1 **Appendix**

²**Genetic architecture of human thinness compared to**

³**severe obesity**

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19 **Abstract**

20 The variation in weight within a shared environment is largely attributable to genetic factors. Whilst 21 many genes/loci confer susceptibility to obesity, little is known about the genetic architecture of 22 healthy thinness. Here, we characterise the heritability of thinness which we found was comparable 23 to that of severe obesity (h^2 =28.07 vs 32.33% respectively), although with incomplete genetic 24 overlap (r=-0.49, 95% CI [-0.17, -0.82], *p*=0.003). In a genome-wide association analysis of thinness 25 (n=1,471) vs severe obesity (n=1,456), we identified 10 loci previously associated with obesity, and 26 demonstrate enrichment for established BMI-associated loci $(p_{\text{binomial}}=3.05\times10^{-5})$. Simulation 27 analyses showed that different association results between the extremes were likely in agreement 28 with additive effects across the BMI distribution, suggesting different effects on thinness and 29 obesity could be due to their different degrees of extremeness. In further analyses, we detected a and the ovel obesity and BMI-associated locus at *PKHD1* (rs2784243, obese vs. thin $p=5.99x10^{-6}$, obese vs. 31 controls $p=2.13x10^{-6}$ $p_{BM}=2.3x10^{-13}$), associations at loci recently discovered with much larger 32 sample sizes (e.g. *FAM150B* and *PRDM6-CEP120*), and novel variants driving associations at 33 previously established signals (e.g. rs205262 at the *SNRPC*/*C6orf106* locus and rs112446794 at the 34 *PRDM6-CEP120* locus). Our ability to replicate loci found with much larger sample sizes 35 demonstrates the value of clinical extremes and suggest that characterisation of the genetics of 36 thinness may provide a more nuanced understanding of the genetic architecture of body weight 37 regulation and may inform the identification of potential anti-obesity targets.

38 **Author Summary**

39 Obesity-associated disorders are amongst the leading causes of morbidity and mortality 40 worldwide. Most genome-wide association studies (GWAS) have focused on body mass index (BMI= 41 weight in Kg divided by height squared $(m²)$) and obesity, but to date no genetic association study 42 testing thin and healthy individuals has been performed. In this study, we recruited a first of its kind 43 cohort of 1,471 clinically ascertained thin and healthy individuals and contrasted the genetic 44 architecture of the trait with that of severe early onset obesity. We show that thinness, like obesity, 45 is a heritable trait with a polygenic component. In a GWAS of persistent healthy thinness vs. severe 46 obesity with a total sample size of 2,927, we are able to find evidence of association in loci that 47 have only been recently discovered using large cohorts with >40,000 individuals. We also find a 48 novel BMI-associated locus at *PKHD1* in UK Biobank highlighted by our association study. This work 49 illustrates the value and increased power brought upon by using clinically ascertained extremes to 50 study complex traits and provides a valuable resource on which to study resistance to obesity in an 51 increasingly obesogenic environment.

52 **Introduction**

53 The rising prevalence of obesity is driven by changes in the environment including the consumption 54 of high calorie foods and reduced levels of physical activity [1]. However, within a given 55 environment, there is considerable variation in body weight; some people are particularly 56 susceptible to severe obesity, whilst others remain thin [2,3]. Family, twin and adoption studies 57 have consistently demonstrated that 40-70% of the variation in body weight can be attributed to 58 heritable factors [4]. As a result, many studies have focused on the genetic basis of body mass index 59 (BMI) and/or obesity. To date >250 common and low-frequency obesity-susceptibility loci have 60 been identified [5-10]. Additionally, studies of people at one extreme of the distribution (severe 61 obesity) have led to the identification of rare, penetrant genetic variants that affect key molecular 62 and neural pathways involved in human energy homeostasis [11-14]. These findings have provided 63 a rationale for targeting these pathways for therapeutic benefit. In contrast, little is known about 64 the specific genetic characteristics of persistently thin individuals (thinness defined using WHO 65 criteria BMI<18kg/m²). Understanding the mechanisms underlying thinness/resistance to obesity 66 may highlight novel anti-obesity targets for future drug development.

67 A small number of previous studies have found that thinness appears to be a trait that is at least as 68 stable and heritable as obesity [15-18]. A large study of 7,078 UK children and adolescents, found 69 that the strongest predictor of child/adolescent thinness was parental weight status. The 70 prevalence of thinness was highest (16.2%) when both parents were thin and progressively lower 71 when both parents were normal weight, overweight or obese [19].

72 One approach to studying thinness is to study individuals from a population-based cohort for a 73 quantitative or continuous trait. For example, it is possible to generate a "case-control" study by 74 taking the extremes of the population distribution for a continuous trait such as BMI, an approach 75 used effectively by Berndt *et al.* 2013 [20] who analysed the top and bottom 5% in cohorts 76 participating in the GIANT Consortium. However, by their very definition, such population-based 77 cohorts often contain a limited number of people at the "extremes" (i.e. severe obesity and 78 thinness) [20]. To date, other GWAS approaches that included thin individuals have either used 79 them exclusively as controls to contrast with extreme obesity [21], or have not ascertained for 80 healthy thinness [22]. Here, we use a different study design, and one that has been used to 81 increase power to detect genetic association, in particular for disorders where there is a large 82 environmental component (e.g. asthma, type 2 diabetes and obesity), enriching our case series with 83 affected individuals that may be more genetically loaded. This selection is usually done by selecting 84 individuals who may have a more extreme form of disease, are younger (less time for environment 85 to impact their disease) and perhaps have family members also affected with the same condition. 86 To complement this approach to the selection of cases, controls are also selected to increase the 87 chances that they do not have the disease or are unlikely to develop the disease later in life [21]. 88 This is normally done by selecting contrasting controls, or "super-controls". However, the low 89 prevalence of thinness in countries such as the UK and the fact that people who are well but 90 constitutionally thin do not routinely come to medical attention, poses challenges to recruitment of 91 a cohort of healthy thin individuals. We were able to take advantage of the UK National Health 92 Service (NHS) research infrastructure to recruit from primary care (**Methods**) using body mass index

93 (BMI: weight in kg/height in metres²) criteria and personal review of individual case files to identify 94 a cohort of approximately 2000 UK European descent thin adults (STudy Into Lean and Thin 95 Subjects, STILTS cohort; mean BMI = 17.6 kg/m²) who are well, without medical conditions or eating 96 disorders (**Methods**). 74% of the STILTS cohort have a family history of persistent thinness 97 throughout life, suggesting we have enriched for genetically driven thinness.

98 Here, we present a new, and the largest-to-date, GWAS focused on persistent healthy thinness and 99 contrast the genetic architecture of this trait with that of severe early onset obesity ascertained in 100 the clinic. We explored whether the genetic loci influencing thinness are the same as those 101 influencing obesity, i.e., are these two clinically ascertained traits reverse sides of the same "coin", 102 or whether there are important genetic differences between them. We show that persistent 103 thinness and severe early onset obesity are both heritable traits (h^2 =28.07% and h^2 =32.33%, 104 respectively) that share a number of associated loci, and both are enriched for established BMI 105 associated loci (binomial $p=3.05x10^{-5}$ and $9.09x10^{-13}$, respectively). Nonetheless, we also detected 106 important differences, with some loci more strongly associated at the upper clinical end of the BMI 107 distribution (e.g. *FTO*), some at the lower end (e.g. *CADM2*), whilst other loci are equivalently 108 associated with both clinical ends of the BMI spectrum (e.g. *MC4R*). Simulation tests showed that 109 these results did not significantly deviate from additive effects and most likely reflect the different 110 degrees of extremeness present in our clinically ascertained cohorts, where severely obese 111 individuals represent a more significant deviation from the mean than healthy thin individuals do 112 (the same degree of thinness may not be compatible with healthy human life)*.* These data support 113 expansion of genetic studies of persistent thinness as an approach to gain further insights into the

114 biology underlying human energy homeostasis, and as an alternative approach to uncovering 115 potential anti-obesity targets for drug development.

