Genome-wide changes in lncRNA, alternative splicing, and cortical patterning in autism

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Summary Paragraph (196 words)

The genetic contributions to autism spectrum disorder (ASD) are substantial and profoundly heterogeneous,

potentially converging on common molecular and cellular pathways that still are not well understood[1-3].

Here, through genome-wide transcriptome analysis in the largest cohort of postmortem ASD brains

analyzed to date[4-7], we interrogate the noncoding transcriptome, alternative splicing, and upstream

molecular regulators to broaden our understanding of molecular convergence in ASD. Our analyses reveal

dysregulation of primate-specific long noncoding RNAs (lncRNAs), downregulation of the alternative

splicing of activity-dependent neuronal exons, and attenuation of normal gene expression differences

between frontal and temporal lobes in ASD. We further demonstrate that a genetically defined subtype of

ASD, Duplication 15q Syndrome (dup15q), shares the core transcriptomic signature observed in idiopathic

ASD. Co-expression network analysis reveals age related changes in microglial and synaptic function that

plateau after the first decade of life, and suggests that genetic risk for ASD may influence changes in

regional cortical gene expression. Our work implicates SOX5, a transcription factor involved in neuron fate

specification, in contributing to these diminished regional differences. These data and analyses show how

diverse genetic perturbations can lead to phenotypic convergence at multiple biological levels in a complex

neuropsychiatric disorder.

Main Text (2206 words)

We performed rRNA-depleted RNA-sequencing in 251 postmortem frontal and temporal cortex (FC

and TC) and cerebellum (CB) samples from 48 ASD and 49 control (CTL) subjects (Methods and Extended

Data Fig. 1a-h). We first validated differential gene expression (DGE) between ASD and CTL cortex (CTX)

by comparing with different individuals previously profiled by microarray[8], and found strong concordance

($R^2 = 0.60$, Figure 1a, Extended Data Fig. 1i), constituting an independent technical and biological

replication of shared molecular alterations in ASD CTX.

We next combined covariate-matched idiopathic ASD samples to evaluate changes across the entire

transcriptome and found 584 genes with increased and 558 with decreased expression in ASD relative to

CTL CTX (Figure 1b, Benjamini-Hochberg FDR < 0.05, linear mixed effects model, Methods). This DGE

signal is consistent across methods, unrelated to major confounders, and found in over two-thirds of ASD

samples (Extended Data Fig. 1j-m). We also performed a classification analysis to confirm that gene

expression in ASD can robustly separate samples by disease status (Extended Data Fig. 2a) and confirmed

the technical quality of our data with qRT-PCR (Extended Data Fig. 2b-c). We next evaluated enrichment

for pathways and cell types (Extended Data Fig. 2d-e), and found that the downregulated set is enriched for

neuronal genes and pathways, such as interneuron-enriched *PVALB* and *SYT2*, while the upregulated gene

set is enriched for genes expressed in microglia and astrocytes[8].

Although there was no significant DGE in CB (no genes significant at FDR < 0.05, P value

distributions in Figure 1b), similar to previous observations in a smaller cohort[8], there was a replication

signal in CB and overall concordance between ASD-related fold changes in CTX and CB (Extended Data

Fig. 2f-h). The lack of significant DGE in CB is explained by the consistently stronger changes in CTX

relative to CB (Extended Data Fig. 2h), which suggests that the CTX is more selectively vulnerable to these

transcriptomic alterations. We also compared our results to an RNA-seq study of protein coding genes in

ASD and CTL in occipital cortex[4]. Despite significant technical differences that reduce power to detect

DGE and different brain regions profiled in that study, there was a weak but significant correlation in fold

changes, which was due mostly to upregulated genes in both studies (P = 0.038, Extended Data Fig. 2i-j).

We next explored lncRNAs, most of which have little functional annotation. There were 60

lncRNAs in the DGE set (FDR < 0.05, Extended Data Fig. 2k), and multiple lines of evidence, including

developmental regulation in RNA-seq datasets and epigenetic annotations, support the functionality of most

of these lncRNAs (Supplementary Table 2). Moreover, 20 of these lncRNAs have been shown to interact

with miRNA protein complexes, and 9 with the FMRP protein, whose mRNA targets are enriched in ASD

risk genes[9,10]. As a group, these lncRNAs are enriched in the brain relative to other tissues (Extended Data

Fig. 2l-m) and most that have been evaluated across species exhibit primate-specific expression patterns in

brain[11], which we confirm for many by RNA-seq (Supplementary Information, Extended Data Fig. 3a-h).

We highlight two primate-specific lncRNAs, *LINC00693* and *LINC00689*. Both interact with

miRNA processing complexes and are typically downregulated during development, but upregulated in

ASD CTX relative to controls (Figure 1c-d, Extended Data Fig. 2n). These data demonstrate that

dysregulation of lncRNAs, many of which are brain-enriched, primate-specific, and predicted to affect

protein expression through miRNA or FMRP associations, is an important component of the transcriptomic

signature of ASD.

