

advances.sciencemag.org/cgi/content/full/6/30/eaba3064/DC1

# Supplementary Materials for

## **Diverse noncoding mutations contribute to deregulation of cis-regulatory landscape in pediatric cancers**

Bing He, Peng Gao, Yang-Yang Ding, Chia-Hui Chen, Gregory Chen, Changya Chen, Hannah Kim, Sarah K. Tasian, Stephen P. Hunger, Kai Tan\*

\*Corresponding author. Email: tank1@email.chop.edu

Published 24 July 2020, *Sci. Adv.* **6**, eaba3064 (2020) DOI: 10.1126/sciadv.aba3064

### **The PDF file includes:**

Supplementary Methods Figs. S1 to S6 Tables S1 to S4 References

### **Other Supplementary Material for this manuscript includes the following:**

(available at advances.sciencemag.org/cgi/content/full/6/30/eaba3064/DC1)

Table S2

## **Supplementary Methods**

# **Disease-relevant cell types used to construct the enhancer and enhancer-promoter catalogs**

For B-cell acute lymphoblastic leukemia (B-ALL), we used data of the following cell types: GM12878, CD19+ B cell, naïve B cell, total B cell. For acute myeloid leukemia (AML), we used data of the following cell types: K562, NB4, monocyte, monocyte progenitor, megakaryocyte, eosinophil, erythroblast, neutrophil, macrophage. For neuroblastoma (NBL), we used data of the following cell types: SK-N-SH, SH-SY5Y, neural crest cell, IMR-5/75. For Wilms tumor (WT), we used data of the following tissue/cell types: adult kidney, HEK293, IMR-5/75, RT407, G401, 786-O. For osteosarcoma (OS), we used data of the following cell types: Osteoblast, U2OS, SaOS2. The sources of the data sets are provided in Table S1.

#### **Prediction of active enhancers using histone mark ChIP-Seq data**

Enhancers were predicted using the Chromatin Signature Inference using Artificial Neural Network (CSI-ANN) algorithm (*13*). The inputs to the algorithm are normalized ChIP-Seq signals of three histone marks associated with enhancers (H3K4Me1, H3K4Me3, H3K27Ac). We used public histone mark ChIP-Seq data of human cell/tissue types relevant to the five cancer types in this study (Table S1). Raw ChIP-Seq data were first mapped to human GRCh37 genome using Bowtie2 (v2.1.0). CSI-ANN combines signals of all histone marks and uses an artificial neural network-based classifier to make predictions of active enhancers. A training set for the classifier was prepared using ENCODE data of GM12878, K562, and hESC cells. Specifically, a set of promoter-distal p300 binding sites

(2.5 kbp away from RefSeq TSS) in all three cell types was selected. The top 500 distal p300 sites that overlap with H3K4Me1 and H3K27Ac peaks, but not with H3K4Me3 peaks (promoter mark), were selected as the positive training set. One thousand randomly selected genomic regions and 500 active promoter regions were used as the negative training set. Enhancers were predicted using a false discovery rate (FDR) cutoff of 0.05. Predicted enhancers that overlap by >500 bp were merged by selecting the enhancer with the highest CSI-ANN score.

#### **Prediction of SNVs that disrupt transcription factor binding**

We used the Find Individual Motif Occurrences (FIMO) software to scan the 100 bp sequences flanking SNVs. A collection of transcription factor DNA binding motifs from the Cis-BP database (v1.02) was used for motif scan (*48*). Motif score differences between the sequences harboring the alternative alleles of the SNV were computed. To determine if one of the alleles of a SNV causes significance change in the TF motif score, a p-value for the TF motif score difference was calculated using a null distribution computed with all SNPs identified by the 1000 Genome Project. P-values were adjusted for multiple testing using the Benjamini-Hochberg method.

#### **Prediction of enhancer-promoter interactions**

Target promoters of enhancers were predicted using the Integrated Method for Predicting Enhancer Targets (IM-PET) algorithm (*14*). It predicts enhancer-promoter interactions by integrating four features derived from transcriptome, epigenome, and multiple genome sequence data, including: 1) enhancer-promoter activity correlation, 2) transcription factorpromoter co-expression, 3) enhancer-promoter co-evolution, and 4) enhancer-promoter distance. Public histone mark ChIP-Seq and RNA-Seq data (Table S1) were used to compute values of features 1, 2 and 4. Values of feature 3 were computed based on sequence conservation across 15 mammalian species (human, chimp, gorilla, orangutan, gibbon, rhesus, baboon, marmoset, tarsier, mouse lemur, tree shrew, mouse, rat, rabbit, and guinea pig). We used an FDR cutoff of 0.01 for making predictions.

#### **Parameter optimization of the weighted elastic net model**

The translocation t(14,X) is known to hijack a super enhancer on chromosome 14 to near *CRLF2* gene and result in the overexpression of *CRLF2*. To optimize parameters of the weighted elastic net (WEN) model, we constructed the mutation count matrix of *CRLF2* disrupting its cis-regulatory elements. We used 10-fold cross-validation to tune the parameters of the WEN model. In each iteration, we used the data of 147 patients for training the model. The trained model was then used to predict *CRLF2* expression using data from the remaining 16 patients. Since our model predicts expression value with cisregulatory mutations (e.g. enhancer mutations or mutations disrupt enhancer-promoter interactions) (predictors), we define a mean squared error as the difference between expected expression value based on the fitted model and observed expression value of *CRLF2*. The model fitting of the weighted elastic net is done using the Least Angle Regression (LARS) algorithm implemented in the "AdapEnetClass" R package. The WEN model has two adjustable parameters: penalty parameter  $\lambda_2$  and forward selection step of LARS algorithm. The penalty parameter  $\lambda_2$  controls the strength of the penalty term in the ridge regression and LASSO regression. The forward step of the LARS algorithm controls

the number of predictors considered by the model. We tested a combination of six different  $\lambda_2$  values (0, 0.1, 0.5, 1, 2, 3) and fifteen forward steps (1-15). We also performed the tenfold cross validation using permutated CRLF2 expression values. The model generated using real data out-performed the ones generated using permutated data, suggesting the robustness of the trained model (Fig. S1M). We also tested the sensitivity of prediction result on parameter setting. We made predictions using three  $\lambda_2$  values, 0.1, 0.2, and 0.3. Generally with the increase of  $\lambda_2$ , the number of predicted genes decreased modestly (4% decrease with  $\lambda_2$  = 0.2 and 15% decrease with  $\lambda_2$  = 0.3). And the genes predicted with  $\lambda_2$  = 0.2 or 0.3 were roughly a subset of genes predicted with  $\lambda_2$  = 0.1 (Fig. S1M). Based on these analyses, we chose to use  $\lambda_2 = 0.1$  and forward step = 15 to make the final predictions in this study.