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117 **Results**

118 **Heritability of persistent thinness and severe early onset obesity**

119 To investigate the heritability of healthy thinness and contrast it with that of severe early onset 120 childhood obesity we obtained genotype data for 1,622 persistently thin healthy individuals 121 (STILTS), 1,985 severe childhood onset obesity cases (SCOOP; European ancestry individuals from 122 the GOOS cohort) and 10,433 population-based individuals (UKHLS) used as a common set of 123 controls (**Methods, S1 Table**). All participants were genotyped on the Illumina Core Exome array, 124 including 551,839 markers. After sample and variant quality control, we retained 1,471 thin 125 individuals, 1,456 obese individuals, 6,460 control individuals in the BMI range 19-30 kg/m² (non-126 extremes). 477,288 directly genotyped variants were included in the analysis (**Methods**); 54% 127 common variants (minor allele frequency (MAF) ≥1% amongst controls) and 46% rare variants 128 (MAF<1% amongst controls), of which most were protein-coding (96.8%). We then imputed 129 genotypes to a combined UK10K+1000G reference panel and, using LD score regression, we 130 estimated that a subset of 1,197,969 HapMap3 markers accounted for 32.33% (95% CI 23.75%- 131 40.91%) of the phenotypic variance on the liability scale in severe early onset obesity, and 28.07% 132 (95% CI 13.80%-42.34%) in persistent thinness, suggesting both traits are similarly heritable 133 (**Methods**). The heritability estimates reported here were used mainly to establish the fact that

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138 **Contribution of known BMI associated loci to thinness and severe early onset obesity**

139 To investigate the role of established common variant European BMI associated loci, we studied the 140 97 loci from GIANT [24] in persistent thinness vs severe early onset obesity and performed three-141 way association analyses: obese vs. thin, obese vs controls, controls vs. thin (**Methods, S1 Table**). 142 After quality control, 41,266,535 variants remained for association analyses in the three cohorts: 143 SCOOP vs STILTS, SCOOP vs UKHLS and UKHLS vs STILTS. Of the 97 established BMI associated loci 144 from GIANT [24], we found that 40 were nominally significant (*p*<0.05) in SCOOP vs UKHLS and 15 in 145 UKHLS vs STILTS (**S2 Table**). Direction of effect was consistent for all of these loci, which was more 146 than expected by chance (binomial $p=9.09\times10^{-13}$ and binomial $p=3.05\times10^{-5}$, respectively). Overall, 147 the proportion of phenotypic variance explained by the 97 established BMI associated loci was 148 10.67% in SCOOP vs UKHLS, and 4.33% in STILTS vs UKHLS (**Methods**). Evaluation of association 149 results in thin (STILTS) and obese (SCOOP) individuals, compared to the same controls (UKHLS), 150 suggested that the results are not a mirror image of each other (**Figs 1-2**), **however we found little** 151 **evidence of non-additive effects at the loci explaining this discrepancy (see below).** We observed 152 a striking difference in association results in the *FTO* locus where the lead intronic obesity risk 153 variant, rs1558902, showed a moderate effect size and modest evidence of association in controls

175 **an important role in systemic energy homeostasis [25] and variants near the gene have also been** 176 **recently linked to habitual physical activity in humans [26].** Since SCOOP participants are 177 significantly younger than UKHLS, we used summary statistics from a subset of the ALSPAC cohort 178 [27] which consists of 4,964 children aged 13-16 to test if the observed OR differences in SCOOP vs 179 UKHLS, compared to STILTS vs UKHLS, were due to age effects in SCOOP (**Methods**). For the 97 180 GIANT loci overall there were no significant differences in the ORs when comparing SCOOP to 181 UKHLS or SCOOP to ALSPAC (z-test, p>0.05) except for rs2245368 (*PMS2L11* locus, z-test 182 $p=3.81x10^5$, **S4 Table**). In combination, these results suggest that the observed differences in ORs 183 and p-values could have arisen because our severe obese cases are much more extreme (i.e. 184 deviate more from the mean) than the healthy thin individuals, and that our obese and thin sample 185 sizes gave us limited power to detect significant differences compared to the additive model.

186 **Fig 1. Odds ratio comparison for established BMI associated loci.** Odds ratios for SCOOP vs UKHLS 187 (x-axis) and UKHLS vs STILTS (y-axis) comparisons are shown for the 97 known BMI loci from GIANT 188 [24]. Colours of data points represent nominal significance in both analyses (red), only SCOOP vs. 189 UKHLS (green), only STILTS vs UKHLS (blue) or in neither analysis (purple). Error bars represent 95% 190 confidence intervals for the odds ratios for SCOOP vs UKHLS (x-axis) and for UKHLS vs STILTS (y-191 axis). A subset of data points with larger separation from the red diagonal line (x=y) are labelled.

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193 Next we investigated the association of a genetic risk score, generated from the 97 BMI associated 194 loci from GIANT [24] on BMI category (i.e. thin, normal, obese) using an ordinal logistic regression

195 (**Methods**). As expected, the standardised BMI genetic risk score was strongly associated with BMI 196 category (weighted score $p=8.59\times10^{-133}$). We found that the effect of a one standard deviation 197 increase in the standardised BMI genetic risk score was significantly larger for obese vs. (thin & 198 normal) than for (obese & normal) vs. thin $(p=7.48 \times 10^{-11}$, **S1 Appendix**) with odds ratio and 95% 199 confidence intervals of 1.94 (1.83, 2.07) and 1.50 (1.42, 1.59) respectively. However, using the 200 simulations described above (**Methods**), we confirm that the larger OR for obese vs. (thin & normal) 201 is not significantly different (*p*=0.41) than what we would expect given an additive genetic model, 202 and the different degrees of extremeness in our thin and obese cases. Mean GRS in each BMI 203 category was also not significantly different from that predicted via simulations (**S1 Fig**, **Methods**).

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205 **Genetic Correlation between persistent thinness, severe early onset childhood obesity and BMI**

206 Given the observed differences in association results from thin and obese individuals, compared to 207 the same set of control individuals, we next explored the genetic correlation of severe early onset 208 obesity, persistent thinness and BMI using LD score regression (**Methods**). For this, we used 209 summary statistics from the SCOOP vs UKHLS, STILTS vs UKHLS and BMI data from participants in 210 UK Biobank (UKBB, **Methods**). As expected from the association results, the genetic correlation of 211 severe early onset obesity and BMI was high (r=0.79, 95% CI [0.69, 0.89], $p=1.14\times10^{-52}$). We also 212 observed weaker negative correlation between persistent thinness and BMI (r=-0.69, 95% CI [-0.86, 213 -0.51], $p= 1.17x10^{-14}$), and between persistent thinness and severe obesity (r=-0.49, 95% CI [-0.17, 214 -0.82], *p*=0.003). As an inverse genetic correlation between BMI, obesity and anorexia nervosa (a

215 disorder that is characterised by thinness and complex behavioural manifestations) has recently 216 been reported [28], we also tested for genetic correlation with anorexia nervosa, and found that 217 neither severe early onset obesity, nor persistent thinness, were significantly correlated with 218 anorexia nervosa (r=-0.05, 95% CI [-0.15,0.05], *p*=0.33 and r=0.13, 95% CI [-0.02,0.28], *p*=0.09, 219 respectively; **Methods**).

