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Parent-of-origin specific allelic associations among 106 genomic loci for age at menarche

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Abstract

Age at menarche is a marker of timing of puberty in females. It varies widely between individuals, is a heritable trait and is associated with risks for obesity, type 2 diabetes, cardiovascular disease, breast cancer and all-cause mortality¹. Studies of rare human disorders of puberty and animal models point to a complex hypothalamic-pituitary-hormonal regulation^{2,3}, but the mechanisms that determine pubertal timing and underlie its links to disease risk remain unclear. Here, using genome-wide and custom-genotyping arrays in up to 182,416 women of European descent from 57 studies, we found robust evidence $(P<5\times10^{-8})$ for 123 signals at 106 genomic loci associated with age at menarche. Many loci were associated with other pubertal traits in both sexes, and there was substantial overlap with genes implicated in body mass index and various diseases, including rare disorders of puberty. Menarche signals were enriched in imprinted regions, with three loci (DLK1/WDR25, MKRN3/MAGEL2 and KCNK9) demonstrating parent-of-origin specific associations concordant with known parental expression patterns. Pathway analyses implicated nuclear hormone receptors, particularly retinoic acid and gamma-aminobutyric acid-B2 receptor signaling, among novel mechanisms that regulate pubertal timing in humans. Our findings suggest a genetic architecture involving at least hundreds of common variants in the coordinated timing of the pubertal transition.

Overall project management

JRBP, FD, CEE, PS, DJT, DFE, KS, JMM, KKO

Core analyses

JRBP, FD, CEE, PS, TF, DJT, DIC, TE

Individual study analysts

AAR, AD, AG, AJ, AT, AVS, BZA, BF, CEE, DFG, DIC, DJT, DLC, DLK, EA, EKW, EM, EMB, ET, FD, GM, GmM, IMN, JAV, JD, JH, JRBP, JT, JZ, KLL, KM, LLP, LMR, LMY, LS, MM, NF, NTs, PK, PS, RM, SK, SS, SSU, TC, TE, TF, TFo, THP, WQA,

Individual study data management and generation

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Supplementary Information Supplementary information contains: Supplementary Tables and Figures, acknowledgements, author disclosures.

Data deposition statement

Plots of all 106 menarche loci and genome-wide summary level statistics are available at the ReproGen Consortium website: www.reprogen.org.

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Genome-wide array data were available on up to 132,989 women of European descent from 57 studies, and data on up to ~25,000 single nucleotide polymorphisms (SNPs), or their proxy markers, that showed sub-genome-wide significant associations (P<0.0022) with age at menarche in our previous genome-wide association study (GWAS)⁴ were available on an additional 49,427 women (Supplementary Table 1). Association statistics for 2,441,815 autosomal SNPs that passed quality control measures (including minor allele frequency >1%) were combined across all studies by meta-analysis.

3,915 SNPs reached the genome-wide significance threshold (P<5×10⁻⁸) for association with age at menarche (Figure 1). Using GCTA⁵, which approximates a conditional analysis adjusted for the effects of neighbouring SNPs (Extended Data Figure 1 and Supplementary Table 2), we identified 123 independent signals for age at menarche at 106 genomic loci, including 11 loci containing multiple independent signals (Extended Data Tables 1-4; plots of all loci are available at www.reprogen.org). Of the 42 previously reported independent signals for age at menarche⁴, all but one (rs2243803, *SLC14A2*, P=2.3×10⁻⁶) remained genome-wide significant in the expanded dataset.

To estimate their overall contribution to the variation in age at menarche, we analysed an additional sample of 8,689 women. 104/123 signals showed directionally-concordant associations or trends with menarche timing (binomial sign test P_{Sign} =2.2×10⁻¹⁵), of which 35 showed nominal significance (P_{Sign} <0.05) (Supplementary Table 3). In this independent sample, the top 123 SNPs together explained 2.71% (P<1×10⁻²⁰) of the variance in age at menarche, compared to 1.31% (P=2.3×10⁻¹⁴) explained by the previously reported 42 SNPs. Consideration of further SNPs with lower levels of significance resulted in modest increases in the estimated variance explained with increasingly larger SNP sets, until we included all autosomal SNPs (15.8%, S.E. 3.6%, P=2.2×10⁻⁶), indicating a highly polygenic architecture (Extended Data Figure 2).