The statistical significance of each regression coefficient was computed using the "AdapEnetClass" R package. The p-values were adjusted for multiple-testing with the Benjamini-Hochberg method. As a result, our method selects mutations that are significantly associated with the gene expression change in the patients with an adjusted  $p$ -value  $< 0.05$ .

#### **Evaluation of false prediction rate using an independent cohort**

To validate the recurrence of predicted causal noncoding mutations, we followed the method described in (*49*) to generate the quantile-quantile (QQ) plot. We downloaded simple somatic mutations and somatic structural variants in 2,715 donors from the ICGC data portal. For each genes affected by noncoding mutations, the number of mutated patients, k, was used as the test statistic. In our analysis with TARGET data, 2% of SNVs in enhancer/promoter regions affect gene expression, and 24% of structural variant break points affect gene expression. To compute the background mutation rate (BMR) for each gene in each ICGC donor, we counted the number of structural variants in 200 kbp region and the number of SNVs in enhancers/promoters and computed the BMR under the assumption that the causal noncoding mutations rate is the same as the TARGET data. Then we computed the probability of having observed k or more mutations in n patients in the gene of interest using a Poisson binomial model:

$$
P(K \ge k) = \sum_{l=k}^{n} \sum_{A \in F_l} \prod_{i \in A} p_i \prod_{j \in A^c} (1 - p_j)
$$

where  $F_l$  is the set of all subsets of k integers that can be selected from  $\{1, 2, ..., n\}$ ,  $p_i$  or  $p_j$ is the probability that patient *i* or patient *j* has the mutation; A is a set of k integers that can be selected from  $\{1, 2, \ldots, n\}$  and  $A^c$  is the complement of A. We used an approximation for the Poisson binomial distribution implemented in the Python package, poibin. The QQ plot shows the observed P values versus P-values based on random expectation.

#### **Replication timing analysis**

Genome-wide replication timing data for GM12878, K562, SK-N-SH, HEK293, and U2OS cells were downloaded from the Replication Domain database (*50*). These data were generated using the repli-seq method (*51*). Briefly, cells were sorted into early (S) and late (G1) phase fractions on the basis of DNA content using flow cytometry. BrdUlabeled DNA from each fraction was immunoprecipitated, amplified, and sequenced. The replication timing was measured as the  $log<sub>2</sub>$  ratio of early over late fraction reads in 5 kb bins. The replication timing for each gene was calculated as the average log<sub>2</sub> ratio of early over late fraction reads across the whole gene body.

#### **Regulon disruption of transcription factors in cancer patients**

Regulon of a transcription factor is defined as the set of target genes of the TF. To identify the target gene, the enhancer and promoter sequences of the gene is scanned for binding motif hit of the TF using Find Individual Motif Occurrences (FIMO) and an FDR cutoff of 0.01 (*52*). The regulon of a given TF is defined as disrupted if at least one of the following three scenarios is observed: 1) coding region of the TF gene is mutated; 2) at least one TF binding site in the enhancer/promoter of a target gene is mutated; 3) at least one enhancer-promoter interaction involving the TF and a target gene is disrupted by a SV. We ranked the transcription factors according to the number of patients with regulon disruption by combined coding and noncoding mutations.

#### **Mutual exclusivity and co-occurrence of mutations**

We tested mutual exclusivity and co-occurrence of mutations for genes mutated in at least 5 patients. For a given gene pair, we performed Fisher's exact test using the Comet R package (*53*). The Benjamini-Hochberg method was used to correct for multiple testing.

## **Clustering of cancer subtypes**

We first generated a joint mutational profile for each patient covering both coding and noncoding mutations. These include: non-silent point mutations in the coding region, copy number alterations in the coding region, gene fusion, SNVs or small indels in enhancers/promoters of the gene, copy number alterations affecting enhancers and

enhancer rearrangement. We performed hierarchical clustering to identify patient groups based on their joint mutational profiles. We used the elbow method to determine the optimal number of clusters. To do so, we cut the hierarchical clustering dendrogram to generate different numbers of clusters ranging from two to fifteen. For each number of clusters, the total within-cluster sum of square (WSS) was calculated. The curve of WSS versus the number of clusters was plotted. The location of a bend in the plot was used to determine the optimal number of clusters**.**

### **RT-qPCR**

Total RNA was isolated using the RNeasy micro kit (Qiagen) including on-column DNase digestion to remove genomic DNA. cDNA was synthesized from total RNA using the highcapacity cDNA reverse transcription kit (Applied Biosystems) according to the manufacturer's instructions. qPCR reactions were performed on a Bio-Rad CFX Connect real-time PCR system with iQ™ SYBR<sup>®</sup> Green Supermix (Bio-Rad) according to manufacturers' instructions. Relative gene expression was calculated using the 2<sup>-ΔΔCt</sup> method using *Tbp* as the reference gene. Each sample was assayed in duplicate, and at least three independent samples were analyzed for each experimental condition.

#### **Luciferase reporter assay**

Candidate enhancer (~3 kb) was cloned into the luciferase reporter vector pGL3 (Promega) using in-fusion HD cloning kit (Clontech). A super core promoter 1 (SCP1) (*54*) was used as the basal promoter. A negative control region of similar length with no enhancer-associated histone modification signals was also cloned into the same vector as a negative control. Reporter constructs were co-transfected with the internal control construct pRL-TK (Promega) into Ba/F3 cells by electroporation. 48h post transfection, cells with three independent transfections were harvested and measured for firefly and Renilla luciferase activities using the dual-luciferase reporter assay system (Promega). Firefly luciferase activity of individual transfections was normalized against Renilla luciferase activity.

## **sgRNA design**

The sgRNAs targeting *CHD4* were designed by Feng Zhang's laboratory (*55*). The sequences for non-targeting control sgRNAs were based on a previous publication (*56*). All sequences are listed in Table S4.

#### **Competition growth assay**

NALM-6 and REH cells stably expressing Cas9 (NALM6-Cas9 and REH-Cas9) were separately transduced with the lentiviral vectors carrying *CHD4*-sgRNA-GFP or SafesgRNA-mCherry. Three days post transduction, transduced cells were pooled together. Depletion of fluorescence signal was measured by flow cytometry at indicated time points.