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221 **Association signals for persistent thinness and severe early onset obesity replicate established** 222 **BMI associated loci**

223 Given available genome-wide directly genotyped and imputed data we sought evidence for novel 224 signals associated with either end of the BMI distribution (persistent thinness or severe early onset 225 obesity; **Methods**) **but found no novel replicating loci (details below).** In all three **discovery** 226 analyses, in addition to loci mapping to established BMI and obesity loci, we identified *PIGZ* and 227 *C3orf38*, two **putative** novel loci in the thin vs control analysis, that reached conventional genome-228 wide significance (GWS) (p≤5x10⁻⁸) (**Tables S5-S7, Fig 2**). However, an additional 125 SNPs, in 118 229 distinct loci, reached the arbitrary threshold of $p \leq 10^{-5}$ in at least one analysis, for which we sought 230 replication (**Tables S5-S7**)**.**

231 **Fig 2. Miami plot of SCOOP vs. UKHLS and STILTS vs. UKHLS.** Miami plot produced in EasyStrata 232 [29], Red=SCOOP vs. UKHLS; Blue=STILTS vs. UKHLS. Red lines indicate genome-wide significance threshold at $p=5x10^{-08}$. Orange lines indicate discovery significance threshold at $p=1x10^{-05}$. Black 234 labels highlight known BMI/obesity loci that were taken forward for replication and yellow peaks

235 indicate those that met genome-wide significance after replication. Grey labels highlight novel loci 236 with $p < 5x10^{-08}$ that did not replicate.

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238 As our obese and thin cases (SCOOP and STILTS) lie at the very extreme tails of the BMI distribution, 239 there are few comparable replication datasets. We therefore used the UKBB dataset and selected 240 individuals at the top (BMI>=40, N= 7,526) and bottom end of the distribution (BMI≤19, N= 3,532) 241 to more closely match the BMI criteria of our clinically ascertained thin and obese individuals. We 242 used 20,720 samples from the rest of the UKBB cohort as a control set (**Methods**, **S2 Fig**). In cases 243 where lead variants or proxies (r^2 >0.8) were not currently available in the full UKBB genetic release 244 we used results from the interim release using 2,799 individuals with BMI>=40, 1,212 with BMI<=19 245 and 8,193 controls (**Methods**). We noted a significant negative genetic correlation for our obese 246 replication cohort with anorexia nervosa (r= -0.24, 95% CI [-0.37,-0.11], *p*=0.01) and a positive 247 genetic correlation for our thin cohort (r=0.49, 95% CI [0.22-0.76] *p*=0.0003). We also observed 248 significant genetic correlation between obesity in the discovery and replication cohorts (r=0.84, 249 95% CI [0.65-1] $p=5.05x10^{-17}$ and between thinness in the discovery and replication cohorts (r= 250 0.62, 95% CI [0.20-1] *p*=0.004).

251 To further increase power, we took advantage of publicly available summary statistics from the 252 GIANT Extremes obesity meta-analysis [20], the EGG childhood obesity study [30], and our own 253 previous study on non-overlapping SCOOP participants (SCOOP 2013) [31], as additional replication 254 datasets. For SCOOP vs. STILTS we used the GIANT BMI tails meta-analysis results [20] (up to 7,962

255 cases/8,106 controls from the upper/lower 5th percentiles of the BMI trait distribution). For SCOOP 256 vs. UKHLS we used the GIANT obesity class III summary statistics [20] (up to 2,896 cases with BMI 257 ≥40kg/m² vs 47,468 controls with BMI <25 kg/m²), the EGG childhood obesity study [30] (children 258 with BMI ≥95th percentile of BMI vs 8,318 children with BMI <50th percentile of BMI) and SCOOP 259 2013 [31]. Fixed effect meta-analyses yielded genome-wide significant signals at well-known BMI 260 associated loci in both the obese vs. thin, and obese vs. control analyses, and both the *PIGZ* and 261 *C3orf38* loci identified at the discovery stage failed to replicate when combined with additional data 262 **(Table 1, S7 Table).** However, the *SNRPC* locus described here (rs75398113), though not 263 independent from the previously described *SNRPC*/*C6orf106* locus (rs205262, r^2 = 0.29) [24], 264 appears to be driving the previously reported association at this locus (rs205262 conditioned on 265 rs75398113, *pconditioned*=0.7, **S8 Table**). Both SNPs are eQTLs for *C6or106* and *UHRF1BP1* in multiple 266 tissues including brain and colon tissues on GTEx however neither of these are obvious biological 267 candidates linked to energy homeostasis.

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182 **Table 1 - GWAS results for SNPs meeting** *p***<5x10-8** 269 **in all three analyses.** EA= Effect allele (BMI 270 increasing allele); NEA= Non-effect allele; OR = Odds ratio; 95% CI = 95% confidence interval for the 271 odds ratio; EAF = effect allele frequency. Positions mapped to hg19, Build 37. \textdegree rs12995480 used as 272 proxy in GIANT. ^brs2384054 used as proxy in GIANT. ^crs12641981 used as proxy in GIANT. ^drs663129 273 used as proxy in GIANT, EGG and SCOOP 2013. ^ers13007080 used as proxy in GIANT, EGG and 274 SCOOP 2013. ^frs7138803 used as proxy in SCOOP 2013. ^grs6722587 used as proxy in GIANT, EGG 275 and SCOOP 2013. ^hrs4132288 used as proxy in GIANT, EGG and SCOOP 2013. ⁱrs1460940 used as

276 proxy in GIANT, EGG and SCOOP 2013. $\frac{1}{2}$ rs1366333 used as proxy in GIANT, EGG and SCOOP 2013. 277 ^kGIANT BMI tails [20]. ^IGIANT obesity class III [20].

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279 Finally, we used the independent BMI dataset from UKBB (**Methods**) to investigate whether any of 280 the loci meeting our arbitrary $p ≤ 10^{-5}$ in discovery efforts, were independently associated with BMI 281 as a continuous trait. This identified a novel BMI-associated locus near *PKHD1* (SCOOP vs. STILTS 282 $p=5.99x10^{-6}$, SCOOP vs. UKHLS $p=2.13x10^{-6}$, BMI $p=2.3x10^{-13}$, **S9 Table**). Furthermore, we note that 283 when comparing the signals we took for replication (based on case control analyses) with 284 association results with BMI as a continuous trait derived from an independent set of samples from 285 UKBB, there are more directionally consistent and nominally significant associations with BMI than 286 expected by chance suggesting that amongst these loci, there may be additional real associations 287 (binomial p=4.88x10⁻⁴, and binomial p=9.77x10⁻³, respectively, Methods, S9 Table)."

288 Despite the smaller sample size, the obese vs thin comparison had increased power to detect some 289 loci (**S3 Fig**), including a recently discovered variant near *FAM150B* [32] (rs62107261, MAF= ~5%)*,* 290 which did not meet our $p<10^{-5}$ threshold to be taken forward for replication in obese vs controls 291 analysis $(p=2.36x10^{-4})$.

292

293 **Discussion**

294 Here we present results from the largest to-date GWAS performed on healthy individuals with 295 persistent thinness and provide the first insights into the genetic architecture of this trait. To our

296 knowledge, there are only two other studies using thin individuals with comparable mean BMIs 297 **[21,22]**. The study by Hinney *et al*. **[21]** (N=442), was only able to detect *FTO* at genome-wide 298 significance level with rs1121980 having a similar effect to that which we report (OR=1.66 vs OR= 299 1.69 in our data). In the Scannell Bryan *et al***. [22]** study, Bangladeshi individuals were reportedly 300 thin and malnourished, and a single suggestive association was found with an intronic variant in 301 NRXN3 (rs12882679, $p=9.57\times10^{-7}$) which is not significant in our study ($p=0.77$).