Previous studies have evaluated alternative splicing in ASD and its relation to specific splicing

regulators in small sets of selected samples across individuals[8,12,13]. Given the increased sequencing depth,

reduced 5′-3′ sequencing bias, and larger cohort represented here, we were able to perform a more

comprehensive analysis of differential alternative splicing (DS, Extended Data Fig. 4a). We found a

significant DS signal over background in CTX (1127 DS events in 833 genes, Methods), but not CB (P

value distributions in Extended Data Fig. 4b-c). We confirmed that confounders do not account for the DS

signal, reproduced the global DS signal with an alternative pipeline[14], and performed technical validation

with RT-PCR (Extended Data Fig. 4d-g, Extended Data Fig. 5a), confirming the robustness of the DS

analysis. Remarkably, DS analysis identified a convergent molecular signature that is not dependent on

DGE (Extended Data Fig. 4h), consistent with the observation that splicing alterations are related to

common disease risk independently from gene expression changes[15].

Cell-type specific enrichment and pathway analysis of alternative splicing demonstrated that most

DS events involve exclusion of neuron-specific exons (Figure 1e, Extended Data Fig. 4i). We next asked

whether the shared splicing signature in ASD could be explained by perturbations in splicing factors known

to be important in nervous system function[8,13] (Extended Data Figure 4j), and found a high correlations

between splicing factor expression and DS in CTX (Figure 1f), but not CB (Figure 1g). The absence of

neuronal splicing factor DGE or correlation with splicing changes in CB is consistent with the absence of a

DS signal in CB, and suggests that these splicing factors are contributing to CTX biased DS. Previous

experimental perturbation of three of these factors, *Rbfox1*[16], *SRRM4*[17], and *PTBP1*[18] shows strong overlap

with ASD CTX DS changes and supports these predicted relationships (Figure 1h, Extended Data Fig. 5b).

Given that DS events in ASD CTX significantly overlap those that are targets of neuronal splicing factors,

we hypothesized some may be involved in activity-dependent gene regulation. We asked whether these

events coincide with those shown to be regulated by neuronal activity[19] and found significant enrichment

(Figure 1h). This overlap supports a model of ASD pathophysiology based on changes in excitation and

inhibition balance and neuronal activity[20] and suggests that alterations in transcript structure are likely an

important component.

Lastly, when we compared the first principal component across samples for protein coding DGE,

lncRNA DGE, and DS across individuals (Figure 1i), we observed remarkably high correlations ($R^2 > 0.8$),

indicating for the first time that molecular convergence is likely a unitary phenomenon across multiple

levels of transcriptome regulation in ASD.

Previous analysis suggested that the typical pattern of transcriptional differences between FC and TC

may be attenuated in ASD[8]. We confirmed this in our larger cohort and identified 523 genes as significantly

different between FC and TC in CTL, but not ASD (Figure 2a), which we refer to as the "Attenuated

Cortical Patterning" (ACP) set (Extended Data Fig. 6a). We demonstrated the robustness of attenuation in

cortical patterning in ASD by confirming that the ACP set is not more variable compared with other genes,

that attenuation of cortical patterning is robust to removing previously used samples[8], and that the effect can

also be observed using a different classification approach (Extended Data Fig. 6b-h).

Pathway and cell-type analysis show that the ACP set is enriched for *Wnt* signaling, calcium

binding, and neuronal genes (Extended Data Fig. 6i-j, Supplementary Information). We next explored

potential regulators of cortical patterning by transcription factor (TF) binding site enrichment (Extended

Data Fig. 6k). Among those identified, the TF SOX5 was of particular interest because of its known role in

mammalian corticogenesis[21,22], its sole membership in the ACP set, and its correlation with predicted targets

in CTL, which is lost in ASD (Figure 2b-d). Overexpression of *SOX5* in human neural progenitors validated

that a significant proportion of ACP genes are regulated by SOX5, and that predicted SOX5 targets exhibit a

net downregulation, consist with its repressive function (Figure 2e; Extended Data Fig. 6l-m). This supports

the prediction that attenuated patterning of SOX5 between cortical regions contributes to direct alterations in

SOX5 targets and likely to indirect alterations in SOX5 non-targets in the ACP set.

We also evaluated DGE and DS in 9 individuals with Duplication 15q Syndrome (dup15q), among

the most common and penetrant forms of ASD, using independent controls (Extended Data Fig. 7a-b).

Significant upregulation in the 15q11.1-13.2 region (*cis*) is evident in duplication carriers, but not idiopathic

ASD (Figure 3a). Remarkably, genome-wide (*trans)* DGE and DS patterns are highly concordant between

dup15q and ASD (Figure 3b-c, Extended Data Fig. 7c-e). Moreover, alterations in dup15q CTX are

approximately three times the magnitude of those observed in idiopathic ASD CTX, and appear more

homogeneous than in idiopathic ASD (Figure 3d; Extended Data Fig. 7f-g). DGE analyses in CB confirmed

a weaker signal compared to CTX and demonstrated that *cis* changes in dup15q CB (Extended Data Fig. 7h-

j) exhibit greater concordance with CTX than *trans* changes (Extended Data Fig. 7k-l), further supporting

the observation that CTX exhibits a selective vulnerability to transcriptomic alteration in ASD. Taken

together, DGE and DS analyses in dup15q provide further biological validation of the ASD transcriptomic

signature and demonstrate that a genetically defined form of ASD exhibits similar changes as idiopathic

ASD.