To test the relevance of menarche loci to the timing of related pubertal characteristics in both sexes, we examined their further associations with refined pubertal stage assessments in an overlapping subset of 10 to 12 years old girls (n=6,147). A further independent sample of 3,769 boys had similar assessments at ages 12 to 15 years. 90/106 menarche loci showed consistent directions of association with Tanner stage in boys and girls combined $(P_{Sign}=1.1\times10^{-13})$, 86/106 in girls only $(P_{Sign}=6.2\times10^{-11})$ and 72/106 in boys only $(P_{Sign}=0.0001)$, suggesting that the menarche loci are highly enriched for variants that regulate pubertal timing more generally (Supplementary Table 4).

Six independent signals were located in imprinted gene regions⁶, which is an enrichment when compared to all published genome-wide-significant signals for any trait/disease⁷ (6/123, 4.8% vs 75/4332, 1.7%; Fisher's Exact test P=0.017). Departure from Mendelian inheritance of pubertal timing has not been previously suspected, therefore we sought evidence for parent-of-origin specific allelic associations in the deCODE Study, which included 35,377 women with parental origins of alleles determined by a combination of genealogy and long-range phasing⁶.

Two independent signals (#85a-b; rs10144321 and rs7141210) lie on chromosome 14q32 harbouring the reciprocally imprinted genes DLK1 and MEG3, which exhibit paternalspecific or maternal-specific expression, respectively, and may underlie the growth retardation and precocious puberty phenotype of maternal uniparental disomy-148. In deCODE, for both signals the paternally-inherited alleles were associated with age at menarche (rs10144321, P_{pat} =3.1×10⁻⁵; rs7141210, P_{pat} =2.1×10⁻⁴), but the maternallyinherited alleles were not (P_{mat} =0.47 and 0.12, respectively), and there was significant heterogeneity between paternal and maternal effect estimates (rs10144321, P_{het} =0.02; rs7141210, P_{het} =2.2×10⁻⁴) (Figure 2; Supplementary Table 5). Notably, rs7141210 is reportedly a cis-acting methylation-QTL in adipose tissue⁹ (Extended Data Table 5) and the menarche age-raising allele was also associated with lower transcript levels of DLK1 (Supplementary Tables 6 and 7)¹⁰, which encodes a transmembrane protein involved in adipogenesis and neurogenesis. In deCODE data, the maternally-inherited rs7141210 allele was correlated with blood transcript levels of the maternally-expressed genes MEG3 $(P_{mat} < 5.6 \times 10^{-53})$, MEG8 $(P_{mat} = 4.9 \times 10^{-41})$ and MEG9 $(P_{mat} = 5.4 \times 10^{-5})$; however, lack of any correlation with the paternally-inherited alleles (P_{pat} =0.18, P_{pat} =0.87 and P_{pat} =0.37, respectively) suggests that these genes do not explain this paternal-specific menarche signal.

Signal #86 (rs12148769) lies in the imprinted critical region for Prader Willi Syndrome (PWS), which is caused by paternal-specific deletions of chromosome 15q11-13 and includes clinical features of hypogonadotropic hypogonadism and hypothalamic obesity¹¹; conversely a small proportion of cases have precocious puberty. For rs12148769, only the paternally-inherited allele was associated with age at menarche (P_{pat} =2.4×10⁻⁶), but the maternally-inherited allele was not (P_{mat} =0.43; P_{het} =5.6×10⁻³) (Figure 2). Recently, truncating mutations of *MAGEL2* affecting the paternal alleles were reported in PWS; all four reported cases had hypogonadism or delayed puberty¹¹, whereas paternally-inherited deleterious mutations in *MKRN3* were found in patients with central precocious puberty³. It is as yet unclear which of these paternally-expressed genes explains this menarche signal.