302 Using genome-wide genotype data we show that persistent healthy thinness, similar to severe 303 obesity (h²=32.33%), is a heritable trait (h²=28.07%). Persistent healthy thinness and severe 304 childhood obesity are negatively correlated (r=-0.49, 95% CI [-0.17, -0.82], *p*=0.003), and share a 305 number of genetic risk loci. Nonetheless, the genetic overlap between the two clinically ascertained 306 traits appears to be incomplete, as highlighted by some loci which were more strongly associated 307 at one end of the BMI distribution (e.g. *CADM2*), while others, appeared to exert effects across the 308 entire BMI spectrum (e.g. *MC4R* [9,33,34]). Further exploration by simulation demonstrated that 309 these differences are likely to be due to the different degrees of extremeness of the two clinical 310 cohorts (i.e. a similar degree of thinness to that of the obese cohort may not be compatible with 311 healthy human life) and not due to a deviation from additive effects of the tested loci on BMI, with 312 the possible exception of *CADM2* which deviated from expectation with nominal significance in 313 both the obese and the thin analysis (**S3 Table**). This is in contrast with earlier studies which 314 suggested larger effects at the higher end of the BMI distribution [35,36] but in agreement with 315 more recent observations contrasting the bottom 5% and top 5% of the BMI tails where associated 316 loci were also consistent with additive effects [20]. This is also in contrast with a previous study on

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321 Focusing on the 97 previously established BMI associated loci [24], we show that the percentage of 322 phenotypic variance explained by these loci is lower in persistently thin (4.33%) compared to obese 323 individuals (10.67%), and that the effect of an increase/decrease in the BMI genetic risk score was 324 much larger, on average, for obese individuals than for thin individuals (one standard deviation 325 increase in the standardised BMI genetic risk score of 1.94, 95% CI (1.83, 2.07) and 1.50, 95% CI 326 (1.42, 1.59), respectively) which is consistent with the difference in BMI units amongst categories. 327 And, although our analysis using age-matched controls from ALSPAC suggested that the observed 328 differences in ORs, comparing obese vs control individuals to controls vs thin individuals, was 329 unlikely to be due to age effects, we cannot completely exclude the possibility that different effects 330 of age and sex in our discovery cohorts (**S1 Table**), and gene-by-environment interactions, could be 331 influencing some of the results we observe. For example, gene-by-environment interactions and 332 age effects have been previously reported at the *FTO* locus [38-41] where a larger effect is detected 333 in younger adults. **It is worth noting though that non-additive effects have also been observed in** 334 **the** *FTO* **locus [42].**

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336 In studying thin individuals there are often concerns regarding the prevalence of eating disorders, 337 notably anorexia nervosa amongst participants. We sought to carefully exclude eating disorders at 338 two phases of recruitment (by medical history and by questionnaire). Additionally, we demonstrate 339 that in our cohort of healthy thin individuals, anorexia nervosa is unlikely to be a confounder as the 340 two traits are genetically only weakly correlated (r=0.13, 95% CI [-0.02,0.28], *p*=0.09). This was not 341 the case for the UKBB replication cohort where a positive genetic correlation was observed (r= 0.49) 342 95% CI [0.22-0.76] *p*=0.0003). The positive genetic correlation with anorexia was still observed after 343 removing individuals with medical conditions that could explain their low BMI (r=0.62, 95% CI 344 [0.30,0.92], *p*=0.0001, **Methods)**. These results highlight the importance of the careful phenotyping 345 performed in the recruitment phase and the utility of the STILTS cohort as a resource to study 346 healthy and persistent thinness.

347 In the genome-wide association analyses amongst the signals we took forward for replication, in 348 addition to detecting established BMI-associated loci, we find a novel BMI-association at *PKHD1* in 349 the UKBB BMI dataset (rs10456655, β =0.10, p=2.3x10⁻¹³, **S9 Table**), where a proxy for this variant 350 (rs2579994, r^2 =1 in 1000G Phase 3 CEU) has been previously nominally associated with waist and 351 hip circumference ($p=5.60x10^{-5}$ and $p=4.40x10^{-4}$ respectively) [43]. In addition, we found 352 associations at loci that have only recently been established using very large sample sizes. 353 *FAM150B*, was only suggestively associated at discovery stage in Tachmazidou *et al.* (2017) [32] 354 (n=47,476, p=2.57×10⁻⁵) whereas it reached genome-wide significance when contrasting SCOOP vs 355 STILTS (n=2,927, p=2.07x10⁻⁸, **S5 Table**). Also, *PRDM6-CEP120* [5] was recently discovered in a 356 Japanese study with a sample size of 173,430 and has not been previously reported in a European

357 population. In our study, a signal near the locus (rs112446794, r^2 =0.36) showed suggestive evidence 358 of association in SCOOP vs UKHLS ($p=2.08\times10^{-6}$, **S6 Table**) with a significantly smaller sample size. 359 Conditional analysis reveals the lead SNP in this study drives the association of the previously 360 established signal (**S8 Table**). *CEP120* codes for centrosomal protein 120. Variants near this locus 361 have been previously associated with height [44] and waist circumference in East Asians [45]. 362 Missense variants in the gene itself have been associated with rare ciliopathies [46,47]. Lastly, 363 amongst the signals we took for replication, and after removing known and newly established loci, 364 we still observe an enrichment of directionally consistent and nominal associations in the analysis 365 of BMI as a continuous trait, suggesting that some of these results may warrant additional 366 investigation, in particular in similarly ascertained thin and obese cohorts. One such example is 367 rs4447506, near *PIK3C3,* which was not only nominally significant and consistent in the 368 independent UKBB BMI analysis ($p=1.5x10^{-6}$, **S9 Table**), but also in the Locke *et al.* (2015) [24] BMI 369 results (*p*= 0.01), and in the GIANT BMI tails analysis we used as replication (**S5 Table**). We also 370 note, that despite not reaching genome-wide significance in our discovery cohorts, we observe 371 directionally consistent suggestive associations at a number of loci previously associated with BMI 372 tails and with different obesity classes [20] (**S10 Table**)**.** Altogether, these results highlight some 373 power advantages of using clinically ascertained extremes of the phenotype distribution to detect 374 associations and suggest that healthy thinness falls at the lower end of the polygenic BMI spectrum. 375 It is worth noting though that these clinically ascertained extremes display evidence of incomplete 376 genetic correlation with BMI, in contrast to previously described obesity classes (S4 Fig), so it is 377 plausible that additional loci might be uncovered by focusing on clinical extremes.

378 As our results were based on clinically ascertained participants which met very specific criteria, it is 379 worth noting these conclusions cannot be straightforwardly extrapolated to the general population. 380 Experiments in animals have identified loci/genes associated with thinness/decreased body weight 381 due to reduced food intake/increased energy expenditure/resistance to high fat diet-induced 382 obesity [48,49], mechanisms that we hypothesise may contribute to human thinness. The STILTS 383 cohort, being uncorrelated to anorexia nervosa, is an excellent resource in which to conduct such 384 additional genetic exploration. Further genetic and phenotypic studies focused on persistently thin 385 individuals may provide new insights into the mechanisms regulating human energy balance and 386 may uncover potential anti-obesity drug targets.

387 **Methods**

388 **ETHICS STATEMENT**

389 The study was reviewed and approved by the South Cambridgeshire Research Ethics Committee 390 (12/EE/0172). All participants provided written informed consent prior to inclusion.

