Supplementary information

Appendix 1

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Fig. S1. SETX deficiency promotes chromosome fragility.

(A) DAP1-banding (gray-scale) images of M-FISH karyotypes shown in Fig 1F. Black arrows indicate chromosome aberrations.

(B) Western blot analysis of HAP1 WT and D*SETX* cells made by CRISPR/Cas9-mediated gene $targeting. \beta-tubulin, loading control.$

(C) M-FISH and DAPI-banding of metaphase spreads from HAP1 WT and Δ *SETX* cells showing deletions, translocations and chromosome fragility. Representative karyotypes are shown. Arrows indicate chromosome aberrations.

(D) Quantification of metaphases with indicated number of aberrations, as in (C). 30 metaphases were analyzed per condition.

(E) Immunostaining of HAP1 WT and D*SETX* cells with 53BP1 (red) antibody. Nuclear DNA was stained with DAPI (blue). Representative images of G1-phase cells are shown. White arrowheads indicate micronuclei.

(F) Quantification of 53BP1 nuclear bodies in G1 cells, as in (E). Cells were treated with or without cordycepin.

(G) Quantification of cells with indicated number of micronuclei, as in (E). Cells were treated with or without cordycepin.

Data are representative of three independent experiments. *P<0.05, **P<0.01 and ***P<0.001 by Mann-Whitney test. P \geq 0.05 is considered not significant (ns). Error bars represent s.e.m.

Fig. S2. Overlap analysis of CNCs identified in AOA2-P1 fibroblasts by array CGH.

(A) Pie chart representations of CNCs identified in the aCGH experiments described in Fig. 2A and B. Data from two independent experiments (replicates 1 and 2) are shown.

(B) Venn diagram of AOA2-P1 fibroblast gain or loss regions (red) and fragile sites (green) as in Fig 2C-E. Total genomic area and intersected area are reported.

(C) Top: Histogram showing overlaps between 1000 permuted AOA2-P1 fibroblast gain regions with CFSs. Bottom: Overlaps between 1000 permuted AOA2-P1 fibroblast loss regions with CFSs. Red line indicates the degree of overlap (in kb). P values for the overlap compared to permutations are indicated, with P<0.05 considered a significant enrichment/depletion.

(D) As (C) showing the overlaps between AOA2-P1 fibroblast gain and loss regions with the C/RFS.

(E) As (C) showing the overlaps between AOA2-P1 fibroblast gain and loss regions with the NFS.

Fig. S3. Genomic aberrations associated with AOA2 LCLs and mouse *Setx* k/o. (A) Pie chart representations of CNCs detected in two independent aCGH experiments (replicates 1 and 2) with genomic DNA from control (C1-C4 and C1.1) and AOA2 (P1-P4 and P1.1) LCLs.

(B) Western blot analysis of *Setx^{+/+}* and *Setx^{-/-}* MEFs. β-tubulin, loading control.

(C) As (A) but with genomic DNA from *Setx+/+* and *Setx-/-* MEFs, testis and cerebellum. (D) Ideograms indicating the chromosomal locations of CNCs. Regions of gain and loss are indicated with red and green bars, respectively.

Fig. S4. Differentially expressed genes identified in *SETX*-deficient human and mouse cells. (A) Heatmap of gene expression abundance across P1 and C1 LCLs. The top 10 most downregulated and 10 most upregulated genes, based on a fold change of normalized read count, are shown. Data are presented as log2(RPKM+0.01).

(B) As (A), using RNA-seq analyses from C2 and P2 LCLs.

(C) As (A), using RNA-seq analyses from C3 and P3 LCLs.

(D) As (A), using RNA-seq analyses from C4 and P4 LCLs.

(E) Heatmap of gene expression abundance, highlighting differences in expression between AOA2 and paired control LCLs from DESeq2 analysis (FDR≤0.05). All the downregulated (41) and upregulated (55) genes based on fold change are presented. Data are rlog transformed to stabilize variance and normalize with respect to library size, then scaled per-gene using a z-score.

(F) As (A), using RNA-seq analyses from *Setx*+/+ and *Setx*-/-mouse MEFs.