Signal #57 (rs1469039) is intronic in KCNK9, which shows maternal-specific expression in mouse and human brain 12 . Concordantly, only the maternally-inherited allele was associated with age at menarche (P_{mat} =5.6×10⁻⁶), but the paternally-inherited allele was not (P_{pat} =0.76; P_{het} =3.7×10⁻³) (Figure 2). The menarche age-increasing allele was associated with lower transcript levels of KCNK9 in deCODE's blood expression data when maternally-inherited (P_{mat} =0.003), but not when paternally-inherited (P_{pat} =0.31). KCNK9 encodes TASK-3, which belongs to a family of two-pore domain potassium channels that regulate neuronal resting membrane potential and firing frequency.

The two remaining signals located within imprinted regions (rs2137289 and rs947552) did not demonstrate either paternal or maternal-specific association. We then systematically tested all 117 remaining independent menarche signals for parent-of-origin specific associations with menarche timing and found only 4 (3.4%) with at least nominal associations (P_{het} <0.05; Supplementary Table 5), which was proportionately fewer than signals at imprinted regions (4/6 (67.0%), Wilcoxon rank sum test P=0.009).

Three menarche signals were in genes encoding JmjC-domain-containing lysine-specific demethylases (enrichment P=0.006 for all genes in this family); signal #1 (rs2274465) is intronic in KDM4A, signal #37 (rs17171818) is intronic in KDM3B, and signal #59b (rs913588) is a missense variant in KDM4C. Notably, KDM3B, KDM4A, and KDM4C all encode activating demethylases for Lysine-9 on histone H3, which was recently identified as the chromatin methylation target that mediates the remarkable long-range regulatory effects of IPW, a paternally-expressed long noncoding RNA in the imprinted PWS region on chromosome 15q11-13, on maternally-expressed genes at the imprinted DLK1-MEG3 locus on chromosome 14q32¹³. Examination of sub-genome-wide signals showed another potential locus intronic in KDM4B (rs11085110, P=2.3×10⁻⁶). Pubertal onset in female mice is reportedly triggered by DNA methylation of the Polycomb group silencing complex of genes (including CBX7 near signal #105) leading to enrichment of activating lysine modifications on histone H3¹⁴. Specific histone demethylases could potentially regulate cross-links between imprinted regions to influence pubertal timing.

Menarche signals also tended to be enriched in/near genes that underlie rare Mendelian disorders of puberty (enrichment P=0.05)^{2,3}. As well as rs12148769 near to MKRN3, signals were found near LEPR/LEPROT (signal #2; rs10789181), which encodes the leptin receptor, and immediately upstream of TACR3 (signal #32; rs3733631), which encodes the receptor for Neurokinin B. A further variant ~10 kb from GNRH1 approached genome-wide significance (rs1506869, $P=1.8\times10^{-6}$) and was also associated with GNRH1 expression in adipose tissue ($P=3.7\times10^{-5}$). Signals #34 (rs17086188) and #103 (rs852069) lie near *PCSK1* and PCSK2, respectively, indicating a common function of the type 1 and 2 prohormone convertases in pubertal regulation. Signals in/near several further genes with relevance to pituitary development/function included: signal #20 (rs7642134) near POU1F1, signal #39 (rs9647570) within TENM2, and signal #42 (rs2479724) near FRS3. Furthermore, signals #71 (rs7103411) and #92 (rs1129700) are cis-eQTLs for LGR4 and TBX6, respectively, both of which encode enhancers for the pituitary development factor SOX2. Signals #52 (rs6964833 intronic in GTF2I) and #104 (rs2836950 intronic in BRWDI) were found in critical regions for complex conditions that include abnormal reproductive phenotypes, Williams-Beuren syndrome (early puberty)¹⁵, and Down syndrome (hypogonadism in boys), respectively¹⁶.