## **Supplementary Figures**

## **Figure S1. Identification of putative causal noncoding mutations affecting enhancer/promoter functions.**

**(A)** Pipeline for calling single nucleotide variants (SNVs) and small insertions and deletions (indels) (size < 60bp). We used GATK Haplotypecaller (v3.8) and Freebayes (v1.0.2) to call SNVs and small indels. The p-value is calculated using Fisher's exact test to test whether the mutant read count in the tumor is significantly higher than normal. All p-values were adjusted for multiple testing. **(B)** Quality assessment of identified SNVs and small indels using a set of 735 high-confidence SNVs. The high-confidence set was generated by the TARGET project for B-ALL, AML, NBL, and WT and were validated using multiple experimental protocols including WES, RNA-Seq and PCR. **(C)** Mutation rates of all SNVs, SNVs in coding region, promoter region and enhancer region. **(D)** Mutation rates of SNVs across five cancer types. **(E)** Genomic distribution of identified SNVs and small indels. Other intergenic, intergenic regions other than promoters and enhancers. **(F)** Pipeline for calling structural variants (SVs). We used Delly (v0.7.2) and Lumpy (v0.2.13) to call SVs. **(G)** Number of identified SVs in each cancer type; **(H)** Quality assessment of identified SVs using 12 known SVs in 212 leukemia patients. **(I)** Corroborating evidence for the predicted enhancers in five cancer types. Percentage of overlap of our predicted enhancers with one or more lines of corroborating evidence is shown. Numbers in the brackets denote the number of enhancers identified in the cancer-relevant cell types. Data sources of the public ATAC-Seq data are summarized in Table S1. **(J)** Overlap of enhancer-promoter interactions predicted by IM-PET and published high-resolution chromatin interactions. **(K)**  Validation of noncoding mutation recurrence in a pan-cancer cohort from ICGC. The quantile-quantile (QQ) plot shows the observed empirical P values of mutation recurrence (n = 2,706 samples) compared to P values based on random expectation for all noncoding mutations in the TARGET cohort. **(L)** Number of predicted causal mutations for each mutation type normalized by the total number of mutations. **(M)** Parameter optimization of the weighted elastic net model. We tested all combinations of 6 different  $\lambda_2$  values (0, 0.1, 0.5, 1, 2, 3) and fifteen forward selection steps (1-15) of the LARS algorithm. Left, Mean squared errors of 10-fold cross validation using different parameter settings. Right, Number of genes with predicted causal noncoding mutations using different  $\lambda_2$  values (0.1, 0.2, 0.3).



## **Figure S2. Example predicted enhancer hijacking events in pediatric cancers and experimental validations.**

**(A)** Left, Genome browser view of enhancer hijacking to *CRLF2* via the t(14;X)(q32;p22) translocation. Shown tracks are histone modification ChIP-Seq data in CD19<sup>+</sup> B cell and identified SV break points (BPs). The hijacked enhancers predicted to regulate *CRLF2* are highlighted in brown. Right, Expression level of *CRLF2* in patients with and without the translocations. **(B)** Top, Genome browser view of enhancer hijacking to *TERT. TERT* has multiple translocation partners in neuroblastoma patients, including (t(10;5)(p22;p15), t(5;5)(q34;p15), and t(5;5)(q12;p15). Shown tracks are histone modification ChIP-Seq data in normal neural crest cells and identified SV break points (BPs). The hijacked enhancers predicted to regulate *TERT* are highlighted in brown. Bottom, Expression level of *TERT* in patients with and without the translocations. **(C)** We obtained WGS and RNA-Seq data from a recent published pediatric MPAL cohort (Alexander *et al. Nature*. 2018). MPAL, mixed phenotype acute leukemia. Among 94 MPAL patients, 15 had translocations near *ZNF384* and *CHD4*. The expression level of *CHD4* is significantly higher in those patients. **(D)** Time to relapse of patients with and without the *ZNF384*/*CHD4* rearrangement. **(E)** Enrichment of CHD4 targets among down-regulated genes in patients with *CHD4* translocation. CHD4 targets are defined as genes whose enhancer or promoter is bound by CHD4 according to the ChIP-Seq data in GM12878 cells. Down-regulated genes in patients with CHD4 translocation were identified using edgeR (q-val < 0.05). The proportion of all genes bound by CHD4 was calculated as the negative control. Hypergeometric p-value is shown. **(F)** Genome browser view of *PAX5, IRF4, EBF1, and TCF3*. Shown tracks are histone modifications and CHD4 ChIP-Seq signals in GM12878 cells. **(G)** Expression levels of *PAX5, IRF4*, *EBF1*, and *TCF3* in patients with and without CHD4 enhancer hijacking. **(H)** Schematic for the generation of t(6;15)(qF2:qE1) translocation in Ba/f3 cells. The translocation does not create fusion gene involving *CHD4* or *ZNF384*. Instead, it hijacks the enhancer of *EP300* to the vicinity of the *CHD4* promoter. **(I)** Relative mRNA levels of *TCF3*, *PAX5*, and *EBF1* in Ba/F3 cells with and without the introduced translocation. P values were calculated using one-sided Student's t-test (n=2).



## **Figure S3. Additional examples of enhancer alterations in pediatric cancers.**

**(A)** Genome browser view of *ATG3* enhancer deletion. The enhancers are highlighted in brown. Tracks shown are average H3K4Me1, H3K4Me3, and H3K27Ac signals in human CD19+ B cells. P-value of one-sided t-test is shown (n=153). **(B)** Genome browser view of *GATA2* gene and its regulating enhancers. The enhancers are highlighted in brown. Tracks shown are average H3K4Me1, H3K4Me3, and H3K27Ac signals in 13 myeloid cell types, and frequency of the identified SNVs in AML patients. *IDH2* expression values in two groups of patients are shown in the right panel. P-value of one-sided t-test is shown (n=153). **(C)** Genome browser view of *GFI1B* gene and its regulating enhancers. P-value of one-sided t-test is shown (n=153).



Patients w/ Enh or Pro Mutation □ Patients w/o Enh or Pro Mutation

## **Figure S4. Coding and noncoding mutations affect different pathways.**

**(A)** Heatmap showing p-values of enriched pathways among genes with coding mutations (red) and noncoding mutations (blue). Pathways highlighted in red are metabolic pathways. **(B)** Replication timing of metabolic genes. Genome-wide replication timing data for GM12878, K562, SK-N-SH, HEK293, and U2OS cells were downloaded from the Replication Domain database. The replication timing was measured as the  $log<sub>2</sub>$  ratio of the array signals in early (S) phase over the array signals in late (G1) phase in 5 kb bins. The list of metabolic genes (2071) is curated from the metabolic pathways of KEGG, Reactome, and NCI-Nature pathway databases. P-value of one-sided t-test is shown (n=21,841).