(G) As (A), using RNA-seq analyses from HAP1 WT and Δ *SETX* cells.

(A) RNAPII traveling ratio (TR) distribution of all genes (n=20265) in HAP1 WT and Δ *SETX* cells, along with input controls. The y-axis indicates percent of all genes. Higher TR values indicate a higher degree of RNAPII pausing.

(B) As (A), except TR was analyzed only for genes with RNAPII peak over TSS (n=10132).

(C) As Fig 4C, except that cumulative curves of RNAPII RoTR from two independent ChIP-seq experiments are shown.

(D) Nucleotide frequencies in the [-800, +400] region around the TSS of 7492 genes identified in the RoTR analysis. GC skew and GC content (GC%) in the region are shown.

(E) DRIP-qPCR assays were carried out using HAP1 WT and D*SETX* cells, either untreated or treated with RNase A or RNase H. The *SETX*-target gene promoter and negative control (SNRPN) regions were analyzed. Data represent the mean \pm s.e.m of three independent experiments.

(F) As Fig 4E, except that Ensembl genes are stratified into short/medium/long groupings based on the quantiles from the gene-width distributions. 'short' = shortest 20%, 'medium' = middle 40-60% of widths and 'long' = longest 20%.

Fig. S6. Transcription stress causes chromosome instability in the absence of SETX.

(A) Schematic of aCGH experiments carried out with HAP1 WT and $\triangle SFTX$ cells. On day 1 and day 4 post seeding, ΔSETX cells were transfected with or without GFP-RNaseH1 (RNH1) or GFP-RNH1^{D210N}. On day 7, aCGH was performed with WT vs WT, WT vs $\triangle SETX$, WT vs $\triangle SETX +$ RNH1 and WT vs $\Delta SETX$ + RNH1^{D210N}. Donut chart representations of CNCs identified in the aCGH experiments described in Fig 5A and D. Data from two independent experiments (replicates 1 and 2) are shown.

(B) Representative genome browser screenshot of RNAPII pausing over the indicated genomic region that is amplified in D*SETX* (red) compared to WT (blue) cells. R-loops are shown in black. All genes in the region are shown below. Scale bar, 50kb.

(C) ChIP-qPCR analyses at *WWOX*, *CDH13 and SNRPN* (negative control) genes using a g-H2AX antibody was carried out with cross-linked chromatin from HAP1 WT and $\triangle SETX$ cells. Fold enrichment was calculated as a ratio of γ -H2AX antibody signal versus control IgG. Data represent the mean \pm s.e.m of three independent experiments.

Fig. S7. Model for the role of Senataxin in response to transcription stress (RNAPII pausing, ROS damage).

Senataxin facilitates R-loop repair (RLR) by promoting the removal of R-loops at transcription sites, particularly near regions of RNAPII pausing, and thereby protects against genome stability. In the absence of SETX, CSB recognizes stalled RNAPII and transcription-coupled repair (TCR) proteins/recombination factors (e.g. RAD52) are recruited to resolve and repair transcription bubbles containing R-loops, but at the expense of faithful maintenance of the genome.

*Appendix 1***, Supplementary Methods & Data Analyses**

Quantification and statistical analysis. Statistical details of experiments, including statistical tests, number of events quantified, standard deviation, standard error of the mean, and statistical significance, are reported in the figures and figure legends. GraphPad Prism7 or 8 software (GraphPad) was used for the statistical analyses of cell biology experiments.

Analysis of array comparative genomic hybridization data. Data extraction, analysis and visualization were performed using Agilent Cytogenomics 2.7.11.0 software for human samples or the Agilent Feature Extraction 12.0.0.7 and Agilent Genomic Workbench 7.0.4.0 software for mouse samples (Agilent Technologies). Analysis settings were as follows: genome, hg19 (human) or mm9 (mouse); aberration algorithm, ADM-2; threshold: 6.0; window size, 2 kb; aberration filter, \geq 3 probes and $log2$ ratio \geq 0.25. The following log2ratio were used to score the aberrations: Amplification, log2ratio \geq 2; Gain, log2ratio between 0.25 to 2; Loss, log2ratio between -0.25 to -1 ; Deletion, log2ratio ≤ 1 .