Including signals described above, we identified 29 menarche signals in/near genes with possible roles in hormonal functions (Figure 3, Supplementary Table 8), many more than the three signals we described previously (*INHBA*, *PCSK2* and *RXRG*)⁴. Two signals were found in/near genes related to steroidogenesis. Signal 35 (rs251130) was a *cis*-eQTL for *STARD4*, which encodes a StAR-related lipid transfer protein involved in the regulation of intra-cellular cholesterol trafficking. Signal #9 (rs6427782) is near *NR5A2*, which encodes a nuclear receptor with key roles in steroidogenesis and estrogen-dependent cell proliferation.

We observed that SNPs in/near a custom list of genes that encode nuclear hormone receptors, co-activators or co-repressors were enriched for associations with menarche timing (enrichment $P=6\times10^{-5}$). Individually, nine genome-wide significant signals mapped to within 500 kb of these genes, including those encoding the nuclear receptors for oestrogen, progesterone, thyroid hormone and 1,25-dihydroxyvitamin D3. Several nuclear

hormone receptors are involved in retinoic acid (RA) signaling. SNPs in/near *RXRG* and *RORA* reached genome-wide significance, and three other genes contained sub-genome-wide signals (*RXRA* [rs2520094, P=4×10⁻⁷], *RORB* [rs4237264, P=9.4×10⁻⁶], *RXRB* [rs241438, P=7.1×10⁻⁵]). Two other genome-wide significant signals mapped to genes with roles in RA function (#67 *CTBP2* and #101 *RDH8*). The active metabolites of vitamin A, all-*trans*-RA and 9-*cis*-RA, have differential effects on GnRH expression and secretion¹⁷. Other possible mechanisms linking RA signaling to pubertal timing include inhibition of embryonic GnRH neuron migration, and enhancement of steroidogenesis and gonadotrophin secretion¹⁸. The relevance of our findings to observations of low circulating vitamin A levels and use of dietary vitamin A in delayed puberty¹⁹ are yet unclear.

To identify other mechanisms that regulate pubertal timing, we tested all SNPs genomewide for collective enrichment across any biological pathway defined in publicly available databases. The top ranked pathway reaching study-wise significance (FDR=0.009) was gamma-aminobutyric acid (GABA_B) receptor II signaling (Extended Data Table 6); each of the nine genes in this pathway contained a SNP with sub-genome-wide significant association with menarche (Extended Data Table 7). Notably, GABA_B receptor activation inhibits hypothalamic GnRH secretion in animal models²⁰.

Regarding the relevance of our findings to other traits, we confirmed⁴ and extended the overlap between genome-wide significant loci for menarche and adult BMI²¹. At all nine loci (in/near *FTO*, *SEC16B*, *TMEM18*, *NEGR1*, *TNN13K*, *GNPDA2*, *BDNF*, *BCDIN3D* and *GPRC5B*) the menarche age-raising allele was also associated with lower adult BMI (Supplementary Table 9). Three menarche signals overlapped known loci for adult height²². The menarche age-raising alleles at signals #47c (rs7759938, *LIN28B*) and #83 (rs1254337, *SIX6*) were also associated with taller adult height, which is directionally concordant with epidemiological observations. Conversely, the menarche age-raising allele at signal #48 (rs4895808, *CENPW/NCOA7*) was associated with shorter adult height (Supplementary Table 9).

Further menarche signals overlapped reported GWAS loci for other traits, but in each case at only a single locus, therefore possibly reflecting small-scale pleiotropy rather than a broader shared genetic aetiology. Signal #26 (rs900400) was a *cis*-eQTL for *LEKR1*, and is the same lead SNP associated with birth weight. The menarche age-raising allele was also associated with higher birth weight, directionally concordant with epidemiological observations. Signal #48 (rs4895808, a *cis*-eQTL for *CENPW*) is in LD (r^2 =0.90) with the lead SNP for the autoimmune disorder type 1 diabetes, rs9388489. which also showed robust association with menarche timing (P=6.49×10⁻¹²). Signal #41 (rs16896742) is near *HLA-A*, which encodes the class I, A major histocompatibility complex, and is a known locus for various immunity or inflammation-related traits. Signal #50 (rs6933660) is near *ESR1*, which encodes the oestrogen receptor, a known locus for breast cancer. and bone mineral density. Notably, the menarche age-raising allele at rs6933660 was associated with higher femoral neck bone mineral density (P=6×10⁻⁵)27, which is directionally discordant with the epidemiological association. Signal #70 (rs11022756) is intronic in *ARNTL*, a known locus for circulating plasminogen activator inhibitor type 1 (PAI-1)

levels²⁹; the reported lead SNP (rs6486122) for PAI-1²⁹ also showed robust association with menarche timing (P=9.3×10⁻¹⁰).