A)



## **Figure S5. Putative causal noncoding mutations defines novel B-ALL subgroups.**

**(A)** Genome browser view of enhancer hijacking of *SUPT7L*. Shown tracks are histone modification ChIP-Seq data in CD19<sup>+</sup> B cells and SV break points (BP). The hijacked enhancer predicted to regulate *SUPT7L* is highlighted in brown. **(B)** Expression level of *SUPT7L* in patients with and without the inversions. **(C)** Contingency matrix indicates patient mutation status of *TCF3* and *SUPT7L*. **(D)** Time to relapse of patients with *TCF3-PBX1* and Inv(2) mutations. P-value of one-sided log-rank test is shown (n=159). **(E)** Genome browser view of enhancer rearrangement of *MIR663B.* Shown tracks are histone modifications in CD19+ B cells, and identified SV break points. The enhancer regulating *MIR663B* is highlighted in brown. **(F)** Expression levels of *ANKRD30BL, MIR663B, CCL17, CD40, PIK3CD* in patients with and without the translocation. Pvalues of one-sided t-test are shown (n=163).



## **Figure S6. Putative causal noncoding mutations defines novel patient subgroups for AML, NBL, WT.**

**(A)** Genome browser view of enhancer rearrangement of *ERBB2*. Shown tracks are histone modification ChIP-Seq data in neural crest cell (*Prescott et al. Cell. 2015*) and identified SV break points. The enhancers predicted to regulate *ERBB2* are highlighted in brown. **(B)** Expression level of *ERBB2* in patients with and without the EP disruption. P-value of one-sided t-test is shown (n=100). **(C)** Time to relapse of patients with and without the *ERBB2* EP disruption. P-value of one-sided log-rank test is shown (n=100). **(D)** Genome browser view of enhancer copy number change of *TGM6*. Shown tracks are histone modification ChIP-Seq data in neural crest cells and identified CNVs. The enhancer predicted to regulate *TGM6* is highlighted in brown. **(E)** Expression level of *TGM6* in patients with and without enhancer duplication. P-value of one-sided t-test is shown (n=100). **(F)** Time to relapse of patients with and without the *TGM6* enhancer duplication. P-value of one-sided log-rank test is shown (n=100). **(G)** Genome browser view of enhancer deletion of *ZNF37A* in AML patients. Shown tracks are histone modification ChIP-Seq data in human myeloid cells, and identified deletions. The enhancer predicted to regulate *ZNF37A* is highlighted in brown. **(H)** Expression level of *ZNF37A* in patients with and without the enhancer deletion. P-value of one-sided t-test is shown (n=153). **(I)** Time to relapse of patients with and without the *ZNF37A*  enhancer deletion. P-value of one-sided log-rank test is shown (n=153). **(J)** Genome browser view of enhancer rearrangement of *GAS6*. Shown tracks are histone modification ChIP-Seq data in HEK293 cells, and identified SV break points. **(K)**  Expression level of *GAS6* in patients with and without the EP disruption. P-value of onesided t-test is shown (n=53). **(L)** Time to relapse of patients with and without the *GAS6* EP disruption. P-value of one-sided log-rank test is shown (n=53).