GREAT analysis. Genomic Regions Enrichment of Annotations Tool (GREAT) was performed as described (1).

Analysis of gene expression data. Affymetrix gene expression data were analysed using Bioconductor 2.5 (https://www.bioconductor.org) running on R version 2.10.0 (2). Probeset expression measures were calculated using the Robust Multichip Average (RMA) method with the oligo package (3, 4). Differential gene expression was assessed between AOA2 and control sample groups using an empirical Bayes t-test (limma package) (5). p-values were adjusted for multiple testing correction using the Benjamini-Hochberg method (6). Probesets that exhibited an adjusted p-value of 0.05 or less were called differentially expressed. Differentially expressed probes were used to determine pathway and biological process enrichment using the Clarivate Analytics Metacore pathway analysis tool. Pathways or processes that showed FDR < 0.05 were called as enriched.

Circos plots. The Bioconductor package ggbio was used to construct the circos plots (7). The genomic locations of Aphidicolin Sensitive breakome Regions (ASR), Common Fragile Sites (CFS), Common and Rare Fragile Sites (CRFS), Early Replicating Fragile Sites (ERFS) and Neocarzinostatin Sensitive breakome Regions (NSR) were described previously (8-12). The RDC genes were described previously (13, 14).

Alignment and quantification of mRNA-seq data. Reads were aligned either against hg19 (human) or mm9 (mouse) and their respective Refseq annotations using STAR v2.5.1b (15) via the transcript quantification software RSEM v1.2.31 (16). The resulting genome alignment BAM files were sorted and indexed using SAMtools 1.3.1 (17). Duplicate reads were marked using Picard 2.1.1 (http://broadinstitute.github.io/picard). The resulting gene-level estimated read counts were rounded to integers and further analyzed for differential expression using the Bioconductor package DESeq2 1.12.3 (18).

Differential expression of mRNA-seq data. Genes changing between AOA2 and control lymphoblastoid cell lines were tested in paired fashion. Significant genes were thresholded based on a Benjamini-Hochberg FDR \leq 0.05, absolute fold-change \geq 1.5 and a minimum normalized read count > 10 in either the AOA2 or control samples. Data were rlog transformed for heatmap visualization, providing variance shrinkage and normalizing with respect to library size. The heatmap showing 4 AOA2 LCLs was additionally scaled by taking gene-wise z-scores. Genes changing between human HAP1 WT and $\triangle SETX$ samples were assessed using an absolute fold change > 1.5 , together with a normalized read count > 10 in either the $\triangle SETX$ or WT sample. The top 10 largest changing genes in each direction were used for heatmap visualization. Genes changing between mouse Setx^{+/+} and Setx^{-/-} MEFs were assessed using an absolute fold change > 2, together with a normalized read count > 30. The top 10 largest changing genes in each direction were used for heatmap visualization.

Gene Set Enrichment Analysis. Pre-ranked Gene Set Enrichment Analysis (GSEA) analysis was conducted using Bioconductor's "fgsea" package against the Gene Ontology: Biological Process gene collection defined in the Bioconductor package org.Hs.eg.db. Entrez Gene IDs were used for gene-term mappings. Gene sets containing <100 or >500 genes were discarded prior to testing. Genes not associated with an Entrez gene ID were discarded prior to testing. Genes were ranked on the Wald test statistic from the differential expression analysis. Results were thresholded using a Benjamini-Hochberg adjusted pvalue<0.05.

Overlap test. Permutation-based overlap tests were performed to assess whether human and mouse CNCs, gains and losses, were enriched for various fragile sites and/or genic regions. Gains and losses were considered independently and the analysis was restricted to the autosomes. Each gains/loss list was permuted 1000 times by assigning random genomic windows in either the hg19 (human) or mm9 (mouse) genome, with sizes equal to the original regions. These permuted windows were not permitted to overlap gaps in the reference genome, overlap each other, or overlap regions in the original gains/losses list. The permutations were then compared to each fragile site list or gene list, and the total number of overlapping base pairs determined. The number of overlapping base pairs between the true regions and the list of interest was compared to the permutation distribution by calculating a z-score and an associated two-tailed p-value. Overlap tests were also carried out to determine if gains and losses were associated with upregulated and downregulated genes. The locations of differentially regulated genes for both human and mouse were determined by comparison with the hg19 and mm9 NCBI RefSeq databases (19). For humans, 1250/1310 upregulated genes and 1046/1089 downregulated genes were identified, and for mouse, 666/684 upregulated genes and 458/470 downregulated genes. The locations were then used as the basis for overlap testing versus the gain/loss regions.