Our findings indicate both BMI-related and BMI-independent mechanisms that could underlie the epidemiological associations between early menarche and higher risks of adult disease¹. These include actions of *LIN28B* on insulin sensitivity through the mTOR pathway, GABA_B receptor signaling on inhibition of oxidative stress-related \(\theta\)-cell apoptosis, and *SIRT3* (mitochondrial sirtuin 3), which could link early life nutrition to metabolism and ageing. Finally, only few parent-of-origin specific allelic associations at imprinted loci have been described for complex traits⁶. Our findings implicate differential pubertal timing, a trait with putative selection advantages³⁰, as a potential additional target for the evolution of genomic imprinting.

METHODS

GWAS meta-analysis

We performed an expanded GWAS meta-analysis for self-reported age at menarche in up to 182,416 women of European descent from 58 studies (Supplementary Table 1). All participants provided written informed consent and the studies were approved by the respective Local Research Ethics committees or Institutional Review Boards. Consistent with our previous analysis protocol⁴, women who reported their age at menarche as < 9 years or > 17 years were excluded from the analysis; birth year was included as the only covariate to allow for the secular trends in menarche timing. Genome-wide SNP array data were available on up to 132,989 women from 57 studies. Each study imputed genotype data based on HapMap Phase II CEU build 35 or 36. Data on an additional 49,427 women from the Breast Cancer Association Consortium (BCAC) were generated on the Illumina iSelect "iCOGS" array³¹. This array included up to ~25,000 SNPs, or their proxy markers, that showed sub-genome-wide associations (P<0.0022) with age at menarche in our earlier GWAS⁴. SNPs were excluded from individual study datasets if they were poorly imputed or were rare (MAF < 1%). Test statistics for each study were adjusted using study-specific genomic control inflation factors and where appropriate individual studies performed additional adjustments for relatedness (Supplementary Table 1). Association statistics for each of the 2,441,815 autosomal SNPs that passed OC in at least half of the studies were combined across studies in a fixed effects inverse-variance meta-analysis implemented in $METAL^{32}$.

On meta-analysis, 3,915 SNPs reached the genome-wide significance threshold ($P < 5 \times 10^{-8}$) for association with age at menarche (Figure 1). The overall GC inflation factor was 1.266, consistent with an expected high yield of true positive findings in large-scale GWAS meta-analysis of highly polygenic traits³³.

Selection of independent signals

Given the genome-wide results of the meta-analysis, SNPs showing evidence for association at genome-wide significant P-values were selected and clumped based on a physical (kb)

threshold <1 Mb. The lead SNPs of the 105 clumps formed constitute the list of SNPs independently associated with age at menarche (Extended Data Tables 1-4).

To augment this list we performed approximate conditional analysis using GCTA software³⁴, where the LD between variants was estimated from the Northern Finland Birth Cohort (NFBC66) consisting of 5,402 individuals of European ancestry with GWAS data imputed using CEU haplotypes from Hapmap Phase II. Assuming that the LD correlations between SNPs more than 10 Mb away or on different chromosomes are zero, we performed the GCTA model selection to select SNPs independently associated with age at menarche at genome-wide significant *P*-values. This software selected as independently associated with age at menarche 115 SNPs at 98 loci, 11 of which had two or more signals of association (six loci contained two signals, four loci contained three signals, and one locus contained four signals). Plots of all 106 loci are available at www.reprogen.org. SNPs with A/T or C/G alleles were excluded from this analysis to prevent strand issues leading to false-positive results.