Patients w/SV

# **Supplementary Tables**

## **Table S1. Published data and software used in this study.**





**Table S2. Enhancer-promoter pairs that are disrupted by noncoding mutations.**  See excel file.

## **Table S3. Known cancer-relevant functions of the top affected TFs in each cancer type.**





# **Table S4. PCR and sgRNA target sequences used in this study.**





#### **REFERENCES AND NOTES**

- 1. X. Ma, Y. Liu, Y. Liu, L. B. Alexandrov, M. N. Edmonson, C. Gawad, X. Zhou, Y. Li, M. C. Rusch, J. Easton, R. Huether, V. Gonzalez-Pena, M. R. Wilkinson, L. C. Hermida, S. Davis, E. Sioson, S. Pounds, X. Cao, R. E. Ries, Z. Wang, X. Chen, L. Dong, S. J. Diskin, M. A. Smith, J. M. Guidry Auvil, P. S. Meltzer, C. C. Lau, E. J. Perlman, J. M. Maris, S. Meshinchi, S. P. Hunger, D. S. Gerhard, J. Zhang, Pan-cancer genome and transcriptome analyses of 1,699 paediatric leukaemias and solid tumours. *Nature* **555**, 371–376 (2018).
- 2. S. N. Gröbner, B. C. Worst, J. Weischenfeldt, I. Buchhalter, K. Kleinheinz, V. A. Rudneva, P. D. Johann, G. P. Balasubramanian, M. Segura-Wang, S. Brabetz, S. Bender, B. Hutter, D. Sturm, E. Pfaff, D. Hübschmann, G. Zipprich, M. Heinold, J. Eils, C. Lawerenz, S. Erkek, S. Lambo, S. Waszak, C. Blattmann, A. Borkhardt, M. Kuhlen, A. Eggert, S. Fulda, M. Gessler, J. Wegert, R. Kappler, D. Baumhoer, S. Burdach, R. Kirschner-Schwabe, U. Kontny, A. E. Kulozik, D. Lohmann, S. Hettmer, C. Eckert, S. Bielack, M. Nathrath, C. Niemeyer, G. H. Richter, J. Schulte, R. Siebert, F. Westermann, J. J. Molenaar, G. Vassal, H. Witt; ICGC Ped Brain-Seq Project; ICGC MMML-Seq Project, B. Burkhardt, C. P. Kratz, O. Witt, C. M. van Tilburg, C. M. Kramm, G. Fleischhack, U. Dirksen, S. Rutkowski, M. Frühwald, Katja von Hoff, S. Wolf, T. Klingebiel, E. Koscielniak, P. Landgraf, J. Koster, A. C. Resnick, J. Zhang, Y. Liu, X. Zhou, A. J. Waanders, D. A. Zwijnenburg, P. Raman, B. Brors, U. D. Weber, P. A. Northcott, K. W. Pajtler, M. Kool, R. M. Piro, J. O. Korbel, M. Schlesner, R. Eils, D. T. W. Jones, P. Lichter, L. Chavez, M. Zapatka, S. M. Pfister, The landscape of genomic alterations across childhood cancers. *Nature* **555**, 321–327 (2018).
- 3. F. K. Lorbeer, D. Hockemeyer, TERT promoter mutations and telomeres during tumorigenesis. *Curr. Opin. Genet. Dev.* **60**, 56–62 (2020).
- 4. D. A. Oldridge, A. C. Wood, N. Weichert-Leahey, I. Crimmins, R. Sussman, C. Winter, L. D. McDaniel, M. Diamond, L. S. Hart, S. Zhu, A. D. Durbin, B. J. Abraham, L. Anders, L. Tian, S. Zhang, J. S. Wei, J. Khan, K. Bramlett, N. Rahman, M. Capasso, A. Iolascon, D. S. Gerhard, J. M. Guidry Auvil, R. A. Young, H. Hakonarson, S. J. Diskin, A. Thomas Look, J. M. Maris, Genetic predisposition to neuroblastoma mediated by a LMO1 super-enhancer polymorphism. *Nature* **528**, 418–421 (2015).
- 5. M. R. Mansour, B. J. Abraham, L. Anders, A. Berezovskaya, A. Gutierrez, A. D. Durbin, J. Etchin, L. Lawton, S. E. Sallan, L. B. Silverman, M. L. Loh, S. P. Hunger, T. Sanda, R. A. Young, A. T. Look, Oncogene regulation. An oncogenic super-enhancer formed through somatic mutation of a noncoding intergenic element. *Science* **346**, 1373–1377 (2014).
- 6. International Cancer Genome Consortium, International network of cancer genome projects. *Nature* **464**, 993–998 (2010).
