitted to the data is:	
y = Xb + Zu + ZWm + e	[1]	
where $\mathbf{y}$ is the vector of phenotypic obser	rvations, $\mathbf{b}$ is the vector of fixed non-genetic effects and $\mathbf{X}$ is the de	esign matrix relating fixed non-genetic effects t
bservations. $\mathbf{Z}$ is the incidence matrix for rand	dom polygenic effects ( $\mathbf{u} \sim N(0, \mathbf{A}\sigma_u^2)$ -where $\mathbf{A}$ is the numerate	or relationship matrix and $\sigma_u^2$ is the polygeni
ariance)- and single locus effects. W is a three c	column matrix that contains information on the genotype of each in	ndividual and $\mathbf{m}$ is the vector of major-genotyp
heans ( $\mathbf{m}' = [-a, d, a]$ ), hence $\mathbf{W}\mathbf{m}$ is the vector	of random effects at the single locus. <b>e</b> (~ N(0, $I\sigma_e^2$ )) is a vector of n	andom errors.
Janss et al. (1995) proposed an efficient s	scheme using the Gibbs sampler for the study of mixed inheritance	e models in animal populations. In our analyses
arried out with software developed at Roslin Ins	stitute by Ricardo Pong-Wong (Walling et al., 2002), we used the s	ampling scheme they described (see Janss et a
1995) and Janss et al. (1997) for details) to obta	ain marginal posterior distributions for the major locus parameters	(frequency and additive and dominance effect
opulation mean and polygenic and residual vari	iances. For each iteration of the Gibbs sampler, every bird was as	ssigned a genotype. Averaging over all retaine
erations provides major locus genotype probabili	ities $(p_{BB}, p_{Bb} \text{ and } p_{bb})$ for each bird in the pedigree.	
The variance explained by the major locu	s $(\sigma_m^2)$ is defined as:	
$\sigma_{\rm m}^{2} = 2 p_{\rm B} (1 - p_{\rm B}) [a + d ((1 - p_{\rm B}) - p_{\rm B})]^{2} +$	$(2 p_{\rm B} (1 - p_{\rm B}) d)^2$ [2]	
(Falconer and Mackay, 1996) and was	computed from the major locus genotypic effects and allele freq	uency sampled at each iteration. Likewise, w
alculated the degree of dominance as d/a.		

We used non-informative prior distributions, uniform on  $(-\infty; +\infty)$  for fixed non-genetic effects and d, on  $[0; +\infty)$  for a and on [0; 1] for major allele B frequency. We used an inverse-gamma prior distribution on  $(0; +\infty)$  for variances with a flat prior for log(variance). This type of prior distribution for variances should cause the mean of the marginal posterior distributions to tend towards zero if the data available do not support variation of the random effects. All genotypes were initialized as Bb.

Six runs of the Gibbs sampler were carried out for the analysis of each data set, with different starting values. Differences in parameter estimates obtained from different chains may reflect problems of mixing. Individual chains were composed by 255000 iterations that were collected after allowing for a burn-in period of 5000 iterations, keeping each 100<sup>th</sup> iteration from this point onwards. In order to assess if the burn-in period and thinning parameter we used were adequate, we studied the marginal posterior distributions of the sampled parameters obtained from each run of the Gibbs sampler. For data set 1 analyses, the marginal posterior means, that is the parameter's a-posteriori expectation, the posterior standard deviations and the Monte Carlo standard deviations are reported. The Monte Carlo standard deviation of the marginal posterior mean was computed following Geyer (1992) as suggested by Sorensen et al. (1995) and the effective number of samples per chain, i.e. the number of independent samples per chain for each parameter, was estimated. Following the results obtained when studying the behaviour of the individual chains for data set 1, no formal assessment of convergence was carried out for data set 2 analyses, but a visual inspection of individual chains was carried out for each of the analyses. After studying individual chains, the samples were pooled across chains and the mean of the pooled distribution and its standard deviation were used as summary statistics. Janss et al. (1995) suggested the use of the ratio of the density at  $\sigma_m^2 = 0$  of the marginal posterior distribution of  $\sigma_m^2$  and the density at the global mode as a criterion to test the significance of the single locus component. They inferred the presence of a single locus (0.05 significance level) if the density at the global mode was 20 times larger than that at  $\sigma_m^2 = 0$ . We used the same criterion. 