To summarize the information obtained from the single-SNP and GCTA analyses, the 105 SNPs selected from the uni-variate analysis and the 115 SNPs selected from the GCTA model selection analysis were combined into a single list of signals independently associated with age at menarche (Supplementary Table 2), using the following selection process (Extended Data Figure 1). For loci with no evidence of allelic heterogeneity, if the univariate signal was genome-wide significant, the lead uni-variate SNP was selected (94 independent association signals follow this criterion); otherwise the lead GCTA SNP was selected instead (one independent signal). For loci where evidence for allelic heterogeneity was found, all signals identified in the GCTA joint model were selected if GCTA selected the uni-variate index SNP (21 independent signals at 8 loci) or a very good proxy (r2>0.8) (7 independent signals at 3 loci). When instead GCTA selected a SNP independent from the uni-variate index SNP, both the lead uni-variate SNP and all signals identified in the GCTA joint model were selected (0 independent signals).

To determine likely causal genes at each locus, we used a combination of criteria. The gene nearest to each top SNP was selected by default. This gene was replaced or added to if the top SNP was (in high LD with) an expression quantitative-trait locus (eQTL) or a non-synonymous variant in another gene, or if there was an alternative neighbouring biological candidate gene. 31/123 signals mapped as eQTLs in data from Westra *et al.* (E)¹⁰, five were annotated as non-synonymous functional (F), 60 as biological candidates (C), and four mapped to gene deserts (nearest gene >500 kb) (Supplementary Tables 6-8). We also used publicly available whole blood and adipose tissue methylation-QTL data to map 9/123 signals to *cis*-acting changes in methylation level (Extended Data Table 5)⁹.

Follow up in the EPIC-InterAct study

We used an independent sample of 8689 women from the EPIC-InterAct study³⁵ to follow-up our menarche signals. To test associations between each identified SNP and age at menarche with correction for cryptic relatedness, we ran a linear mixed model association test implemented in GCTA³⁴ (--mlma-loco option), adjusting for birth year, disease status and research centre. Given the relatively small sample size compared to our discovery set,

directional consistency with results from the discovery-meta analysis was assessed using a binomial sign test. Variance explained by menarche loci was estimated using restricted maximum likelihood analysis in GCTA³⁴. In addition to the 123 confirmed menarche loci, variance explained in subsets of menarche loci below the genome-wide significance thresholds was also assessed.

eQTL analyses

In order to estimate the potential downstream regulatory effects of age at menarche associated variants, we used publicly available blood eQTL data (downloadable from http://genenetwork.nl/bloodeqtlbrowser/) from a recently published paper by Westra et al. (2013)¹⁰. Westra et al. conducted *cis*-eQTL mapping by testing, for a large set of genes, all SNPs (HapMap2 panel) within 250 kb of the transcription start site of the gene for association with total RNA expression level of the gene. The publicly available data contain, for each gene, a list of all SNPs that were found to be significantly associated with gene expression using a False Discovery Rate (FDR) of 5%. For a detailed description of the quality control measures applied to the original data, see Westra et al¹⁰. Their meta-analysis was based on a pooled sample of 5,311 individuals from 7 population-based cohorts with gene expression levels measured from full blood. We used the software tool SNAP (http://www.broadinstitute.org/mpg/snap/) to identify variants in close linkage disequilibrium (*r*² 0.8) with the trait associated variants. All eQTL effects at FDR 5% and also lists of the strongest SNP effect for all the significant genes are shown in Supplementary Table 7.