We next applied Weighted Gene Co-expression Network Analysis (WGCNA, Methods), and

identified 24 co-expression modules and evaluated their biological functions and association with ASD

(Extended Data Fig. 8a-d). Of the 6 modules associated with ASD, 3 are upregulated, 3 are downregulated,

and 5 show significant cell-type enrichment (Figure 4a-b). This analysis corroborates and extends previous

work by identifying sub-modules of those previously identified, demonstrating greater biological specificity

(Extended Data Fig. 8e, Extended Data Fig. 9a). It also confirms that downregulated modules are enriched

for synaptic function and neuronal genes, upregulated modules are enriched for inflammatory pathways and

glial function[4,8], and microglial and synaptic modules exhibit significant anticorrelation (Figure 4c).

Furthermore, the downregulated modules CTX.M10 and CTX.M16 are enriched for genes previously

related to neuronal firing rate, consistent with the overlap of dysregulated splicing with events regulated by

neuronal activity (Extended Data Fig. 9b, Figure 1h). One glial and one neuronal module are highlighted in

Figures 4d-e (remainder in Extended Data Fig. 9c-e). Remarkably, the upregulated module CTX.M20 was

not found in previous analyses, overlaps significantly with the ACP set (FDR < 0.05, Extended Data Fig.

9a), and contains genes implicated in development and regulation of cell differentiation (Figure 4f).

We further leveraged our large sample and younger age-matched ASD and CTL samples to detect

differences in developmental trajectories in ASD compared to CTL. We identified a remarkable difference

in CTX.M19 and CTX.M20 during the first two decades of life (Figure 4g, additional age trajectories in

Extended Data Fig. 9f) that is most consistent with an evolving process during early brain development that

stabilizes starting in late childhood and early adolescence. We also found preservation of most CTX

modules in CB, but with weaker associations to ASD (Extended Data Fig. 10a-h, Supplementary Table 4),

consistent with the DGE analysis showing that ASD-related changes are of substantially lesser magnitude in

CB.

To determine the role of genetic factors in transcriptomic dysregulation, we evaluated enrichment in

genes affected by ASD-associated rare mutations and common variants (Extended Data Fig. 9a). One

module, CTX.M24, exhibits significant enrichment for rare mutations found in ASD, while rare *de novo*

mutations associated with intellectual disability are most strongly enriched in CTX.M22 (FDR < 0.05,

Extended Data Fig. 9a). Remarkably, CTX.M24 is significantly enriched for lncRNAs, genes expressed

highly during fetal cortical development, and genes harboring protein disrupting mutations found in ASD,

suggesting that lncRNAs will be important targets for investigation in ASD[10,23] (FDR < 0.05, Extended Data

Fig. 9a, Extended Data Fig. 9g). In contrast, enrichment for common variation is observed in CTX.M20

(FDR < 0.1, Extended Data Fig. 9h-1, Methods). Since CTX.M20 is enriched for the ACP gene set, this is

the first link between common variation and regional attenuation of gene expression in ASD. Several other

ASD-associated modules show a weaker common variant signal for ASD including CTX.M16, which also

shows a signal for schizophrenia. However, other phenotypes with far larger and better-powered genome-

wide association studies (GWAS) also demonstrate enrichment (Extended Data Fig. 9h-i). It will be

necessary to perform this analysis with larger ASD GWAS in the future to fully understand the extent and

specificity of the contribution of common variation to ASD risk.

These data contribute to a consistent emerging picture of ASD molecular pathology[4,7,8,10,23-25].

Parsimony suggests that rather than a secondary environmental hit, the highly overlapping patterns observed

in idiopathic ASD and Duplication 15q Syndrome, represent an evolving adaptive or maladaptive response

to a primary insult. Although we observe no significant association of the ASD-associated transcriptome

signature with either clinical or technical confounders, some of the changes likely represent consequences or

compensatory responses, rather than causal factors. In this regard, it is notable that the observed

transcriptome changes suggest an ongoing process triggered largely by prenatal factors[3,10,23], but that

evolves during the first decade of postnatal brain development.

We interpret these data to suggest that aberrant microglial-neuronal interactions begin in the first

decade of life, becoming more evident after late childhood. Remarkably, this corresponds to the period of

synapse elimination and stabilization after birth in humans[26,27], which may have significant implications for

intervention. Our analyses also reveal primate specific lncRNAs likely relevant to understanding higher

cognition[11,28], and that because of their co-expression with genes harboring ASD-associated protein coding

mutations are potential candidate ASD risk loci. As future investigations pursue the full range of causal

genetic variation contributing to ASD risk, these data will be valuable for interpreting genetic and epigenetic

studies of ASD and the relationship between ASD and other neuropsychiatric disorders.

Figures & Figure Legends (605 words)

Figure 1 | Transcriptome-wide differential gene expression and alternative splicing in ASD. a,

Replication of protein coding differential gene expression (DGE) in ASD vs CTL by comparing previously

evaluated (16 ASD vs 16 CTL on microarray[8]) and new age and sex-matched ASD samples in cortex (CTX,

15 ASD and 17 CTL). **b,** P value distribution of the linear mixed effect model DGE results for CTX and

cerebellum (CB). **c,** *LINC00693* and *LINC00689* are upregulated across ASD samples and downregulated

during cortical development[29]. **d,** UCSC genome browser track displaying reads per million (RPM) in ASD

and CTL samples along with sequence conservation for *LINC00693* and *LINC00689*. **e,** Cell-type

enrichment analysis of differential alternative splicing (DS) events from CTX using exons with ΔPSI > 50%

in each cell type compared to the others[30]. **f-g,** Correlation between the first principal component of the

CTX DS set and gene expression of neuronal splicing factors in CTX and CB (ASD vs CTL DGE P value in

parentheses). **h,** Enrichment among ASD DS events and events regulated by splicing factors and neuronal

activity. **i,** Correlations between the first principal component (PC) across the ASD versus CTL analyses for

different transcriptome subcategories. Bottom left: scatterplots of the PC for ASD (red) and CTL (black)

individuals. Top right: pairwise correlation values between PCs.