In order to ease computation, the segregation analyses were carried out using SaO phenotypes adjusted for the fixed effects of hatch week (210 and 133 levels respectively for data sets 1 and 2) and age of the dam at laying (10 and 9 levels respectively for data sets 1 and 2). Adjusted SaO phenotypes were obtained from trivariate analyses of SaO, Weight and Flesh data, performed fitting an animal model within a Restricted Maximum Likelihood (REML) framework using ASREML (Gilmour et al., 2000). These analyses assumed that all three traits are under the genetic control of an infinite number of loci with small additive effects. If a major locus was involved in the genetic control of a trait, its segregation variance would contribute to the estimated  $\sigma_{\mu}^{2}$  with the remainder included in the estimated  $\sigma_{e}^{2}$ , together with polygenic non-additive variance, since the infinitesimal model does not accommodate non-additive genetic variation (although it can be extended to do so) or changes in variance caused by changes in major locus allele frequency (Turelli and Barton, 1994). Only adjusted phenotypes from birds that originally had SaO records were used, but the pedigree included contemporary unrecorded birds. This allowed us to obtain genotype probabilities for all birds in the pedigree. Analyses of Genotype Probabilities and Allele Frequencies. Some exploratory analyses were carried out on genotype probabilities obtained from data set 2 analyses. From each iteration of the Gibbs sampler, genotype configurations were obtained for all birds in the pedigree. Averaging over all retained iterations, probabilities of each bird being BB, Bb or bb could be obtained. For each bird, as many sets of genotype probabilities as chains were produced and an overall estimate of each genotype probability was obtained by averaging the results from each chain. Genotypic frequencies at a given moment in time could be obtained by averaging the frequencies of birds in the chosen period and estimates of major allele frequencies can be obtained as  $p_B = p_{BB} + 0.5 p_{Bb}$  and  $p_b = p_{bb} + 0.5 p_{Bb}$ . Since genotype probability estimates are a function of the individual's phenotypic record and information from its relatives, we divided the population on the basis of the amount of information available for each individual in birds with no record, selection candidates and sires. Most of the results presented will be for the two last

categories since accuracy of estimates should be highest for sires but using estimates from selection candidates as well one can attain a compromise between
 accuracy of estimates and sample size.

*Estimation of the Putative Locus Effect on Weight and Fleshing Score.* In order to investigate the effect of the putative major locus on body weight and fleshing score measured at five weeks of age, the phenotypic values for these traits were regressed on functions of the genotype probabilities estimated from the segregation analysis of data set 2. The model used was:

[3]

 $\mathbf{y} = \mathbf{X}\mathbf{b} + \mathbf{Z}\mathbf{u} + \mathbf{S}\mathbf{c} + \mathbf{R}\mathbf{g} + \mathbf{e}$ 

with elements defined as in [1] and **c**, **S**, **g** and **R** are respectively the vector of random maternal environmental effects for Weight and Flesh and the design matrix relating maternal environmental effects to observations ( $\mathbf{c} \sim N(0, \mathbf{I}\sigma_{em}^2)$ ) and the vector of random maternal genetic effects for Weight and Flesh and the design matrix relating maternal environmental effects to observations ( $\mathbf{g} \sim N(0, \mathbf{A}\sigma_{gm}^2)$ ). **X** now includes  $c_a = (p_{BB} - p_{bb})$  and  $c_d = p_{Bb}$ , allowing one to estimate respectively the additive and the dominance effect of the putative locus on the traits. A trivariate analysis was carried out within a REML framework, fitting an animal model using ASREML (Gilmour et al., 2000).

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shows point estimates of the parameters sampled and those derived and the standard deviation of their pooled posterior distributions. All distributions presented zero densities for parameter values equal to zero. Following Janss et al. (1995) we inferred that a locus with large effect on SaO was segregating in the population studied.