Index SNPs (or highly correlated proxies) were also interrogated against a collected database of eQTL results from a range of tissues. Blood cell related eQTL studies included fresh lymphocytes³⁶, fresh leukocytes³⁷, leukocyte samples in individuals with Celiac disease³⁸, whole blood samples^{39–43}, lymphoblastoid cell lines (LCL) derived from asthmatic children^{44,45}, HapMap LCL from 3 populations⁴⁶, a separate study on HapMap CEU LCL⁴⁷, additional LCL population samples^{48–50} (and Mangravite et al. (unpublished)), CD19+ B cells⁵¹, primary PHA-stimulated T cells⁴⁸, CD4+ T cells⁵², peripheral blood monocytes^{51,53,54}, CD11+ dendritic cells before and after *Mycobacterium tuberculosis* infection⁵⁵. Micro-RNA OTLs⁵⁶ and DNase-I OTLs⁵⁷ were also queried for LCL. Nonblood cell tissue eQTLs searched included omental and subcutaneous adipose^{39,50,58}, stomach⁵⁸, endometrial carcinomas⁵⁹, ER+ and ER- breast cancer tumor cells⁶⁰, brain cortex^{53,61,62}, pre-frontal cortex^{63,64}, frontal cortex⁶⁵, temporal cortex^{62,65}, pons⁶⁵, cerebellum^{62,65}, 3 additional large studies of brain regions including prefrontal cortex, visual cortex and cerebellum, respectively⁶⁶, liver^{58,67–70}, osteoblasts⁷¹, intestine⁷², lung⁷³, skin^{50,74} and primary fibroblasts⁴⁸. Micro-RNA OTLs were also queried for gluteal and abdominal adipose⁷⁵. Only results that reach study-wise significance thresholds in their respective datasets were included (Supplementary table 6). Expression data was also available on adipose tissue and whole blood samples from deCODE where parent-of-origin specific analyses were possible.

Parent-of-origin specific associations

Evidence for parent-of-origin specific allelic associations at imprinted loci was sought in the deCODE Study, which included 35,377 women with parental origins of alleles determined

by a combination of genealogy and long-range phasing as previously described⁶. Briefly, using SNP chip data in each proband, genome-wide, long range phasing was applied to overlapping tiles, each 6 cM in length, with 3 cM overlap between consecutive tiles. For each tile, the parental origins of the two phased haplotypes were determined regardless of whether the parents of the proband were chip-typed. Using the Icelandic genealogy database, for each of the two haplotypes of a proband, a search was performed to identify, among those individuals also known to carry the same haplotype, the closest relative on each of the paternal and maternal sides. Results for the two haplotypes were combined into a robust single-tile score reflecting the relative likelihood of the two possible parental origin assignments. Haplotypes from consecutive tiles were then stitched together based on sharing at the overlapping region. For haplotypes derived by stitching, a contig-score for parental origin was computed by summing the individual single-tile scores. Similarly, parent-of-origin specific allelic associations at imprinted loci were also sought in the deCODE blood cells and adipose tissue expression datasets.

Pathway analyses

Meta-Analysis Gene-set Enrichment of variaNT Associations (MAGENTA) was used to explore pathway-based associations in the full GWAS dataset. MAGENTA implements a gene set enrichment analysis (GSEA) based approach, as previously described⁷⁶. Briefly, each gene in the genome is mapped to a single index SNP with the lowest P-value within a 110 kb upstream, 40 kb downstream window. This P-value, representing a gene score, is then corrected for confounding factors such as gene size, SNP density and LD-related properties in a regression model. Genes within the HLA-region were excluded from analysis due to difficulties in accounting for gene density and LD patterns. Each mapped gene in the genome is then ranked by its adjusted gene score. At a given significance threshold (95th and 75th percentiles of all gene scores), the observed number of gene scores in a given pathway, with a ranked score above the specified threshold percentile, is calculated. This observed statistic is then compared to 1,000,000 randomly permuted pathways of identical size. This generates an empirical GSEA P-value for each pathway. Significance was determined when an individual pathway reached a false discovery rate (FDR) < 0.05 in either analysis. In total, 2529 pathways from Gene Ontology, PANTHER, KEGG and Ingenuity were tested for enrichment of multiple modest associations with age at menarche. MAGENTA software was also used for enrichment testing of custom gene sets.