391 **COHORTS**

392 SCOOP, STILTS and UKHLS cohorts were used for the heritability, genetic correlation, genetic risk 393 score and association analyses with established BMI loci, as well as, used as a discovery cohort in 394 the genome-wide association study (GWAS) and gene-based tests. UK Biobank samples were used 395 for genetic correlation analysis and in the replication stages of the GWAS and gene-based tests. 396 ALSPAC was used as an additional control dataset to UKHLS for comparison against SCOOP in the 397 established BMI loci analysis.

398

399 **STILTS**

400 The aim was to recruit a new cohort of UK European people who are thin (defined as a body mass 401 index < 18kg/m^2) and well. After ethical committee approval (12/EE/0172), we worked with the 402 NIHR Primary Care Research Network (PCRN) to collaborate with 601 GP practices in England. Each 403 practice searched their electronic health records using our inclusion criteria (age 18-65 years, 404 BMI \leq 18 kg/m²) and exclusion criteria (medical conditions that could potentially affect weight 405 (chronic renal, liver, gastrointestinal problems, metabolic and psychiatric disease, known eating 406 disorders). A small number of individuals (n=43) with a BMI of 19.0 kg/m² were included as they

407 had a strong family history of thinness. The case notes of each potential participant were reviewed 408 by the GP or a senior nurse with clinical knowledge of the participant to exclude other potential 409 causes of low body weight in discussion with the study team. Through this approach we identified 410 25,000 individuals who fitted our criteria for inclusion in the study. These individuals were invited 411 to participate in the study; approximately 12% (2,900) replied consenting to take part. We obtained 412 a detailed medical and medication history, screened for eating disorders using a questionnaire 413 (SCOFF) that has been validated against more formal clinical assessment [50]. We excluded all 414 participants who stated that they exercised every day/more than 3 times a week/whose reported 415 activity exceeded 6 metabolic equivalents (METs) for any duration or frequency 416 (http://www.who.int/dietphysicalactivity/physical activity intensity/en/). With these rather strict 417 criteria for exercise, we sought to limit the contribution of exercise as a contributor to the thinness 418 of participants in the STILTS cohort. We excluded people who were thin only at a certain point in 419 their lives (often as young adults) to focus on those who were persistently thin/always thin 420 throughout life as we hypothesised that this group would be enriched for genetic factors 421 contributing to their thinness. We asked a specific question to identify these individuals: "have you 422 always been thin?" Only those who answered positively were included. Questionnaires were 423 manually checked by senior clinical staff for these parameters and for reported ethnicity (non-424 European ancestry excluded). DNA was extracted from salivary samples obtained from these 425 individuals using the Oragene 500 kit according to manufacturer's instructions (**S1 Table**).

426

427 **SCOOP**

436

437 **UKHLS**

438 Understanding Society (UKHLS) is a longitudinal household study designed to capture economic, 439 social and health information from UK individuals[52]. A subset of 10,484 individuals was selected 440 for genome-wide array genotyping. This cohort was used as a control dataset with SCOOP and 441 STILTS cases (**S1 Table**).

442

443 **UK BIOBANK (UKBB)**

444 This study includes approximately 487,411 participants with genetic data released (including 445 ~50,000 from the UKBiLEVE cohort [53]) of the total 502,648 individuals from UK BioBank (UKBB). 446 UKBB samples were genotyped on the UK Biobank Axiom array at the Affymetrix Research Services 447 Laboratory in Santa Clara, California, USA and imputed to the Haplotype Reference Consortium 448 (HRC) panel [54]. UKBiLEVE samples were genotyped on the UK BiLEVE array which is a previous

449 version of the UK Biobank Axiom array sharing over 95% of the markers. To date, 487,411 samples 450 with directly genotyped and imputed data are available and data was downloaded using tools 451 provided by UK Biobank. Extensive data from health and lifestyle questionnaires is currently 452 available as well as linked clinical records. BMI, as well as other physical measurements were taken 453 on attendance of recruitment centre. Severely obese participants in the available data were defined 454 as those with BMI ≥ 40 kg/m² (N=9,706) and thin individuals were defined as those with BMI \leq 19 455 kg/m² (N=4,538). Given that it has been previously shown that type I error rate for variants with a 456 low minor allele count (MAC) is inadequately controlled for in very unbalanced case-control 457 scenarios[55], we randomly subsampled 35,000 individuals from the original 487,411 genotyped 458 individuals and removed those with BMI≤19 or BMI ≥30, to generate an independent control set. 459 The 25,856 participants remaining after BMI exclusions from the tails, generated a non-extreme set 460 of individuals kept as putative controls (**S2 Fig**). The other 452,411 genotyped samples were kept as 461 the BMI dataset for downstream analyses (**S11 Table, S2 Fig**). An interim release consisting of a 462 subset 152,249 individuals from UKBB was released in May 2015. This interim release was imputed 463 to a combined UK10K and 1000G Phase 3 reference panel and contains several variants which are 464 not currently present in the HRC panel, as such it was used in some of the analyses described.

465

466 **ALSPAC**

467 The Avon Longitudinal Study of Parents and Children (ALSPAC) [27,56], also known as Children of 468 the 90s, is a prospective population-based British birth cohort study. Ethical approval for the study 469 was obtained from the ALSPAC Ethics and Law Committee and the Local Research Ethics

470 Committees. Please note that the study website contains details of all the data that is available 471 through a fully searchable data dictionary (http://www.bris.ac.uk/alspac/researchers/data-472 access/data-dictionary/). Further information about this cohort, including details of the genotyping 473 and imputation procedures, can be found in **S2 Appendix**. This analysis was restricted to a subset 474 of unrelated (identity-by-state < 0.05 [57]) children with genetic data and BMI measured between 475 the age of 12 and 17 years (n=4,964, 48.5% male). The mean age of the children was 14 years and 476 the mean BMI 20.5.

477

478 **GENOTYPING AND QUALITY CONTROL**

479 **SCOOP, STILTS and UKHLS**

480 For the SCOOP cohort, DNA was extracted from whole blood as previously described [31]. For the 481 STILTS cohort, DNA was extracted from saliva using the Oragene saliva DNA kits (online protocol) 482 and quantified using Qubit. All samples from SCOOP, STILTS and UKHLS were typed across 30 SNPs 483 on the Sequenom platform (Sequenom Inc. California, USA) for sample quality control. Of the 3,607 484 SCOOP and STILTS samples submitted for Sequenom genotyping, 3,280 passed quality controls 485 filters (90.9% pass rate). Of the 10,433 UKHLS samples, 9,965 passed Sequenom sample quality 486 control (95.5% pass rate). Subsequently, UKHLS controls were genotyped on the Illumina 487 HumanCoreExome-12v1-0 Beadchip. The 3,280 SCOOP and STILTS samples, and 48 overlapping 488 UKHLS samples (to test for possible array version effects) were genotyped on the Illumina 489 HumanCoreExome-12v1-1 Beadchip by the Genotyping Facility at the Wellcome Sanger Institute 490 (WSI). Genotype calling was performed centrally for all batches at the WSI using GenCall. Criteria

491 for excluding samples were as follows: i) concordance against Sequenom genotypes <90%; ii) for 492 each pair of sample duplicates, exclude one with highest missingness; iii) sex inferred from genetic 493 data different from stated sex ; iv) sample call rate <95%; v) sample autosome heterozygosity rate 494 >3 SDS from mean done separately for low (<1%) and high MAF(>1%) bins; vi) magnitude of 495 intensity signal in both channels <90%; and vii) for each pair of related individuals (proportion of 496 IBD (PI_HAT) >0.05), the individual with the lowest call rate was excluded. We performed SNP QC 497 using PLINK v1.07[58]. Criteria for excluding SNPs was: i) Hardy-Weinberg equilibrium (HWE) 498 p<1x10⁻⁶; ii) Call rate <95% for MAF≥5%, call rate <97% for 1% ≤MAF<5%, and call rate <99% for 499 MAF <1%. SMARTPCA v10210 [59] was used for principal component analysis (PCA). To verify the 500 absence of array version effects we used PCA on the subset of shared controls genotyped on both 501 versions of the array. Cut-offs for samples that diverged from the European cluster were chosen 502 manually after inspecting the PCA plot. SNPs with discordant MAFs in the different versions of the 503 array were excluded. After removal of non-European samples and 13 samples due to cryptic 504 relatedness, 1,456 SCOOP and 1,471 STILTS samples remained for analysis. For UKHLS, 82 samples 505 were removed after applying a strict European filter and 680 related samples were removed after 506 applying a "3rd degree" kinship filter in KING[60]. A total of 9,203 samples remained, of which 6,460 507 had a BMI >19 and <30 ("controls").