- 7. P. A. Northcott, C. Lee, T. Zichner, A. M. Stütz, S. Erkek, D. Kawauchi, D. J. H. Shih, V. Hovestadt, M. Zapatka, D. Sturm, D. T. W. Jones, M. Kool, M. Remke, F. M. G. Cavalli, S. Zuyderduyn, G. D. Bader, S. VandenBerg, L. A. Esparza, M. Ryzhova, W. Wang, A. Wittmann, S. Stark, L. Sieber, H. Seker-Cin, L. Linke, F. Kratochwil, N. Jäger, I. Buchhalter, C. D. Imbusch, G. Zipprich, B. Raeder, S. Schmidt, N. Diessl, S. Wolf, S. Wiemann, B. Brors, C. Lawerenz, J. Eils, H.-J. Warnatz, T. Risch, M.-L. Yaspo, U. D. Weber, C. C. Bartholomae, C. von Kalle, E. Turányi, P. Hauser, E. Sanden, A. Darabi, P. Siesjö, J. Sterba, K. Zitterbart, D. Sumerauer, P. van Sluis, R. Versteeg, R. Volckmann, J. Koster, M. U. Schuhmann, M. Ebinger, H. L. Grimes, G. W. Robinson, A. Gajjar, M. Mynarek, K. von Hoff, S. Rutkowski, T. Pietsch, W. Scheurlen, J. Felsberg, G. Reifenberger, A. E. Kulozik, A. von Deimling, O. Witt, R. Eils, R. J. Gilbertson, A. Korshunov, M. D. Taylor, P. Lichter, J. O. Korbel, R. J. Wechsler-Reya, S. M. Pfister, Enhancer hijacking activates GFI1 family oncogenes in medulloblastoma. *Nature* **511**, 428–434 (2014).
- 8. R. J. H. Ryan, Y. Drier, H. Whitton, M. J. Cotton, J. Kaur, R. Issner, S. Gillespie, C. B. Epstein, V. Nardi, A. R. Sohani, E. P. Hochberg, B. E. Bernstein, Detection of enhancer-associated rearrangements reveals mechanisms of oncogene dysregulation in B-cell lymphoma. *Cancer Discov.* **5**, 1058–1071 (2015).
- 9. S. K. Tasian, M. L. Loh, Understanding the biology of CRLF2-overexpressing acute lymphoblastic leukemia. *Crit. Rev. Oncog.* **16**, 13–24 (2011).
- 10. J. M. Zook, B. Chapman, J. Wang, D. Mittelman, O. Hofmann, W. Hide, M. Salit, Integrating human sequence data sets provides a resource of benchmark SNP and indel genotype calls. *Nat. Biotechnol.* **32**, 246–251 (2014).
- 11. J. A. Perry, A. Kiezun, P. Tonzi, E. M. Van Allen, S. L. Carter, S. C. Baca, G. S. Cowley, A. S. Bhatt, E. Rheinbay, C. S. Pedamallu, E. Helman, A. Taylor-Weiner, A. McKenna, D. S. DeLuca, M. S. Lawrence, L. Ambrogio, C. Sougnez, A. Sivachenko, L. D. Walensky, N. Wagle, J. Mora, C. de Torres, C. Lavarino, S. Dos Santos Aguiar, J. A. Yunes, S. R. Brandalise, G. E. Mercado-Celis, J. Melendez-Zajgla, R. Cárdenas-Cardós, L. Velasco-Hidalgo, C. W. M. Roberts, L. A. Garraway, C. Rodriguez-Galindo, S. B. Gabriel, E. S. Lander, T. R. Golub, S. H. Orkin, G. Getz, K. A. Janeway, Complementary genomic approaches highlight the PI3K/mTOR pathway as a common vulnerability in osteosarcoma. *Proc. Natl. Acad. Sci. U.S.A.* **111**, E5564–E5573 (2014).
- 12. K. G. Roberts, Y. Li, D. Payne-Turner, R. C. Harvey, Y.-L. Yang, D. Pei, K. McCastlain, L. Ding, C. Lu, G. Song, J. Ma, J. Becksfort, M. Rusch, S.-C. Chen, J. Easton, J. Cheng, K. Boggs, N. Santiago-Morales, I. Iacobucci, R. S. Fulton, J. Wen, M. Valentine, C. Cheng, S. W. Paugh, M. Devidas, I.-M. Chen, S. Reshmi, A. Smith, E. Hedlund, P. Gupta, P. Nagahawatte, G. Wu, X. Chen, D. Yergeau, B. Vadodaria, H. Mulder, N. J. Winick, E. C. Larsen, W. L. Carroll, N. A. Heerema, A. J. Carroll, G. Grayson, S. K. Tasian, A. S. Moore, F. Keller, M. Frei-Jones, J. A. Whitlock, E. A. Raetz, D. L. White, T. P. Hughes, J. M. Guidry Auvil, M. A. Smith, G. Marcucci, C. D. Bloomfield, K. Mrózek, J. Kohlschmidt, W. Stock, S. M. Kornblau, M. Konopleva, E. Paietta, C.-H. Pui, S. Jeha, M. V. Relling, W. E. Evans, D. S. Gerhard, J. M. Gastier-Foster, E. Mardis, R. K. Wilson, M. L. Loh, J. R. Downing, S. P. Hunger, C. L. Willman, J. Zhang, C. G. Mullighan, Targetable kinaseactivating lesions in Ph-like acute lymphoblastic leukemia. *N. Engl. J. Med.* **371**, 1005–1015 (2014).
- 13. H. A. Firpi, D. Ucar, K. Tan, Discover regulatory DNA elements using chromatin signatures and artificial neural network. *Bioinformatics* **26**, 1579–1586 (2010).
- 14. B. He, C. Chen, L. Teng, K. Tan, Global view of enhancer-promoter interactome in human cells. *Proc. Natl. Acad. Sci. U.S.A.* **111**, E2191–E2199 (2014).
- 15. A. Khan, X. Zhang, dbSUPER: A database of super-enhancers in mouse and human genome. *Nucleic Acids Res.* **44**, D164–D171 (2016).
- 16. Y. Drier, M. J. Cotton, K. E. Williamson, S. M. Gillespie, R. J. H. Ryan, M. J. Kluk, C. D. Carey, S. J. Rodig, L. M. Sholl, A. H. Afrogheh, W. C. Faquin, L. Queimado, J. Qi, M. J. Wick, A. K. El-Naggar, J. E. Bradner, C. A. Moskaluk, J. C. Aster, B. Knoechel, B. E. Bernstein, An oncogenic

