A genome-wide atlas of recurrent repeat expansions in human cancer

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1 Abstract

2	Expansion of a single repetitive DNA sequence, termed a tandem repeat (TR), is
3	known to cause more than 50 diseases. However, repeat expansions are often not explored
4	beyond neurological and neurodegenerative disorders. In some cancers, mutations
5	accumulate in short tracts of TRs (STRs), a phenomenon termed microsatellite instability
6	(MSI); however larger repeat expansions have not been systematically analyzed in cancer.
7	Here, we identified TR expansions in 2,622 cancer genomes, spanning 29 cancer types. In 7
8	cancer types, we found 160 recurrent repeat expansions (rREs); most of these (155/160)
9	were subtype specific. We found that rREs were non-uniformly distributed in the genome
10	with an enrichment near candidate cis-regulatory elements, suggesting a role in gene
11	regulation. One rRE located near a regulatory element in the first intron of UGT2B7 was
12	detected in 34% of renal cell carcinoma samples and was validated by long-read DNA
13	sequencing. Moreover, targeting cells harboring this rRE with a rationally designed,
14	sequence-specific DNA binder led to a dose-dependent decrease in cell proliferation.
15	Overall, our results demonstrate that rREs are an important but unexplored source of
16	genetic variation in human cancers, and we provide a comprehensive catalog for further
17	study.

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19 Introduction

Expansions of tandem DNA repeats (TRs) are known to cause more than 50 devastating
 human diseases including Huntington's disease and Fragile X syndrome^{1,2}. TR tracts that cause

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human disease are typically large (more than 100 base pairs)¹. However, identifying large TRs
with short-read DNA sequencing methods is difficult because they are ubiquitous in the genome,
and many are too large—larger than the typical sequencing read length—to uniquely map to the
reference genome³. Thus, many large TRs go undetected with current genomic technologies, and
despite their importance to monogenic disease, the frequency and function of recurrent repeat
expansions (rREs) are unknown in complex human genetic diseases, such as cancer⁴.

Previous studies have profiled the landscape of alterations in STRs in cancer genomes^{5–7}. In particular, microsatellite instability (MSI)^{8–10}, defined by an alteration in the lengths of short TRs, is prevalent in various types of cancer including endometrial (30%), stomach (20%), and colorectal cancers (15%)^{5,6,11–12}. However, the systematic analysis of the frequency of genomewide large TR expansions has not been studied in cancer even though it was posited more than 25 years ago¹³.

34 Recently, new bioinformatic tools to identify repeat expansions in short-read whole-35 genome sequencing (WGS) datasets^{14–17} have led to the identification of both known and novel 36 repeat expansions in human disease, primarily in the area of neurological disorders where repeat expansions have historically been studied^{14–22}. Here, we analyzed 2,622 human cancer genomes 37 38 with matching normal samples for the presence of somatic repeat expansions. We identified 160 39 recurrent repeat expansions (rREs) in seven types of cancer, including many rREs located in or 40 near known regulatory elements. One of these rREs is observed in 34% of kidney cancers, and 41 targeting this repeat expansion with sequence-specific DNA binders led to a dose-dependent 42 decrease in cellular proliferation. Overall, our approach reveals a new class of recurrent changes 43 in cancer genomes and provides an initial resource of these changes. Our results also suggest an 44 opportunity for a new class of oncologic TR-targeted therapeutics^{23,24}.

Page 5

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46 Results

47 Recurrent repeat expansions in cancer

48 We collected uniformly-processed alignments of whole-genome sequencing (WGS) of 49 tumor-normal pairs in the International Cancer Genome Consortium (ICGC), The Cancer 50 Genome Atlas (TCGA), both a part of the pan-cancer analysis of whole genomes (PCAWG) 51 datasets²⁵. After filtering, these data consist of 2,622 cancer genomes from 2509 patients across 52 29 different cancer types (Extended Data Figure 1). Each cancer type was treated as its own 53 cohort and analyzed independent of other cancer types. We called somatic recurrent repeat 54 expansions (rREs) with ExpansionHunter Denovo (EHdn) (see Methods), which measures TRs 55 whose length exceeds the sequencing read length in short-read sequencing datasets^{26,27}. That is, 56 EHdn performs case-control comparisons using a non-parametric statistical test to determine 57 whether repeat length is longer in tumor genomes compared to matching normal genomes. This 58 approach is analogous to joint population-level genotyping. 59 We first confirmed the accuracy of EHdn by performing whole-genome short- and long-60 read sequencing on 786-O and Caki-1 cancer lines. We found that EHdn captured 72% of the

61 repeat expansions observed in long-read sequencing (Extended Data Figure 2). We also tested

62 the effect of sequencing coverage on the detection of rREs, and found that EHdn was robust

down to 30x coverage (Extended Data Figure 2). We then analyzed 2,622 matching tumor and
normal genomes with EHdn (285,363 TRs). We identified 578 candidate rREs (locus-level false
discovery rate (FDR) < 10%).