508

509 **UK BIOBANK**

510 Sample QC was performed using all 487,411 samples. Criteria for excluding samples were as 511 follows: i) supplied and genetically inferred sex mismatches; ii) heterozygosity and missingness

512 outliers according to centrally provided sample QC files; iii) samples not used in kinship estimation 513 by UKBB; iv) individuals that did not identify as "white british" or did not cluster with other "white 514 british" in PCA analysis ; v) samples that withdrew consent and vi) for each pair of related 515 individuals (KING kinship estimate>0.0442), we randomly selected an individual preferentially 516 keeping cases if one related individual is a control. After sample QC, thirteen individuals with 517 underlying health conditions that could influence their BMI were also removed, twelve had BMI<14, 518 and one had BMI>74. In the end, 7,526 obese, 3,532 thin and 20,720 non-extreme controls 519 remained for case-control analyses. In addition, 387,164 samples remained for analysis of BMI as a 520 continuous trait. There is an overlap of 10, 282 samples (~2.6% of the BMI dataset) with obese and 521 thin cases (**S2 Fig**). The same procedure was performed on the interim release of 152,249 UKBB 522 samples to produce a set of 2,799 obese, 1,212 thin, 8,193 controls and 127,672 individuals for the 523 independent BMI dataset. All subsequent analyses on UKBB were also performed on this subset to 524 query variants that are not currently available in the full UKBB release.

525

526 **IMPUTATION AND GENOME-WIDE ASSOCIATION ANALYSES**

527 **SCOOP, STILTS and UKHLS single-variant association analysis**

528 Genotypes from SCOOP, STILTS and UKHLS controls were phased together with SHAPEITv2 [61], and 529 subsequently imputed with IMPUTE2 [62,63] to the merged UK10K and 1000G Phase 3 reference 530 panel [64], containing ~91.3 million autosomal and chromosome X sites, from 6,285 samples. More 531 than 98% of variants with MAF ≥0.5% had an imputation quality score of r^2 ≥0.4, however variants 532 with MAF <0.1% had a poor imputation quality with only 27% variants with $r^2 \ge 0.4$ (S5 Fig). First-

551 from GP practices. For the heritability analysis, we used a prevalence estimate of 2.8% for BMI<=19 552 (Claudia Langenberg and Harry Hemingway, personal communication). We also used LD score

553 regression to calculate the genetic correlation of SCOOP with STILTS, SCOOP with UKBB obese, 554 SCOOP with BMI, STILTS with UKBB thin and STILTS with BMI. The genetic correlation between 555 obesity and persistent thinness with anorexia was estimated using the summary statistics from 556 SCOOP vs UKHLS and STILTS vs. UKHLS, and summary statistics available from the Genetic 557 Consortium for Anorexia Nervosa (GCAN) in LD Hub [70]. The same analysis was repeated for UKBB 558 obese vs controls and UKBB thin vs controls. Genetic correlation estimates for BMI vs Overweight, 559 Obesity Class 1, Obesity Class 2 and Obesity Class 3 were also extracted from LD Hub (**S4 Fig**).

560

561 **Comparison with established GIANT BMI associated loci**

562 We obtained the list of 97 established BMI associated loci from the publicly available data from the 563 GIANT consortium [24]. We used this list as we wanted to focus on established common variation in 564 Europeans with accurate effect sizes for simulations. In order to test whether there is evidence of 565 enrichment of nominally significant signals with consistent direction of effect, we performed a 566 binomial test using the subset of signals with nominal significance in the SCOOP vs UKHLS, and 567 STILTS vs UKHLS analyses. Variance explained was calculated using the rms package [71] v4.5.0 in R 568 [72] and Nagelkerke's R^2 is reported. Power calculations were performed using Quanto [73]. To 569 calculate ORs and SE from the ALSPAC BMI summary statistics we used genotype counts from 570 SNPTEST output. We then used a z-test to test for significant differences between the OR calculated 571 using genotype counts of SCOOP and ALSPAC against the SCOOP vs. UKHLS OR.

572

573 **Simulations under an additive model**

574 We created 10,000 simulations of 1 million individuals for the 97 GIANT BMI loci randomly sampling 575 alleles based on the allele frequency from the sex-combined European dataset reported in Locke *et* 576 *al*. [24] using an R script. For each simulated genotype, we simulated phenotypes with DISSECT [74] 577 using the effect size in GIANT and then removed all samples from the lower tail where the 578 phenotype was <3SDs to better reproduce the actual BMI distribution. Afterwards we randomly 579 sampled 1,471 individuals from the bottom 2.8% and 1,456 from top 0.15% and compared against a 580 random set of 6,460 controls from the equivalent percentiles to BMI 19-30. Finally, for each of 581 these loci, we calculated the absolute difference between our observed OR and the mean OR from 582 the simulations and counted how many times we saw an equal or larger absolute difference in the 583 simulated data and assigned a p-value. This was done separately for SCOOP vs UKHLS and STILTS vs 584 UKHLS.

585

586 **Genetic Risk Score**

587 The R package GTX (https://cran.r-project.org/web/packages/gtx/index.html) was used to 588 transpose genotype probabilities into dosages, and a combined dosage score, weighted by the 589 effect size from GIANT, for 97 BMI SNPs [24] was calculated and standardised. We checked whether 590 there was an ordinal relationship between the genetic risk score and BMI category (i.e. thin, 591 normal, or obese) using ordinal logistic regression with the clm function in the ordinal R package. 592 While the assumption of equal variance appears to hold (**S6 Fig**)**,** the proportional odds assumption 593 indicating equal odds between thin, normal, and obese groups is violated for the BMI genetic risk 594 score and some of the principal component covariates (i.e., PC2, PC3, and PC6). As our primary 595 model, we ran a partial proportional odds model adjusting for PC1, PC4, and PC5 and allowing the 596 BMI genetic score, PC2, PC3, and PC6 to vary between BMI category. To check for consistency, we 597 ran a partial proportional odds model adjusting for the first six PCs and allowing only the BMI 598 genetic score to vary between BMI group and a full proportional odds model allowing all six PCs and 599 the BMI genetic score to vary between BMI group (**S1 Appendix**). Using ANOVA, we formally tested 600 the proportional odds assumption for the BMI genetic risk score. A genetic risk score was created 601 and an ordinal logistic regression was run for each of the 10,000 simulations. We compared the 602 observed test statistic testing whether the odds were the same by BMI category to the 10,000 603 simulation test statistics. We calculated the p-value as the number of simulations with a test 604 statistic larger than that observed in the real data. A mean genetic risk score was also calculated for 605 each BMI category (obese, thin and controls) across the 10,000 simulations. A t-test was used to 606 test whether the mean observed GRS score in each category was significantly different from the 607 one estimated using the simulations.