MYB feedback loop drives alternate cell fates in adenoid cystic carcinoma. *Nat. Genet.* **48**, 265–272 (2016).

- 17. M. Peifer, F. Hertwig, F. Roels, D. Dreidax, M. Gartlgruber, R. Menon, A. Krämer, J. L. Roncaioli, F. Sand, J. M. Heuckmann, F. Ikram, R. Schmidt, S. Ackermann, A. Engesser, Y. Kahlert, W. Vogel, J. Altmüller, P. Nürnberg, J. Thierry-Mieg, D. Thierry-Mieg, A. Mariappan, S. Heynck, E. Mariotti, K.-O. Henrich, C. Gloeckner, G. Bosco, I. Leuschner, M. R. Schweiger, L. Savelyeva, S. C. Watkins, C. Shao, E. Bell, T. Höfer, V. Achter, U. Lang, J. Theissen, R. Volland, M. Saadati, A. Eggert, B. de Wilde, F. Berthold, Z. Peng, C. Zhao, L. Shi, M. Ortmann, R. Büttner, S. Perner, B. Hero, A. Schramm, J. H. Schulte, C. Herrmann, R. J. O'Sullivan, F. Westermann, R. K. Thomas, M. Fischer, Telomerase activation by genomic rearrangements in high-risk neuroblastoma. *Nature* **526**, 700–704 (2015).
- 18. M. Qian, H. Zhang, S. K.-Y. Kham, S. Liu, C. Jiang, X. Zhao, Y. Lu, C. Goodings, T.-N. Lin, R. Zhang, T. Moriyama, Z. Yin, Z. Li, T. C. Quah, H. Ariffin, A. M. Tan, S. Shen, D. Bhojwani, S. Hu, S. Chen, H. Zheng, C.-H. Pui, A. E.-J. Yeoh, J. J. Yang, Whole-transcriptome sequencing identifies a distinct subtype of acute lymphoblastic leukemia with predominant genomic abnormalities of EP300 and CREBBP. *Genome Res.* **27**, 185–195 (2017).
- 19. T. B. Alexander, Z. Gu, I. Iacobucci, K. Dickerson, J. K. Choi, B. Xu, D. Payne-Turner, H. Yoshihara, M. L. Loh, J. Horan, B. Buldini, G. Basso, S. Elitzur, V. de Haas, C. M. Zwaan, A. Yeoh, D. Reinhardt, D. Tomizawa, N. Kiyokawa, T. Lammens, B. de Moerloose, D. Catchpoole, H. Hori, A. Moorman, A. S. Moore, O. Hrusak, S. Meshinchi, E. Orgel, M. Devidas, M. Borowitz, B. Wood, N. A. Heerema, A. Carrol, Y.-L. Yang, M. A. Smith, T. M. Davidsen, L. C. Hermida, P. Gesuwan, M. A. Marra, Y. Ma, A. J. Mungall, R. A. Moore, S. J. M. Jones, M. Valentine, L. J. Janke, J. E. Rubnitz, C.-H. Pui, L. Ding, Y. Liu, J. Zhang, K. E. Nichols, J. R. Downing, X. Cao, L. Shi, S. Pounds, S. Newman, D. Pei, J. M. Guidry Auvil, D. S. Gerhard, S. P. Hunger, H. Inaba, C. G. Mullighan, The genetic basis and cell of origin of mixed phenotype acute leukaemia. *Nature* **562**, 373–379 (2018).
- 20. C. Dege, J. Hagman, Mi-2/NuRD chromatin remodeling complexes regulate B and T-lymphocyte development and function. *Immunol. Rev.* **261**, 126–140 (2014).
- 21. J. Sperlazza, M. Rahmani, J. Beckta, M. Aust, E. Hawkins, S. Z. Wang, S. Zu Zhu, S. Podder, C. Dumur, K. Archer, S. Grant, G. D. Ginder, Depletion of the chromatin remodeler CHD4 sensitizes AML blasts to genotoxic agents and reduces tumor formation. *Blood* **126**, 1462–1472 (2015).
- 22. T. J. Pugh, O. Morozova, E. F. Attiyeh, S. Asgharzadeh, J. S. Wei, D. Auclair, S. L. Carter, K. Cibulskis, M. Hanna, A. Kiezun, J. Kim, M. S. Lawrence, L. Lichenstein, A. McKenna, C. S. Pedamallu, A. H. Ramos, E. Shefler, A. Sivachenko, C. Sougnez, C. Stewart, A. Ally, I. Birol, R. Chiu, R. D. Corbett, M. Hirst, S. D. Jackman, B. Kamoh, A. H. Khodabakshi, M. Krzywinski, A. Lo, R. A. Moore, K. L. Mungall, J. Qian, A. Tam, N. Thiessen, Y. Zhao, K. A. Cole, M. Diamond, S. J. Diskin, Y. P. Mosse, A. C. Wood, L. Ji, R. Sposto, T. Badgett, W. B. London, Y. Moyer, J. M. Gastier-Foster, M. A. Smith, J. M. G. Auvil, D. S. Gerhard, M. D. Hogarty, S. J. M. Jones, E. S. Lander, S. B. Gabriel, G. Getz, R. C. Seeger, J. Khan, M. A. Marra, M. Meyerson, J. M. Maris, The genetic landscape of high-risk neuroblastoma. *Nat. Genet.* **45**, 279–284 (2013).
- 23. L. Zhuang, Y. Ma, Q. Wang, J. Zhang, C. Zhu, L. Zhang, X. Xu, Atg3 overexpression enhances bortezomib-induced cell death in SKM-1 cell. *PLOS ONE* **11**, e0158761 (2016).
- 24. V. Moignard, I. C. Macaulay, G. Swiers, F. Buettner, J. Schütte, F. J. Calero-Nieto, S. Kinston, A. Joshi, R. Hannah, F. J. Theis, S. E. Jacobsen, M. F. de Bruijn, B. Göttgens, Characterization of transcriptional networks in blood stem and progenitor cells using high-throughput single-cell gene expression analysis. *Nat. Cell Biol.* **15**, 363–372 (2013).
- 25. L. Vassen, H. Beauchemin, W. Lemsaddek, J. Krongold, M. Trudel, T. Möröy, Growth factor independence 1b (gfi1b) is important for the maturation of erythroid cells and the regulation of embryonic globin expression. *PLOS ONE* **9**, e96636 (2014).
- 26. A. Thivakaran, L. Botezatu, J. M. Hönes, J. Schütte, L. Vassen, Y. S. Al-Matary, P. Patnana, A. Zeller, M. Heuser, F. Thol, R. Gabdoulline, N. Olberding, D. Frank, M. Suslo, R. Köster, K. Lennartz, A. Görgens, B. Giebel, B. Opalka, U. Dührsen, C. Khandanpour, Gfi1b: A key player in the genesis and maintenance of acute myeloid leukemia and myelodysplastic syndrome. *Haematologica* **103**, 614–625 (2018).
- 27. D. Hnisz, B. J. Abraham, T. I. Lee, A. Lau, V. Saint-André, A. A. Sigova, H. A. Hoke, R. A. Young, Super-enhancers in the control of cell identity and disease. *Cell* **155**, 934–947 (2013).
- 28. F. Damm, F. Thol, I. Hollink, M. Zimmermann, K. Reinhardt, M. M. van den Heuvel-Eibrink, C. M. Zwaan, V. de Haas, U. Creutzig, J.-H. Klusmann, J. Krauter, M. Heuser, A. Ganser, D. Reinhardt, C. Thiede, Prevalence and prognostic value of IDH1 and IDH2 mutations in childhood AML: A study of the AML-BFM and DCOG study groups. *Leukemia* **25**, 1704–1710 (2011).
- 29. J. L. Patel, J. A. Schumacher, K. Frizzell, S. Sorrells, W. Shen, A. Clayton, R. Jattani, T. W. Kelley, Coexisting and cooperating mutations in NPM1-mutated acute myeloid leukemia. *Leuk. Res.* **56**, 7– 12 (2017).
- 30. S. Gröschel, M. A. Sanders, R. Hoogenboezem, E. de Wit, B. A. M. Bouwman, C. Erpelinck, V. H. J. van der Velden, M. Havermans, R. Avellino, K. van Lom, E. J. Rombouts, M. van Duin, K. Döhner, H. B. Beverloo, J. E. Bradner, H. Döhner, B. Löwenberg, P. J. M. Valk, E. M. J. Bindels, W. de Laat, R. Delwel, A single oncogenic enhancer rearrangement causes concomitant EVI1 and GATA2 deregulation in leukemia. *Cell* **157**, 369–381 (2014).
- 31. J. Sima, D. M. Gilbert, Complex correlations: Replication timing and mutational landscapes during cancer and genome evolution. *Curr. Opin. Genet. Dev.* **25**, 93–100 (2014).
- 32. S. K. Tasian, S. P. Hunger, Genomic characterization of paediatric acute lymphoblastic leukaemia: An opportunity for precision medicine therapeutics. *Br. J. Haematol.* **176**, 867–882 (2017).