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MacLean et al. (1976) suggested applying a transformation to the phenotypic data to remove skewness prior to analysis, but showed that this could considerably reduce the power to detect major genes when present, as well as posing problems for the interpretation of the results (Demenais et al., 1986). Using data set 2, we applied a transformation to SaO data, in order to obtain a trait distribution closer to a Normal. The transformation applied was Ln (100 – SaO), and the transformed trait distribution had a skewness coefficient of -0.29 and a kurtosis coefficient of -0.17. The heritability of Ln (100 – SaO) was 0.14, which is almost identical to that obtained for untransformed data. The outcome of the analysis of transformed data was that a dominant locus with large effect on Ln(100-SaO) (a = d = 0.58  $\sigma_{\rm p}$ ) was segregating in this line, but neither the frequency nor the mode of action of this putative locus were in agreement with the results obtained from untransformed data. Indeed, an allele that increases Ln(100-SaO) would decrease SaO, so the estimated  $p_B = 0.69$  from this analysis needs to be compared to  $(1 - 1)^{-1}$ 0.65) = 0.35. In the same way, if the locus that increases Ln(100-SaO) were dominant, the proportion of birds showing low SaO values would be around 81% compared with the predicted 12% from the untransformed data analysis. Moreover, the correlation between the probability of a bird being heterozygote estimated from transformed and untransformed data was -0.17 (P < 0.001) for birds with SaO data and -0.11 (P = 0.03) for sires with SaO data. The fact that the estimates of p<sub>Bb</sub> are not similar from transformed and untransformed data suggests that these analyses are describing different phenomena. Selection experiments carried out in other broiler populations to study ascites susceptibility tend to suggest that this trait is influenced by a single biallelic major locus that would act in a recessive fashion (see for example, Druyan et al. (2001), Druyan et al. (2002), Wideman and French (1999) and Wideman and French (2000)). This would support the mode of action suggested for SaO by the analysis of untransformed data. We observed that, for the analyses carried out, the total additive variance estimated using a mixed inheritance model was greater than the additive variance estimated using a polygenic model. In order to assess whether this would be expected in the presence of a segregating major gene in a population under selection a simulation study was performed. 125 five-generation pedigrees (base population and four generations of random or phenotypic selection) were simulated with a

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structure chosen to resemble the (real) pedigree analyzed. In each generation, 40 males were mated to eight (different) females that produced three male and three female offspring each (i.e., population size was maintained constant). In the case of phenotypic selection, the 40 males and 320 females with highest phenotypes were selected to produce the next generation. The simulated pedigrees consisted in 9600 individuals. Phenotypes were assumed to be under the control of a gene with large effect and a large number of polygenes with small additive effect, as well as partially determined by the environment. The parameters used for the simulation were the ones presented in Table 6 for data set 2. Data from all animals or from males alone (to mimic our data structure) were analyzed assuming an infinitesimal model, within a REML framework, using ASREML (Gilmour et al., 2000). In a second stage, the pedigrees were analyzed assuming a mixed inheritance model (as described in the materials and methods section) and only data from males were used. Table 8 shows the means and standard deviations of the parameters estimated. In brief, the simulation study showed that, in a population in which both a major gene and polygenic variation are actually present and which is under phenotypic selection, the estimate of the total additive variance is severely biased downward if a purely polygenic model is assumed. Estimates from REML of additive variances obtained by simulation are in close agreement with results obtained when analyzing real data. Assuming a change in major allele frequencies like the one shown in Figure 4 for selection candidates, we estimated that total additive variance would be underestimated by around 22% when assuming a purely polygenic model. Results from simulation show that this underestimation is around 31%. This, together with the fact that total additive variance seems to be well estimated (only slightly overestimated) under random selection, both assuming purely polygenic or mixed inheritance, would support the hypothesis that changes in allele frequencies caused by selection are the source of the observed discrepancies. [TABLE 8]