Figure 2 | Attenuation of cortical patterning in ASD cortex. a, Heatmap of genes exhibiting cortical patterning, with samples sorted by diagnosis and brain region. RIN, RNA integrity number. **b,** Schematic of transcription factor motif enrichment upstream of genes in the Attenuated Cortical Patterning (ACP) set, with the *SOX5* motif sequence logo. **c,** *SOX5* exhibits attenuated cortical patterning in ASD (lines connect FC-TC pairs from the same individual). FPKM: fragments per kilobase million mapped reads. **d,** Correlation between *SOX5* expression and predicted targets in CTL and ASD, with all ACP genes (top left), SOX5 targets from the ACP set (top right), SOX5 non-targets from the ACP set (bottom left), and background (all other genes, bottom right). Plots show the difference in correlation between *SOX5* and other genes in ASD and CTL (ΔR). **e,** Gene Ontology term enrichment for upregulated and downregulated genes with *SOX5* overexpression in neural progenitor cells compared. **f,** Enrichment analysis of the SOX5 differential gene expression (DGE) set in the ACP set and all other genes (background). The P value represents the significance in enrichment over background, two-sided Fisher's exact test.

Figure 3 | Duplication 15q Syndrome recapitulates transcriptomic changes in idiopathic ASD. a, Differential gene expression (DGE) changes across the 15q11-13.2 region for ASD and dup15q compared to CTL, error bars are +/- 95% confidence intervals for the fold changes. Asterisks indicate FDR < 0.05 across

1   this region. **b,** Comparison of DGE effect sizes in dup15q vs CTL and ASD vs CTL. **c,** Comparison of
2   differential alternative splicing effect sizes in dup15q vs CTL and ASD vs CTL. **d,** Average linkage
3   hierarchical clustering of dup15q samples and controls using the DGE and DS gene sets.
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Figure 4 | Co-expression network analysis. a, Signed association of module eigengenes with diagnosis
(Bonferroni-corrected P value from a linear mixed effects model, see Extended Data Fig. 8c and Methods).
Positive values indicate modules with an increased expression in ASD samples. Grey bars with labels
signify 6 ASD-associated modules. **b,** Cell-type enrichments for the ASD-associated modules. **c,**
Comparison of ASD-associated modules against each other by correlating module eigengenes. **d-f,** Module
plots displaying the top 15 hub genes along with the module's Gene Ontology term enrichment. **g,** Plot of
CTX.M20 and CTX.M19 module eigengenes across age. P values are for the difference between temporal
trajectories for ASD and CTL, permutation test (Methods).
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Methods

Brain tissue: Human brain tissue for ASD and CTL individuals was acquired from the Autism Tissue
Program (ATP) brain bank at the Harvard Brain and Tissue Bank (which has since been incorporated into
the Autism BrainNet) and the University of Maryland Brain and Tissue Bank, a Brain and Tissue
Repository of the NIH NeuroBioBank. Sample acquisition protocols were followed for each brain bank, and
samples were de-identified prior to acquisition. Brain sample and donor metadata is available in
Supplementary Table 1.

RNA sequencing, mapping, and quantification: Starting with 1μg of total RNA, rRNA was depleted
(RiboZero Gold, Illumina) and libraries were prepared using the TruSeq v2 kit (Illumina) to construct
unstranded libraries with a mean fragment size of 150bp (range 100-300bp) that underwent 50bp paired end
sequencing on an Illumina HiSeq 2000 or 2500 machine. Paired end reads were mapped to hg19 using
Gencode v18 annotations[31] via Tophat2[32]. Gene expression levels were quantified using union exon models
with HTSeq[33]. This approach counts only reads on exons or reads spanning exon-exon junctions, and is
globally similar to including reads on the introns (whole gene model) or computing probabilistic estimates
of expression levels (Extended Data Figure 1e-g). For additional information on sequencing and read
alignment parameters, please see the Supplementary Information.

Differential gene expression and replication analysis: DGE analysis was performed with expression
levels normalized for gene length, library size, and G+C content (referred to as "Normalized FPKM"). CTX
samples (frontal and temporal) were analyzed separately from CB samples. A linear mixed effects model
framework was used to assess differential expression in $\log_2$(Normalized FPKM) values for each gene for
cortical regions (as multiple brain regions were available from the same individuals) and a linear model was
used for CB (where one brain region was available in each individual, with a handful of technical replicates
removed). The individual donor identifier was treated as a random effect, while age, sex, brain region
(except in the case of CB, where there is only one region), and diagnoses were treated as fixed effects. We
also used technical covariates accounting for RNA quality and batch effects as fixed effects into this model
(Supplementary Information). Significant results are reported at FDR < 0.05, and full results are available in
Supplementary Table 2. We assessed replication between datasets by evaluating the concordance between
independent sample sets by comparing the squared correlation (R^2) of fold changes of genes in each sample
set at a defined statistical cut-off. We set the statistical cut-off in one sample set (the *y* axis in the
scatterplots) and compute the R^2 with fold changes in these genes in the comparator sample set (the *x* axis in
the scatterplots). For details on the regularized regression analyses and cortical patterning analyses, please
see the Supplementary Information. Details for RT-PCR validations are available in the Supplementary
Information.