- 33. M. Pieraccioli, S. Nicolai, C. Pitolli, M. Agostini, A. Antonov, M. Malewicz, R. A. Knight, G. Raschellà, G. Melino, ZNF281 inhibits neuronal differentiation and is a prognostic marker for neuroblastoma. *Proc. Natl. Acad. Sci. U.S.A.* **115**, 7356–7361 (2018).
- 34. J. Dzieran, A. Rodriguez Garcia, U. K. Westermark, A. B. Henley, E. Eyre Sánchez, C. Träger, H. J. Johansson, J. Lehtiö, M. Arsenian-Henriksson, MYCN-amplified neuroblastoma maintains an aggressive and undifferentiated phenotype by deregulation of estrogen and NGF signaling. *Proc. Natl. Acad. Sci. U.S.A.* **115**, E1229–E1238 (2018).
- 35. Z. J. Faber, X. Chen, A. L. Gedman, K. Boggs, J. Cheng, J. Ma, I. Radtke, J.-R. Chao, M. P. Walsh, G. Song, A. K. Andersson, J. Dang, L. Dong, Y. Liu, R. Huether, Z. Cai, H. Mulder, G. Wu, M. Edmonson, M. Rusch, C. Qu, Y. Li, B. Vadodaria, J. Wang, E. Hedlund, X. Cao, D. Yergeau, J. Nakitandwe, S. B. Pounds, S. Shurtleff, R. S. Fulton, L. L. Fulton, J. Easton, E. Parganas, C.-H. Pui, J. E. Rubnitz, L. Ding, E. R. Mardis, R. K. Wilson, T. A. Gruber, C. G. Mullighan, R. F. Schlenk, P. Paschka, K. Döhner, H. Döhner, L. Bullinger, J. Zhang, J. M. Klco, J. R. Downing, The genomic landscape of core-binding factor acute myeloid leukemias. *Nat. Genet.* **48**, 1551–1556 (2016).
- 36. T. Holmlund, M. J. Lindberg, D. Grander, A. E. Wallberg, GCN5 acetylates and regulates the stability of the oncoprotein E2A-PBX1 in acute lymphoblastic leukemia. *Leukemia* **27**, 578–585 (2013).
- 37. L. De Cecco, M. Capaia, S. Zupo, G. Cutrona, S. Matis, A. Brizzolara, A. M. Orengo, M. Croce, E. Marchesi, M. Ferrarini, S. Canevari, S. Ferrini, Interleukin 21 controls mRNA and microRNA expression in CD40-activated chronic lymphocytic leukemia cells. *PLOS ONE* **10**, e0134706 (2015).
- 38. E. Izycka-Swieszewska, A. Wozniak, J. Kot, W. Grajkowska, A. Balcerska, D. Perek, B. Dembowska-Baginska, T. Klepacka, E. Drozynska, Prognostic significance of HER2 expression in neuroblastic tumors. *Modern Pathol.* **23**, 1261–1268 (2010).
- 39. H. Thomas, K. Beck, M. Adamczyk, P. Aeschlimann, M. Langley, R. C. Oita, L. Thiebach, M. Hils, D. Aeschlimann, Transglutaminase 6: A protein associated with central nervous system development and motor function. *Amino Acids* **44**, 161–177 (2013).
- 40. A. S. Algarni, A. J. Hargreaves, J. M. Dickenson, Activation of transglutaminase 2 by nerve growth factor in differentiating neuroblastoma cells: A role in cell survival and neurite outgrowth. *Eur. J. Pharmacol.* **820**, 113–129 (2018).
- 41. N. Stransky, E. Cerami, S. Schalm, J. L. Kim, C. Lengauer, The landscape of kinase fusions in cancer. *Nat. Commun.* **5**, 4846 (2014).
- 42. L. Wang, Y. Sun, Y. Sun, L. Meng, X. Xu, First case of AML with rare chromosome translocations: A case report of twins. *BMC Cancer* **18**, 458 (2018).
- 43. G. Wu, Z. Ma, W. Hu, D. Wang, B. Gong, C. Fan, S. Jiang, T. Li, J. Gao, Y. Yang, Molecular insights of Gas6/TAM in cancer development and therapy. *Cell Death Dis.* **8**, e2700 (2017).
- 44. L. Yang, L. J. Luquette, N. Gehlenborg, R. Xi, P. S. Haseley, C.-H. Hsieh, C. Zhang, X. Ren, A. Protopopov, L. Chin, R. Kucherlapati, C. Lee, P. J. Park, Diverse mechanisms of somatic structural variations in human cancer genomes. *Cell* **153**, 919–929 (2013).
- 45. I. Janoueix-Lerosey, P. Hupé, Z. Maciorowski, P. La Rosa, G. Schleiermacher, G. Pierron, S. Liva, E. Barillot, O. Delattre, Preferential occurrence of chromosome breakpoints within early replicating regions in neuroblastoma. *Cell Cycle* **4**, 1842–1846 (2005).
- 46. P. Kim, F. Cheng, J. Zhao, Z. Zhao, ccmGDB: A database for cancer cell metabolism genes. *Nucleic Acids Res.* **44**, D959–D968 (2016).
- 47. R. Torres, M. C. Martin, A. Garcia, J. C. Cigudosa, J. C. Ramirez, S. Rodriguez-Perales, Engineering human tumour-associated chromosomal translocations with the RNA-guided CRISPR-Cas9 system. *Nat. Commun.* **5**, 3964 (2014).
- 48. M. T. Weirauch, A. Yang, M. Albu, A. G. Cote, A. Montenegro-Montero, P. Drewe, H. S. Najafabadi, S. A. Lambert, I. Mann, K. Cook, H. Zheng, A. Goity, H. van Bakel, J.-C. Lozano, M. Galli, M. G. Lewsey, E. Huang, T. Mukherjee, X. Chen, J. S. Reece-Hoyes, S. Govindarajan, G. Shaulsky, A. J. M. Walhout, F.-Y. Bouget, G. Ratsch, L. F. Larrondo, J. R. Ecker, T. R. Hughes, Determination and inference of eukaryotic transcription factor sequence specificity. *Cell* **158**, 1431– 1443 (2014).
- 49. W. Zhang, A. Bojorquez-Gomez, D. O. Velez, G. Xu, K. S. Sanchez, J. P. Shen, K. Chen, K. Licon, C. Melton, K. M. Olson, M. K. Yu, J. K. Huang, H. Carter, E. K. Farley, M. Snyder, S. I. Fraley, J. F. Kreisberg, T. Ideker, A global transcriptional network connecting noncoding mutations to changes in tumor gene expression. *Nat. Genet.* **50**, 613–620 (2018).
- 50. N. Weddington, A. Stuy, I. Hiratani, T. Ryba, T. Yokochi, D. M. Gilbert, ReplicationDomain: A visualization tool and comparative database for genome-wide replication timing data. *BMC Bioinformatics* **9**, 530 (2008).
- 51. R. S. Hansen, S. Thomas, R. Sandstrom, T. K. Canfield, R. E. Thurman, M. Weaver, M. O. Dorschner, S. M. Gartler, J. A. Stamatoyannopoulos, Sequencing newly replicated DNA reveals widespread plasticity in human replication timing. *Proc. Natl. Acad. Sci. U.S.A.* **107**, 139–144 (2010).
- 52. C. E. Grant, T. L. Bailey, W. S. Noble, FIMO: Scanning for occurrences of a given motif. *Bioinformatics* **27**, 1017–1018 (2011).
- 53. M. D. M. Leiserson, H.-T. Wu, F. Vandin, B. J. Raphael, CoMEt: A statistical approach to identify combinations of mutually exclusive alterations in cancer. *Genome Biol.* **16**, 160 (2015).
- 54. T. Juven-Gershon, S. Cheng, J. T. Kadonaga, Rational design of a super core promoter that enhances gene expression. *Nat. Methods* **3**, 917–922 (2006).
- 55. N. E. Sanjana, O. Shalem, F. Zhang, Improved vectors and genome-wide libraries for CRISPR screening. *Nat. Methods* **11**, 783–784 (2014).
- 56. J. G. Doench, N. Fusi, M. Sullender, M. Hegde, E. W. Vaimberg, K. F. Donovan, I. Smith, Z. Tothova, C. Wilen, R. Orchard, H. W. Virgin, J. Listgarten, D. E. Root, Optimized sgRNA design to maximize activity and minimize off-target effects of CRISPR-Cas9. *Nat. Biotechnol.* **34**, 184–191 (2016).