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	var iv stanua		ons (MCS	D) of MPA	As and offer	ctive numbe	r of indepen	lent samples (ENS) per chain for the major locus
and dominand							_	
	ce (d) effect, l	3 allele fre	quency (p	B), populat	tion mean (	Mean) and	esidual ( $\sigma_e^2$ )	and polygenic $(\sigma_u^2)$ variances. A mean ENS is als
					eacl	h sampled p	arameter	
Parameter	Chain	а	d	р <sub>в</sub>	Mean	$\sigma_e^2$	$\sigma_u^{\ 2}$	
ИРМ	1	7.236	8.089	0.528	-5.642	35.679	5.990	
	2	7.201	8.049	0.524	-5.585	35.320	6.185	
	3	7.241	8.034	0.524	-5.587	35.584	6.232	
	4	7.158	8.113	0.526	-5.594	35.553	6.092	
	5	7.265	8.011	0.527	-5.597	35.817	5.775	
	6	7.214	8.025	0.525	-5.597	35.550	6.062	
PSD	1	0.205	0.321	0.026	0.339	1.213	1.037	
	2	0.192	0.315	0.026	0.338	1.029	0.939	
	3	0.201	0.318	0.026	0.345	1.181	0.988	
	4	0.187	0.323	0.026	0.322	1.080	0.961	
	5	0.203	0.313	0.026	0.331	1.139	0.926	
	6	0.194	0.321	0.026	0.327	1.142	1.040	
ACSD	1	0.053	0.032	0.002	0.045	0.409	0.200	
	2	0.011	0.037	0.001	0.038	0.110	0.141	
	3	0.042	0.027	0.001	0.033	0.241	0.216	
	4	0.013	0.046	0.001	0.035	0.162	0.259	
	5	0.040	0.024	0.001	0.028	0.321	0.172	

	6	0.016	0.023	0.001	0.026	0.213	0.172					
ENS	1	15	102	138	56	9	27					
	2	310	72	421	81	87	44					
	3	23	143	410	109	24	21					
	4	205	49	607	83	45	14					
	5	25	174	516	137	13	29					
	6	143	194	583	163	29	37					
Mean ENS	-	120	122	446	105	34	29					
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Table 4	4. REML	estimates of	f genetic (	$(\sigma_n^2)$ , resid	ual $(\sigma_{0}^{2})$ and	l phenotyp	$(\sigma_n^2)$ varia	nces obtained	for blood oxy	gen saturati	on for both data	a sets
			8	( u //			× P /		J.	8		
						studie	d					
Data set			σ	2	$\sigma_e^2$		$\frac{d}{\sigma_p^2}$					
Data set			σ <sub>u</sub> 14.3		σ <sub>e</sub> <sup>2</sup> 54.06							
Data set 1 2				37		(	$\sigma_p^2$					
Data set 1 2			14.3	37	54.06	(	$\sigma_{\rm p}^2$ 58.43 53.36	h C				
Data set 1 2			14.3	37	54.06	(	$\sigma_{\rm p}^2$ 58.43 53.36	h c				
Data set 1 2			14.3	37	54.06	(	$\sigma_{\rm p}^2$ 58.43 53.36	h C				
Data set 1 2 Page 24: [6] Delete	ed		14.3	37	54.06	(	$\sigma_{\rm p}^2$ 58.43 53.36	h C			3/1/2006 3:56	5:00 Pl
1 2 Page 24: [6] Delete		parameter	14.3 8.1	37 8	54.06 45.18	( Page Bre	σ <sub>p</sub> <sup>2</sup> 58.43 53.36 ak	ndard deviati	ons) obtained	assuming ei		
1 2 Page 24: [6] Deleto Table 8. S	Simulated	-	14.3 8.1	37 8 kets at tab	54.06 45.18	end estima	$\frac{\sigma_{p}^{2}}{58.43}$ $\frac{53.36}{ak}$ tes (with star			U	ther a purely po	olygen
1 2 Page 24: [6] Delete	Simulated	-	14.3 8.1	37 8 kets at tab	54.06 45.18	end estima	$\frac{\sigma_{p}^{2}}{58.43}$ $\frac{53.36}{ak}$ tes (with star			U	ther a purely po	olygen
1 2 Page 24: [6] Deleto Table 8. S	Simulated POLF) or	a mixed in	14.3 8.1 s (in brack heritance	37 8 kets at tab model (M	54.06 45.18 le heading) IX). Estima	pau and estima	$\frac{\sigma_p^2}{58.43}$	eraging estim	nates from 125	replicated p	ther a purely po populations. a an	olygei nd d a
1 2 Page 24: [6] Delete Table 8. S model (POL and 1	Simulated POLF) or	a mixed in	14.3 8.1 s (in brac heritance nce effect	37 8 kets at tab model (M and p <sub>B</sub> is	54.06 45.18 le heading) IX). Estima the B allele	pau and estima ites were ok frequency.	$\frac{\sigma_{p}^{2}}{58.43}$ $\frac{53.36}{ak}$ $\frac{1}{ak}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$	eraging estim <sup>2</sup> ) and polyger	nates from 125 nic (σ <sub>u</sub> ²) variar	replicated p	ther a purely po populations. a an	olyger nd d a
1 2 Page 24: [6] Delete Table 8. S model (POL and 1	Simulated POLF) or	a mixed in	14.3 8.1 s (in brac heritance nce effect	37 8 kets at tab model (M and p <sub>B</sub> is	54.06 45.18 le heading) IX). Estima the B allele	pau and estima ites were ok frequency.	$\frac{\sigma_{p}^{2}}{58.43}$ $\frac{53.36}{ak}$ $\frac{1}{ak}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$ $\frac{1}{bk}$	eraging estim	nates from 125 nic (σ <sub>u</sub> ²) variar	replicated p	ther a purely po populations. a an	olyger nd d a