Differential alternative splicing: Alternative splicing was quantified using the percent spliced in (PSI)
metric using Multivariate Analysis of Transcript Splicing (MATS, v3.08)[34]. For each event, MATS reports
counts supporting the inclusion (I) or exclusion (E) of a splicing event. To reduce spurious events due to
low counts, we required at least 80% of samples to have I + S ≥ 10. For these events, the percent spliced in
is calculated as PSI = I / (I + S) (Extended Data Fig. 4a). Statistical analysis for DS was performed utilizing
the linear mixed effects model as described above for DGE, significant results are reported at FDR < 0.5.
This approach is advantageous over existing methods as it allows modeling of covariates and takes into
consideration the variability in PSI across samples when assessing event significance with ASD
(Supplementary Information) and full DS results are available in Supplementary Table 3. Details for RT-
PCR validations are available in the Supplementary Information.

Duplication 15q syndrome samples and analyses: For dup15q samples, the type of duplication and copy
number in the breakpoint 2-3 region were available from previous work[35]. To expand to the regions

between each of the recurrent breakpoint in these samples, 8/9 dup15q brains were genotyped (one was not
genotyped due to limited tissue availability). The number of copies between each of the breakpoints is
reported in Extended Data Fig. 7a. DGE and DS analysis for this set was performed with independent CTL
samples from the main analysis, though the results were similar using the larger set of controls utilized in
the main analysis (Extended Data Fig. 7d-e).
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Co-expression network analysis: The R package weighted gene co-expression network analysis
(WGCNA) was used to construct co-expression networks using normalized data after the adjustment to
remove variability from technical covariates[36,37] (Supplementary Information). We used the biweight
midcorrelation to assess correlations between $\log_2$(Adjusted FPKM) and parameters for network analysis are
described in Supplementary Information. Notably, we utilized a modified version of WGCNA that involves
bootstrapping the underlying dataset 100 times and constructing 100 networks. The consensus of these
networks (median edge strength across all bootstrapped networks) was then used as the final network[38],
ensuring that a subset of samples do not drive the network structure. For module-trait analyses, the first
principal component of each module (eigengene) was related to ASD diagnosis, age, sex, and brain region
with a linear mixed effects model as above (Supplementary Information). Given that modules are relatively
uncorrelated to each other, significant eigengene-trait results are reported at Bonferroni-corrected $P < 0.05$.
Module temporal trajectories were computed with the LOESS function in R. For both ASD and CTL
samples, the function was used to create quartic splines on module eigengenes (degree=2, span=2/3). The
trend difference statistic was taken as the largest difference between these fitted curves between the ages of
5 and 25. P values were computed using 5,000 permutations. Specifically, ASD and CTL labels were
randomly permuted 5,000 times and splines were fit to the permuted groups, therefore significant P values
reject the null hypothesis of no relationship between age trends and disease status. Detailed statistics for
module membership are available in Supplementary Table 2 and additional characterization of modules is
available in Supplementary Table 4.
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Enrichment analysis of gene sets and common variation: Gene set enrichment analyses were performed
with a two-sided Fisher's exact test (cell type, splicing factor) or with logistic regression (Extended Data
Fig. 9a, Supplementary Information). Results were compared for multiple comparisons by the Benjamini-
Hochberg method[39] when a large number of comparisons were performed. Gene Ontology term enrichment
analysis was performed using GO Elite[40] with 10,000 permutations, and results are presented as enrichment
Z scores. We focused on molecular function and biological process terms for display purposes. Common
variant enrichment was evaluated by analysis of genome-wide association study (GWAS) signal with
stratified linkage disequilibrium (LD) score regression to partition disease heritability within functional
categories represented by gene co-expression modules[41]. This method uses GWAS summary statistics and
LD explicitly modelled from an ancestry matched 1000 genomes reference panel to calculate the proportion
of genome-wide single nucleotide polymorphism (SNP)-based heritability that can be attributed to SNPs
within explicitly defined functional categories. To improve accuracy, these categories were added to a "full
baseline model" which includes 53 functional categories capturing a broad set of genomic annotations as
described by Finucane et al., 2015[42]. Enrichment is calculated as the proportion of SNP-heritability
accounted for by each module divided by the proportion of total SNPs within the module. Significance is
assessed using a block jacknife procedure[42], which accounts for module size and gene length, followed by
FDR correction of P values.
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1   **Extended Data Figures & Legends**