608

609 **Discovery stage GWAS**

199 610 First pass single-variant association analyses results were used as discovery datasets for the GWAS. 611 After association analysis, we removed variants with MAF<0.5%, an INFO score <0.4, and HWE 612 $p<1x10^{-6}$, as these highlighted regions of the genome that were problematic, including CNV regions 613 with poor imputation quality. Quantile-quantile plots indicated that the genomic inflation was well 614 controlled for in SCOOP-UKHLS (λ=1.06) and STILTS-UKHLS (λ =1.04), and slightly higher for SCOOP-615 STILTS (λ =1.08**, S7 Fig**). We used LD score regression [67] to correct for inflation not due to

616 polygenicity. To identify distinct loci, we performed clumping as implemented in PLINK [58] using 617 summary statistics from the association tests and LD information from the imputed data, clumping 618 variants 250kb away from an index variant and with an r^2 >0.1. In order to further identify a set of 619 likely independent signals we performed conditional analysis of the lead SNPs in SNPTEST to take 620 into account long-range LD. A total of 135 autosomal variants with $p<1x10^{-5}$ in any of the three 621 case-control analyses were taken forward for replication in UKBB. All case-control results are 622 reported with the lower BMI group as reference.

623

624 **UKBB association analysis**

625 We tested 1,208,692 SNPs for association under an additive model in SNPTEST using sex, age, 10 626 PCs and UKBB genotyping array as covariates. Three comparisons were done: obese vs thin, obese 627 vs controls and controls vs thin. Variants with an INFO score <0.4, HWE p <1x10⁻⁶ were filtered out 628 from the results. Inflation factors were calculated using HapMap markers. The LD score regression 629 intercepts were 1.0074 in obese vs thin, 1.0057 in obese vs controls and 1.009 in thin vs controls. 630 We used all thin individuals, regardless of health status, as our replication cohort to maximize 631 power. However, using ICD10 codes and self-reported illness data (**Tables S12 and S13**) to remove 632 individuals who had a relevant medical diagnosis before date of attendance at UKBB recruitment 633 centre, yielded 2,518 thin individuals and materially equivalent results (**S8 Fig**).

634

635 **GIANT, EGG and SCOOP 2013 summary statistics**

636 We obtained summary statistics for the GIANT Extremes obesity meta-analysis [20] from 637 http://portals.broadinstitute.org/collaboration/giant/index.php/GIANT consortium data files. 638 Summary statistics for EGG [30] were obtained from http://egg-consortium.org/childhood-639 obesity.html. We used summary statistics from our previous study of 1,509 early-onset obesity 640 SCOOP cases compared to 5,380 publicly available WTCCC2 controls (SCOOP 2013) [31]. Data for 641 the SCOOP cases is available to download from the European Genome-Phenome Archive (EGA) 642 using accession number EGAD00010000594. The control samples are available to download using 643 accession numbers EGAD00000000021 and EGAD00000000023. These replication studies are 644 largely non-overlapping with our discovery datasets and each-other. When a lead variant was not 645 available in a replication cohort, a proxy ($r^2 \ge 0.8$) was used in the meta-analysis.

646

647 **Replication meta-analysis**

648 We meta-analysed summary statistics for the 135 variants reaching p <1x10⁻⁵ in 649 SCOOP/STILTS/UKHLS with the corresponding results from UKBB and study specific replication 650 cohorts (**Tables S5-S7**). For obese vs. thin and obese vs. controls comparisons we used fixed-effects 651 meta-analysis correcting for unknown sample overlap in replication cohorts using METACARPA [75]. 652 For thin vs. controls we used a fixed-effects meta-analysis in METAL [76]. Heterogeneity was 653 assessed using Cochran's Q-test heterogeneity p-value in METAL. A signal was considered to 654 replicate if it met all the following criteria: i) consistent direction of effect; ii) p<0.05 in at least one 655 replication cohort; and iii) the meta-analysis p-value reached standard genome-wide significance 656 ($p<5x10^{-8}$). Given that we are querying additional variants on the lower allele frequency spectrum,

664 **Comparison of newly established candidate loci and UKBB independent BMI dataset**

665 We identified eleven signals in SCOOP vs STILTS, nine in SCOOP vs UKHLS and two in UKHLS vs 666 STILTS that were nominally significant in the UKBB BMI dataset GWAS, and directionally consistent. 667 A binomial test was used to check for enrichment of signals with consistent direction of effect (**S9** 668 **Table**).

669

670 **Lookup of previously identified obesity-related signals in our discovery datasets**

671 We took all signals reaching genome-wide significance, or identified for the first time in the GIANT 672 Extremes obesity meta-analysis [20], with either the tails of BMI or obesity classes, and in childhood 673 obesity studies [30,31] and performed look-up of those signals in all three of our discovery analyses 674 (SCOOP vs STILTS, SCOOP vs UKHLS and UKHLS vs STILTS). ORs and p-values from the previous 675 studies and look-up results from our discovery datasets are reported in **S10 Table**.

677 **Data availability**

678 Summary statistics for the discovery analyses will be available to download from EGA 679 (EGAS00001002624). UKHLS data is available for download in EGA with accession code 680 EGAS00001001232.

Table 1

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Supporting information captions

S1 Appendix. **Assessing equal vs. unequal effects for the genetic risk score.**

S2 Appendix. **The Avon Longitudinal Study of Parents and Children.**

S1 Fig. **Mean GRS for SCOOP and STILTS compared to simulations**. Histogram represents mean GRS scores for each BMI category across 10,000 simulations. Vertical red line highlights the observed value in real data. p=p-value of difference**.**

S2 Fig. **Summary of the UKBB sample sets after QC.** Venn Diagram showing sample numbers and overlap between UKBB sample sets used in genetic correlation (BMI dataset) and GWAS replication (obese, controls, thin) analyses.

S3 Fig. Manhattan plot of SCOOP vs STILTS. Manhattan plot produced in EasyStrata, red line indicates genome-wide significance threshold at p=5x10-08. Orange line indicates discovery significance threshold at p=1x10-05. Black labels highlight known BMI/obesity loci that were taken forward for replication and yellow peaks indicate those that met genome-wide significance after replication.

S4 Fig. Genetic correlation of traits and BMI. Genetic correlation estimates and 95% CI for severe early-onset childhood obesity (SCOOP), healthy persistent thinness (STILTS), Obesity Class 3, Obesity Class 2, Obesity Class 1 and Overweight. Dotted lines represent complete genetic correlation.

S5 Fig. Quality of UK10K+1000G imputed genotypes. Percentage of variants with INFO score (r^2) >0.4, as derived from the IMPUTE2 imputation algorithm, stratified by minor allele frequency across all samples (SCOOP, STILTS and UKHLS).

S6 Fig. Box and density plots of risk score weighted by effect size for 97 BMI associated SNPs from GIANT. A weighted genetic risk score for each individual was obtained by summing genotype dosages multiplied by the effect (beta) estimates from GIANT for each of the 97 SNPs. To check the equal variance assumption, we used a box plot (left) and density plot (right). Density plot: Green = STILTS; Blue = UKHLS; Red = SCOOP.

S7 Fig. Quantile-quantile plots of three discovery analysis cohorts. Q-Q plots of LD Score Regression-corrected p-values for the three analysis cohorts used for the discovery analysis, produced in EasyStrata. Red=SCOOP vs. STILTS; Black=SCOOP vs. UKHLS, Blue=STILTS vs. UKHLS. Variants passing QC and with MAF >=0.5% are shown. LD Score regression intercept (λLD) values before correction are shown for each analysis.

S8 Fig. Quantile-quantile plots for UKBB case-control analysis with different exclusion criteria for thin individuals. Q-Q plot using all thin individuals as cases (Full UKBB) and removing individuals based on ICD10 and self-reported data (ICD10+self-reported filter). Correlation for –log10 p-values is shown (r=0.7462).