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-										$\sigma_{\rm p}^{2}$ , h =				
				poj	pulations u	nder phe	notypic (	PHE) or 1	random (R	AN) select	ion			
Selection	Model	a <sup>1</sup> (6.46)	d (6.60)	р <sub>в</sub> (0.65)	σ <sub>e</sub> <sup>2</sup> (32.67)	σ <sup>2</sup> (3.93)	$\sigma_{am}^{2}$ (9.13)	$\sigma_{dm}^{2}$ (9.02)	σ <sub>m</sub> <sup>2</sup> (18.15)	$\sigma_p^2$ (54.75)	$\sigma_a^2$ (13.06)	h <sub>T</sub> (0.40)	h (0.11)	h <sub>a</sub> (0.24)
PHE	POLF	NA	NA	NA	39.31 (1.18)	6.68 (0.48)	NA	NA	NA	45.99 (1.18)	6.68 (0.48)	NA	0.17 (0.01)	NA
	POL	NA	NA	NA	37.38 (1.42)	8.94 (0.79)	NA	NA	NA	46.32 (1.36)	8.94 (0.79)	NA	0.24 (0.03)	NA
	MIX	6.77 (0.49)	5.99 (0.58)	0.66 (0.03)	32.02 (1.14)	5.01 (0.68)	10.32 (2.24)	7.11 (1.20)	17.43 (2.20)	54.46 (2.16)	15.33 (1.97)	0.41 (0.03)	0.14 (0.02)	0.28 (0.03
RAN	POLF	NA	NA	NA	39.78 (1.41)	15.17 (2.25)	NA	NA	NA	54.95 (2.79)	15.17 (2.25)	NA	0.38 (0.06)	NA
	POL	NA	NA	NA	39.63 (2.02)	15.24 (3.04)	NA	NA	NA	54.87 (3.01)	15.24 (3.04)	NA	0.39 (0.09)	NA
	MIX	6.49 (0.35)	6.42 (1.27)	0.65 (0.03)	32.73 (1.48)	3.76 (1.40)	9.53 (3.35)	8.77 (1.67)	18.30 (2.82)	54.79 (3.08)	13.29 (3.45)	0.40 (0.04)	0.10 (0.04)	0.24 (0.04)

-----Section Break (Next Page)------

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POL	NA	NA	NA	37.38 (1.42)	8.94 (0.79)	NA	NA	NA	46.32 (1.36)	8.94 (0.79)	
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POL	NA	NA	NA	39.63 (2.02)	15.24 (3.04)	NA	NA	NA	54.87 (3.01)	15.24 (3.04)	