Extended Data Figure 1 | Methodology, quality control, and differential expression replication analysis. a, RNA-seq workflow (Supplementary Information for details). **b,** RNA-seq quality and alignment statistics from this study, including RNA integrity number (RIN), sequencing depth (aligned reads), proportion of reads mapping to different genomic regions, and bias in coverage from the 5′ to the 3′ end of transcripts. **c,** RNA-seq read coverage relative to normalized gene length across transcript length across samples. **d,** Dependence between coverage and RIN across gene body. **e-g,** Correlation of transcript model quantifications comparing the union exon model (used in this study), the whole gene model (which includes introns), and the Cufflinks approach[43] to estimating fragments per kilobase of transcript per million mapped reads (FPKMs). **h,** Summary table describing the characteristics of the matched covariate data used in the DGE and DS analysis of ASD in CTX and CB. This includes the number of samples overlapping with our previous work[8], the age and RIN distributions, and the dependence between diagnosis and age and RIN (summarized from Supplementary Table 1). **i,** Independent replication of ASD vs CTL DGE fold changes between previously evaluated and new ASD samples in CTX by RNA-seq using samples from Voineagu et al., 2011 (similar to Figure 1a, but with RNA-seq in all samples). **j,** Correlation of P value rankings with Spearman's correlation across different DGE methods for DGE analysis in CTX, comparing the "full model" (LME P value) described in the Supplementary Information against other methods. Methods include removal of three additional principal components of sequencing surrogate variables (LME with 5 SVs, Supplementary Information), application of a permutation analysis for DGE P value computation (LME P, permuted), application of variance-weighted linear regression for DGE[44] (limma voom), application of surrogate variable (SV) analysis for DGE[45] (full model + 17 SVs), and application of DESeq2 with the full model[46], which uses a negative binomial distribution. **k.** Comparison of fold changes between frontal cortex (FC) and temporal cortex (TC) for all samples, demonstrating similar changes in both regions. **l,** Average linkage hierarchical clustering of samples in ASD CTX using the top 100 upregulated and top 100 downregulated protein coding genes demonstrating that confounders do not drive clustering of about two-thirds of samples. **m,** The first principal component of the CTX DGE set is primarily associated with diagnosis, and not other factors. The red line marks a Bonferroni-corrected P = 0.05.

Extended Data Figure 2 | Transcriptome-wide differential gene expression analysis. **a,** We applied a classification method robust to overfitting (elastic net model[47]) by training on the RNA-seq data from Voineagu et al. 2011 samples (Extended Data Fig. 1h, similar to the comparison in Extended Data Fig. 1i) and classifying ASD vs CTL status in independent samples. Results are shown as a comparison of classification scores (left) and area under the receiver operator characteristic curve (AUROC, right). Approximately 85% of ASD samples are classified successfully around a false positive rate of 20%. **b,** Summary table describing the subset of representative, covariate matched samples used for qRT-PCR validations. Supplementary Table 2 contains the underlying values. **c,** Fold changes from RNA-seq compared against fold changes from qRT-PCR (see Supplementary Table 2 for data). **d,** Gene Ontology (GO) term enrichment analysis of upregulated and downregulated genes in ASD. **e,** Enrichment analysis of cell-type specific gene sets (defined as genes with 5-fold higher expression in the cell type compared to the other cell types, Supplementary Information for details) with genes decreased and increased in ASD. **f-g,** Independent replication analysis of ASD vs CTL DGE fold changes between previously evaluated and new ASD samples from CB by microarray and RNA-seq using samples from Voineagu et al., 2011 (similar to Figure 1a and Extended Data Fig. 1i). **h,** Comparison of fold changes that were significant at FDR < 0.05 in the ASD vs CTL DGE analysis from CTX compared with fold changes observed in CB, revealing strong concordance but a lower average fold change in CB. **i,** Sample summary and quality control (QC) statistics for Gupta et al., 2014. Compare to Extended Data Figure 1b and see Supplementary Information for additional discussion. Compared to this study, samples from this other study were prepared by poly(A) selection RNA-seq, exhibit lower RNA integrity number (RIN, median 4.8 vs 7.3), have lower median sequencing depth (11 million vs 40 million), exhibit greater 5′-3′ bias, and have generally greater variability across all QC metrics. **j,** Comparison of fold-changes for the top significant genes from Gupta et al. 2014 (P < 0.01 as provided in their Supplementary Information) with the fold changes for the same genes in this study. Co-expression network analysis demonstrated that the moderate agreement is largely driven by concordance in upregulation of microglial genes in both studies (see Extended Data Fig. 8e). **k,** Average linkage hierarchical clustering of lncRNAs in the DGE set. FC, frontal cortex; TC, temporal cortex. **l,** Boxplots of the expression values of DGE lncRNAs in multiple tissue types from the Illumina Body Map as processed by Jaffe et al., 2015[29]. Lines above the plot indicate pairwise significance with a one-sided Wilcoxon rank sum test between brain and the other tissues. **m,** Similar to l, except for embryonic stem cells and stem cell derived cell types. **n,** RT-PCR validation of the two lncRNAs shown in Figure 1c-d, P values are computed with a two-sided Wilcoxon rank-sum test.

Extended Data Figure 3 | RNA-seq gene expression on genome browser tracks for selected primate-
specific lncRNAs in human, macaque, and mouse. a, For each lncRNA, expression for representative
samples for ASD vs CTL (top) in human, macaque (middle), and mouse (bottom) are shown. The genome
location for macaque and mouse displayed is syntenic to the human region, with the expected location of the
lncRNA highlighted. **b-g,** Examples of specific transcripts that show primate-specific (in human and
macaque, or only in human, but not in mouse) lncRNAs. **h,** Example of a strongly conserved lncRNA,
which shows robust expression in all three species.
8