Relevance of menarche loci to other traits

We assessed the relevance of identified menarche loci to other traits by comparing SNPs significantly associated with age at menarche with published GWAS findings or by using publicly available data from the Genetic Investigation of Anthropometric Traits (GIANT) consortium^{22,21} and the GEnetic Factors for OS (GEFOS) consortium²⁷. In addition, we requested look-ups up the 123 menarche SNPs for association with puberty timing assessed by Tanner staging in the Early Growth Genetics (EGG) consortium⁷⁷.

Supplementary Material

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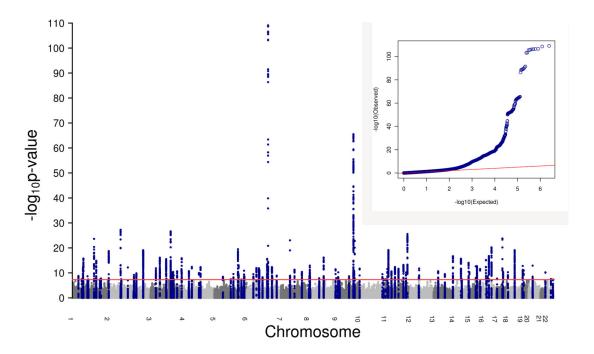


Figure 1. Manhattan and QQ plot of the GWAS for age at menarche

Manhattan (main panel) and quantile-quantile (QQ) (embedded) plots illustrating results of the genome-wide association study (GWAS) meta-analysis for age at menarche in up to 182,416 women of European descent. The Manhattan plot presents the association $-\log_{10}$ P-values for each genome-wide SNP (Y-axis) by chromosomal position (X-axis). The red line indicates the threshold for genome-wide statistical significance (P= 5×10^{-8}). Blue dots represent SNPs whose nearest gene is the same as that of the genome-wide significant signals. The QQ plot illustrates the deviation of association test statistics (blue dots) from the distribution expected under the null hypothesis (red line).

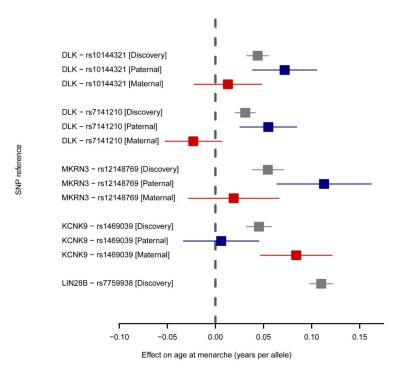


Figure 2. Forest plot of parent-of-origin specific allelic associations at three imprinted menarche loci

The forest plot illustrates the associations of variants in four independent genomic signals for age at menarche that are located in three imprinted gene regions. For each variant, squares (and error bars) indicate the estimated per-allele effect sizes on age at menarche in years (and 95% confidence intervals) from the standard additive models in the combined ReproGen meta-analysis (Black), and separately for the paternally-inherited (Blue) or maternally-inherited allele (Red) in up to 35,377 women from the deCODE study. The association for the menarche locus with the largest effect size at *LIN28B* is also shown for reference, illustrating the similar magnitude of effect size at the *MKRN3* locus when parent-of-origin is taken into account.

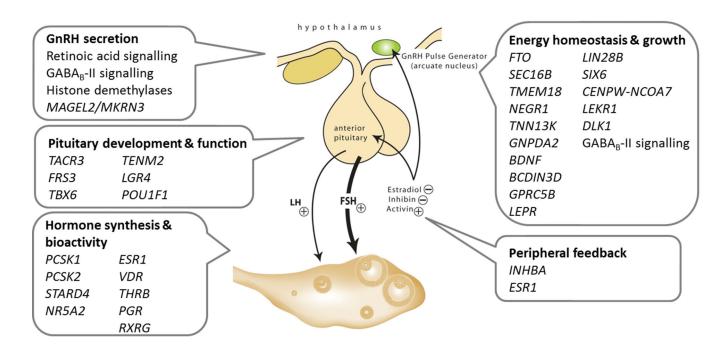


Figure 3. Schematic diagram indicating possible roles in the hypothalamic-pituitary-ovarian axis of several of the implicated genes and biological mechanisms for menarche timing