Alignment of ChIP-seq data. Single-end reads (75 bp) were aligned to the hg19 genome assembly using BWA-MEM 0.7.15 (17) with default settings. BAM files were sorted and indexed using SAMtools 1.3.1 (17). Duplicate reads were marked using Picard 2.1.1 (http://broadinstitute.github.io/picard).

Peak calling. RNAPII peaks from individual HAP1 WT and $\triangle SETX$ replicate samples were called against their respective input controls using MACS2 2.1.1 software (20) with the following command line options: '-g hs -q 0.05 -m 5,50'. Peak sets were thresholded for significance based on a q-value \leq 0.01 and a fold enrichment \geq 5, before taking the intersect of regions common to both WT or $\triangle SETX$ biological replicates. Peaks were further restricted to a set within +/- 500 bp of a Refseq gene's TSS.

Meta-gene profiles. Meta-gene profiles of RNAPII coverage were created using ngs.plot software (21) using standard Ensembl protein-coding gene definitions, n= 20,242. Coverage is represented as Read count Per Million mapped reads (RPM).

Traveling ratios. Travelling ratios were calculated as described (22). Briefly, each transcript was divided into: i) a promoter-proximal bin −30 bp to +300 bp around its TSS and ii) a gene body bin to the TTS. The traveling ratio is the ratio of RNAPII density in the promoter-proximal bin to that in the gene body. The most abundant transcript based on mean promoter RPKM across all samples was taken to be representative of the gene and all other transcripts were discarded. Transcripts for which a travel ratio was calculated to be zero (i.e. no reads in the promoter) or infinite (i.e., no reads in the gene body) in any of the samples were removed from the analysis, n = 20,265 transcripts (genes). An additional pre-filter, limiting the analysis to transcripts with a significant RNAPII peak (see peak calling) over their TSS leaving n = 10,132 transcripts (genes).

Ratio of traveling ratios. The ratio of traveling ratios (RoTR) was defined as the traveling ratio over a specific transcript for an RNAPII sample, divided by the traveling ratio of its respective control on the same transcript. Transcripts were limited to genes with i) a WT or $\triangle SETX$ RNAPII promoter peak, ii) \geq 2kb distant from a neighboring gene on the same strand, and iii) between 2kb and 300kb in width. The most abundant transcript based on mean promoter RPKM across all samples was taken to be representative of the gene and all other transcripts were discarded. For the purposes of visualization, transcripts for which a travel ratio was calculated to be zero (i.e., no reads in promoter) or infinite (i.e., no reads in gene body) in any of the samples were removed from the analysis, leaving 7,492 transcripts (genes). Genes were stratified into width categories based on the quantiles of the gene width distribution: short: <20%, medium: 40-60% and long: >80%. A Wilcoxon rank sum test was used to assess the significance of differences between RoTR distributions.

GCskew. GCskew (strand asymmetry in the distribution of guanines and cytosines) was calculated around the TSS (+/- 400 bp) of the 7492 genes identified in the RoTR analysis as follows: GC skew = $(G - C)/(G + C)$

Base composition. The proportion of each base was calculated around the TSS (+/-400bp or -800 to +400bp) of the 7492 genes identified in the RoTR analysis at single bp resolution. GC-content was calculated as the percentage of the nucleotides that possess either "G" or "C" bases. GCskew was calculated as described. Where appropriate a loess curve was fitted to the data.

BigWig files. BigWig files representing genome-wide read depth coverage were generated from BAM alignment files using BEDtools' genomeCoverageBed function (23). BedGraph files were in turn converted to bigWig format using the bedGraphToBigWig function from the KentTools package (24). Genome browser profiles were generated using the UCSC browser.

*SI Appendix***, Table S1**

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