Extended Data Figure 4 | Splicing analyses and validation in ASD. a, Schematic of the percent spliced in (PSI) metric used for differential alternative splicing (DS)[34]. **b,** Distribution of P values for changes in the PSI between ASD and CTL in CTX for all events and event subtypes. **c,** Distribution of P values for changes in the PSI between ASD and CTL in CB. **d,** Average linkage hierarchical clustering in CTX of ASD and CTL samples using top 100 differentially included and top 100 differentially excluded exons from the differential splicing (DS) set. **e,** The first principal component of the CTX DS set is strongly associated with diagnosis, but not other factors. Red line marks Bonferroni-corrected $P = 0.05$. **f,** Comparison of the CTX DS with the pipeline used here (TopHat2[43] followed by multivariate analysis of transcript splicing, MATS[48]) with PSI values obtained via another method (read alignment by OLego followed by PSI quantification with Quantas[14]). **g,** Comparison of ΔPSI values in nine splicing events between RT-PCR and RNA-seq (see Supplementary Table 3 for data). **h,** DS analysis identifies events independent of differential gene expression (DGE) signal. Top: difference between ASD and CTL in the DS set based on PC1 of the DS set at the PSI level, and PC1 of the gene expression levels of genes in the DS set. Bottom: Same comparison after removing nominally differentially expressed genes ($P < 0.05$). **i,** Gene Ontology term enrichment analysis of genes with differential splicing events in ASD. **j,** Clustering dendrogram and heatmap for neuronal splicing factor gene expression levels across samples demonstrating three major clusters and the known positive correlation between *SRRM4* and *RBFOX1* and anticorrelation between *PTBP1* and *SRRM4*[13,17].

Extended Data Figure 5 | Additional splicing analyses in ASD. a, PCR validation and sashimi plots for nine splicing events delineated in Extended Data Fig. 4d, from the indicated samples (Extended Data Fig. 2b for details on these samples). Notably, these genes are not in the differential gene expression set, but are detected in the differential alternative splicing set due to altered transcript structure. **b,** Heatmap as in Figure 1h for the splicing regulator ESRP[49]. ESRP is not known to be involved in neuronal function, *ESRP1* is not expressed in CTX, and *ESRP2* is expressed but not significantly different between ASD and CTX Therefore, we show *ESRP* enrichment analysis in DS events as a control for Figure 1h.

Extended Data Figure 6 | Attenuation of cortical patterning in ASD. a, Histograms of P values from paired Wilcoxon rank-sum test differential gene expression between 16 frontal cortex (FC) and 16 temporal cortex (TC) in CTL and ASD. **b,** Histogram of Bartlett's test P values for differences in gene expression variance between ASD and CTL for all genes (white) and genes in the Attenuated Cortical Patterning (ACP) set (red). The Kolmogorov-Smirnov (K-S) test P value for a difference between these two distributions is reported. **c,** Histograms of P values from unpaired Wilcoxon rank-sum test differential gene expression between 21 FC and 22 TC samples after removing those used in Voineagu et al., 2011[8]. **d,** Histogram of Bartlett's test P values for differences in gene expression variance between ASD and CTL for all genes (white) and genes in the Attenuated Cortical Patterning (ACP) set (red). The K-S test P value for a difference between these two distributions is reported **e,** Approach to training the elastic net model on BrainSpan[50,51] FC and TC samples and application of the model on 123 cortical samples in this study. **f-h,** Results of learned cortical region classifications with different starting gene sets, with the BrainSpan training set (left), CTL samples (middle), and ASD samples (right) in each panel and the Wilcoxon rank-sum test P value of FC vs TC difference for each comparison. A1C, primary auditory cortex; DFC, dorsolateral prefrontal cortex; MFC, medial prefrontal cortex; STC, superior temporal cortex; AUROC, area under the receiver operator characteristic curve. **i,** Cell-type enrichment analysis for genes in the ACP set. **j,** Gene ontology term enrichment analysis of the ACP set. **k,** Enrichment statistics for transcription factor motifs found to be significantly enriched in the ACP set (see Supplementary Information for details on P value computation). **l,** Average linkage hierarchical clustering of the global gene expression profiles for samples with overexpression of *SOX5* and GFP tag overexpression (controls). **m,** Density plots of fold changes for the subset of ACP genes that are predicted SOX5 targets (top, green) and non-targets (bottom, green) against background (grey). The median $\log_2$(fold change) is marked (red line) and P values are from a one-sided Wilcoxon rank-sum test.

Extended Data Figure 7 | Duplication 15q Syndrome analyses. a, Copy number between breakpoints
(BP) in the 15q region. Genome-wide copy number analysis allowed evaluation of copy number in
additional regions from previous studies[35]. **b,** Sample characteristics for the dup15q analyses, with
additional details available in Supplementary Table 1. **c,** Similar to Figure 3b, but focusing on the lncRNAs
found to be significant in idiopathic ASD samples. **d,** Comparison of differential gene expression (DGE)
fold changes demonstrating that using different CTL samples (CTL samples used in the idiopathic analysis,
column 2 of Extended Data Fig. 7b) for the dup15q cortex (CTX) analysis yields similar findings. **e,** Similar
to (d) except for the differential alternative splicing (DS) analysis. **f,** Comparison of heterogeneity in the
DGE signal using the first principal component of the ASD CTX DGE set across all cortical samples
utilized in DGE analyses. Samples from individuals with diagnoses confirmed by dup15q mutations,
confirmed by ADI-R, and supported by clinical records are all significantly different from controls by two-
sided pairwise Wilcoxon rank sum tests. **g,** Similar to Figure 3d, but with the larger set of controls from the
idiopathic ASD vs CTL analysis in Figure 1. **h-i,** P value distributions for DGE changes outside of the 15q
region for CTX and cerebellum (CB). **j,** Similar to Figure 3a, but for the CB analysis. **k,** Comparison of
significant DGE changes in the duplicated region from CTX with changes in CB. **l,** Comparison of
significant DGE changes outside of the dup15q region in CTX with changes in CB.