S1 Table. Summary of discovery sample sets.

S2 Table. 97 BMI SNPs from the GIANT consortium study and their summary statistics in our three analysis cohorts.

S3 Table. Nominally significant loci for non-additive effect in extremes.

S4 Table. Difference in SCOOP OR when using ALSPAC as control dataset vs. UKHLS.

S5 Table. Discovery, replication and meta-analysis results for 32 SNPs meeting P<10-5 in discovery association results of SCOOP vs STILTS analysis.

S6 Table. Discovery, replication and meta-analysis results for 66 SNPs meeting P<10-5 in discovery association results of SCOOP vs UKHLS analysis.

S7 Table. Discovery, replication and meta-analysis results for 37 SNPs meeting P<10-5 in discovery association results of UKHLS vs STILTS analysis.

S8 Table: Reciprocal analysis of previously established signals and lead signals in this study.

S9 Table. Consistency of the direction of effect in candidate loci meeting p<1x10-5 in the discovery stages with BMI dataset GWAS.

S10 Table. Published loci from GIANT, EGG and SCOOP 2013 not reaching genome-wide significance in our study

S11 Table. Summary of UKBB sample sets.

S12 Table. ICD10 codes used to exclude thin individuals in UKBB

S13 Table. Self-reported illness codes used to exclude thin individuals in UKBB

S2 Table. 97 BMI SNPs from the GIANT consortium study and their summary statistics in our three analysis cohorts.

Appendix A

*GRCh37/hg19 coordinates
**Proxy for rs2033529
Effect = Effect allele (BMI increasing allele); Other = Other allele; EAF = Effect allele frequency

OR.UKHLS= OR when using UKHLS as control group OR.ALSPAC= OR when using age-matched ALSPAC as control group P.Diff=p value for difference

S4 Table. Difference in SCOOP OR when using ALSPAC as control dataset vs. UKHLS

SNP Locus OR.UKHLS OR.ALSPAC P.Diff rs1558902 FTO 1.4287329 1.3427721 2.94E-01

"Interim release used in WissB for these signals. Nobes=2,799. Notine: 1212
BAET flect allele (BMI increasing allele): NEA= Noneffect allele; OR = Odds ratio; 59% Cooffidence interval for the odds ratio; EAF = effect allel

S6 Table. Discovery, replication and meta-analysis results for 66 SNPs meeting P<10-5 in discovery association results of SCOOP vs UKHLS analysis.

S7 Table. Discovery, replication and meta-analysis results for 37 SNPs meeting P<10-5 in discovery association results of UKHLS vs STILTS analysis.

*Interim release used in UKBB for these signals. Nthin=1,212. Ncontrols=8,193
**rs4665779 was used as a proxy in UKBB
EA=Effect allele (BMI increasing allele); NEA= Non-effect allele; OR = Odds ratio; 95% CI = 95% confiden

S10 Table. Published loci from GIANT, EGG and SCOOP 2013 not reaching genome-wide significance in our study Known BMI loci with meta p <5E-8 in GIANT BMI tails study but not in this study (obese vs thin)

S13 Table. Self-reported illness codes used to exclude thin individuals in UKBB Psychiatric 1286 depression 1287 anxiety/panic attacks 1288 nervous breakdown 1289 schizophrenia 1290 deliberate self-harm/suicide attempt 1291 mania/bipolar disorder/manic depression 1469 post-traumatic stress disorder 1470 anorexia/bulimia/other eating disorder 1614 stress 1615 obsessive compulsive disorder (ocd) 1616 insomnia 1408 alcohol dependency 1409 opioid dependency 1410 other substance abuse/dependency 1531 post-natal depression **Liver** 1136 liver/biliary/pancreas problem 1155 hepatitis 1158 liver failure/cirrhosis 1159 bile duct disease 1161 gall bladder disease 1164 pancreatic disease 1507 haemochromatosis 1508 jaundice (unknown cause) 1156 infective/viral hepatitis 1157 non-infective hepatitis 1578 hepatitis a 1579 hepatitis b 1580 hepatitis c 1581 hepatitis d 1582 hepatitis e
1506 primary biliary cirrhosis
1604 alcoholic liver disease / alcoholic cirrhosis
1160 bile duct obstruction/ascending cholangitis
1475 sclerosing cholangitis
1056 pancreatitis
1076 heart failure/pulmonary **Renal** 1192 renal/kidney failure 1192 Tenary Nurrey Tanure
1193 renal failure requiring dialysis
1194 renal failure not requiring dialysis 1194 renal failure not requiring dialysis
1195 other renal/kidney problem
1196 urinary tract infection/kidney infection
1195 prionenphitis
1427 polycystic kidney
1427 polycystic kidney
1620 nephitis
1520 iga nephropathy
16 **Gut** 1154 irritable bowel syndrome 1456 malabsorption/coeliac disease 1457 duodenal ulcer 1459 colitis/not chrons or ulcerative colitis 1461 inflammatory bowel disease 1502 appendicitis 1503 anal problem 1599 constipation 1600 bowel / intestinal perforation 1601 bowel / intestinal infarction 1602 bowel / intestinal obstruction 1603 rectal prolapse 1462 crohns disease 1463 ulcerative colitis **Abdominal** 1400 peptic ulcer **Endocrine** 1224 thyroid problem (not cancer) 1229 parathyroid gland problem (not cancer) 1232 disorder of adrenal gland 1237 disorder of pituitary gland 1239 cushings syndrome 1432 carcinoid syndrome 1682 benign insulinoma 1221 gestational diabetes 1222 type 1 diabetes 1225 hyperthyroidism/thyrotoxicosis 1226 hypothyroidism/myxoedema 1228 thyroid radioablation therapy 1428 thyroiditis 1522 grave's disease 1610 thyroid goitre 1230 parathyroid hyperplasia/adenoma 1611 hyperparathyroidism 1233 adrenal tumour 1234 adrenocortical insufficiency/addison's disease 1235 hyperaldosteronism/conn's syndrome 1236 phaeochromocytoma 1238 pituitary adenoma/tumour 1429 acromegaly 1430 hypopituitarism 1431 hyperprolactinaemia **COPD**
1112 COPD 1112 COPD
Infections
1439 hiv/aids
1567 infectious mononucleosis / glandular fever / epstein barr virus (ebv)
1440 tuberculosis (tb)
1575 herpes simplex **Cancer** (responded yes to "Have you ever been diagnosed with cancer?") Supplementary Tables 1 and 2 are too large to print. They are located here:

Supplementary Table 1

https://docs.google.com/spreadsheets/d/1HYbX5qI81pvMjAM7bn8yWlN34OGtwudpDJLzLVUbu5A/ edit?usp=sharing

Supplementary Table 2

https://docs.google.com/spreadsheets/d/19s_C6eb7uX4etbaTQ0M-XUvYYhOeTutiyIJwM1XwJ4A/edit?usp=sharing

Meta-p= Meta-analysis p-value
Meta-p (no APO) = Meta-analysis p-value after removing APO genes from gene sets (APOB and APOC3)
WES p = p-value in WES dataset
N WES = number of variants tested in WES dataset
WGS p = p-value

APOA1 rs199759119 WGS
CETP - rs142750310 WGS

Supplementary Table 10: Sensitity analyses for rare variant enrichment in tails analysis using different percentile cutoffs to define tails of the phenotypic distribution .5% Percentile upper tails

.5% Percentile lower tails

1 Percentile lower tails

p.wes: permutation p-value in WES

p.wgs: permutation p-value in WGS

meta-p: p-value after meta-analysis using Stouffer's method

Highlighted in yellow are gene sets that are significant after meta-analysis using Stouffer's method and after adjusting for multiple traits (p<=0.00037).