Extended Data Figure 8 | Cortex co-expression network analyses. a, Sample characteristics for the cortex (CTX) network analyses, with additional details available in Supplementary Table 1. **b,** Average linkage hierarchical clustering using the topological overlap metric for co-expression dissimilarity[36]. Modules are identified from this dendrogram, which is constructed from a consensus of 100 bootstrapped datasets[52,53] (Methods). Correlations for each gene to covariates are delineated below the dendrogram (blue = negative, red = positive correlation). Modules are labeled with colors and numerical labels (Supplementary Table 4 for additional details). CTX.M11 is a module of genes that are not co-expressed (grey module) and is not evaluated in further comparisons. **c,** Module-trait associations as computed by a linear mixed effects model with all factors on the x axis used as covariates. Technical covariates were removed as part of adjusting the FPKM values. All P values are displayed where the association passed Bonferroni-corrected $P < 0.05$. **d,** Module enrichments for cell-type specific gene expression patterns. Asterisks indicate FDR < 0.05 across all comparisons. **e,** Enrichment of ASD-associated modules with that from Gupta et al., 2015[4]. Asterisks indicate FDR < 0.05 (Supplementary Table 4 for details).

Extended Data Figure 9 | Additional figures for cortex co-expression network analyses. a, Gene set enrichment analyses comparing the 24 CTX co-expression modules with multiple gene sets from this RNA-seq study, postmortem ASD CTX microarray[8], human cortical development[10], the set of all brain-expressed lncRNAs, genes enriched for ASD-associated rare variants[54], and genes with *de novo* variants associated with intellectual disability (ID)[9]. Boxes are filled if the odds ratio is greater than 0, and the enrichment $P <$ 0.05. Asterisks indicate FDR < 0.05 across all comparisons, controlling for gene length and expression level with logistic regression (Supplementary Information). **b,** Overlap of gene sets between firing-rate and mitochondrial associated modules from Winden et al., 2009[55] with ASD-associated modules in CTX. **c-e,** Module plot of ASD-associated modules not shown in Figure 4 (CTX.M4, CTX.M9, CTX.M10) displaying the top hub genes along with the module's Gene Ontology term enrichment. **f,** Temporal trajectories for 4 modules (CTX.M4, CTX.M9, CTX.M10, CTX.M16) associated with ASD, similar to Fig. 4g. **g,** Module plot and Gene Ontology term enrichment for CTX.M24, which is enriched for ASD-associated rare variants and lncRNAs. **h,** Common variant enrichment across modules as calculated by genome-wide association study (GWAS) enrichment with linkage disequilibrium (LD) score regression[41,42] (Methods). Disease GWAS studies evaluated include ASD[56], schizophrenia[57], inflammatory bowel disease[58], type 2 diabetes mellitus[59], and serum lipid levels[60]. P values are FDR corrected across all GWAS studies and modules. **i,** Plot of the proportion of single-nucleotide polymorphism (SNP)-heritability across diseases for ASD-associated modules. Error bars represent standard errors.

2 **Extended Data Figure 10 | Cerebellum co-expression network analyses. a,** Sample characteristics for the
3 cerebellum (CB) network analyses, with additional details available in Supplementary Table 1. **b,** Modules
4 identified from a dendrogram constructed from a consensus of 100 bootstrapped networks (Methods).
5 Correlations for each gene to each measured factor are delineated below the dendrogram (blue = negative,

red = positive correlation). Modules are labeled alphabetically instead of numerically to distinguish them from the cortex (CTX) modules. Additional information is available in Supplementary Table 4. **c,** Signed association of module eigengenes with diagnosis; positive values indicate modules with an increased expression in ASD samples. Grey bars with labels signify 3 ASD-associated modules. **d,** Cell-type enrichments for the three ASD-associated modules. **e,** Gene set enrichment analyses comparing the 3 ASD-associated CB modules with postmortem ASD CTX microarray, human brain development, 6 CTX ASD-associated modules from this RNA-seq study and firing rate and mitochondrial associated modules from Winden et al., 2009[55]. Boxes are filled if the odds ratio is greater than 0, and the enrichment $P < 0.05$. Asterisks indicate FDR < 0.05 across all comparisons. **f-h**, Module plots of CB.ML, CB.MP, and CB.MT displaying the top hub genes along with the Gene Ontology term enrichment. Additional details, including module preservation statistics for CB in CTX and vice versa, are available in Supplementary Table 4.

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End Notes

None.

Author Contributions

NNP and DHG planned and directed experiments and wrote the manuscript with assistance from all authors. NNP, VS, and TGB performed dissections, RNA-seq analyses, and differential gene expression analysis. NNP and VS performed splicing analyses, MI and BJB provided splicing validation data and assisted with splicing analyses. NNP, VS, SH, GR, MJG, and CH performed co-expression network and associated analyses. NNP, TGB, VL, and JKL performed analyses of Duplication 15q Syndrome samples. VS performed RT-PCR validation experiments and VS, LTU, and JH performed SOX5 validation experiments.

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