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66	EHdn is expected to be sensitive to the copy number variations observed in cancer
67	genomes. We therefore devised and implemented a local read depth filtering method to account
68	for copy number variants, which normalizes the signal originating from repeat reads using the
69	read depth in the vicinity of the TR (see Methods and Extended Data Figure 3). We
70	benchmarked the local read depth normalization approach with simulated chromosomal
71	amplifications ranging from two (diploid) to 10 copies. We found that this filter accounts for
72	changes in chromosomal copy number in a manner superior to the standard global read depth
73	normalization (Fig. S5). Overall, we conclude that local read depth normalization is valuable to
74	identify bona fide rREs in cancer genomes and that many of the rREs that pass the filter are
75	expanded in cancer. For example, without local read depth normalization, we could only detect
76	31% of candidate rREs in independent cohorts of matching tumor-normal tissue samples for
77	breast, prostate, and kidney cancer (15, 18, and 12 patients, respectively). Our local read depth
78	filtering approach removed >75% (418/578) false-positive candidate rREs (Extended Data
79	Figure 3). Importantly, several rRE candidates that were removed are situated in hotspots for
80	chromosomal amplification, such as chromosomal 8q amplifications that
81	increase MYC production in breast cancer (Extended Data Figure 3) ²⁸ . Our analysis suggests
82	that the standalone EHdn method may have selected these loci due to amplification rather than
83	repeat expansions, and thus their removal is important.
84	After implementing our local read depth filtering strategy, we increased our detection rate

to 57% (8/14) in independent cohorts (Extended Data Figure 3). Importantly, the loci we could

- 86 not validate had lower expansion frequencies (5–12%). These rREs may be real but more
- 87 difficult to validate in the small validation cohorts (Table S7). Thus, we believe this number is
- 88 likely an underestimate of the independent detection rate. Of the 14 candidate rREs that failed

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89	our local read depth filter, 29% (4/14) were detected in independent cohorts of samples
90	indicating that the filtering removes most loci that cannot be validated (Extended Data Figure
91	3), but also removes some true positives as well.

92 After accounting for local read depth, we detected 160 rREs in 7 human cancers (Fig. 93 **1b**). We expected high concordance with ExpansionHunter given that this tool is related to 94 EHdn, and indeed we observed a 91% confirmation rate with ExpansionHunter (Extended Data 95 Figure 4). We found that most (80%) of these loci are rarely expanded in the general population 96 (<5% of the time, n = 6,514 genomes, Extended Data Figure 2). rREs were primarily observed 97 in prostate and liver cancer, but we also detected rREs in ovarian, pilocytic astrocytoma, renal 98 cell carcinoma (RCC), chromophobe RCC, and squamous cell lung carcinoma. Thus, rREs are 99 found in tissues derived from each of the three primary germ layers (ectoderm, mesoderm, and 100 endoderm), suggesting these expansions are a phenomenon inherent to the human genome rather 101 than any tissue-specific process. In prostate and liver cancer, most cancer genomes (93% and 102 95%, respectively) contain at least one rRE, with some genomes harboring several rREs (Fig. 103 **1c**). For some pathogenic repeats, a larger TR length at birth predisposes an individual to somatic 104 repeat expansions later in life^{1,2}, but we did not generally observe that with rREs (**Table S8**). 105 Overall, rREs are found in 7 of 29 human cancers examined and are largely cancer subtype-106 specific.

We next examined whether rREs correlate with changes in MSI^{5,6}. We determined 107 108 whether samples harboring an rRE had a higher mutation rate in STRs, which is a hallmark of 109 MSI^{5,29}. We did not observe any significant difference in STR mutation rate for genomes with an 110 rRE compared to those lacking an rRE (two-tailed Wilcoxon rank sum test, P = 0.27, Fig. 1d). 111 We also compared cancer genomes harboring rREs with cancer genomes previously identified as

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112	MSI, using recent results from the PCAWG consortium ²⁹ . We did not observe any enrichment in
113	MSI for samples harboring an rRE, and instead found a weak but significant preference for rREs
114	in microsatellite stable (MSS) samples, not MSI samples (Two-tailed Wilcoxon rank-sum test, P
115	= 0.04, Fig. 1e, see also Extended Data Figure 5). Thus, our findings might suggest a model
116	where rREs are formed by a process that is distinct from MSI.
117	In addition to MSI, different mutational processes lead to a signature of somatic
118	mutations. We tested whether rREs are associated with known mutational signatures by
119	comparing them to 49 signatures of single base substitutions (SBS) and 11 doublet base
120	substitutions (DBS) ³⁰ . We performed a multiple linear regression to predict the number of rREs
121	in a sample based on SBS and DBS signatures, respectively. Only one DBS signature, DBS2,
122	showed a very weak association with rREs ($r^2 = 0.12$) (Extended Data Figure 5).

123

124 rREs overlap regulatory elements

125 Among the 160 rREs, we observed a variety of different motifs (Table S1) whose repeat 126 unit length follows a bimodal distribution, consistent with REs identified in other diseases (Fig. 127 2a, Extended Data Figures 6 and 7)²⁷. rREs are distributed across a range of GC content; 128 approximately half (76/160) have GC content less than 50% (Table S1). Six rREs contained a known pathogenic motif, all of which were GAA³¹. We examined if any motifs were enriched in 129 130 the rRE catalog compared to the tandem repeat finder (TRF) catalog. Although this enrichment 131 could arise from a biological and/or technical process, we found that one of the three enriched 132 motifs was GAA (Fig. 2b). As an example, Friedreich's ataxia is caused by a repeat expansion of 133 a GAA motif in the intron of the frataxin gene. This expansion leads to DNA methylation and the

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134	deposition of repressive chromatin marks, leading to robust repression of the gene and
135	development of disease ³¹ . Because of this, we suspect some of the rREs found in cancer might
136	alter the epigenome and affect gene regulatory networks.
137	rREs were distributed non-uniformly across the genome, with a bias towards the ends of
138	chromosome arms (Fig. 2c, Extended Data Figure 6). This observation is consistent with
139	previous reports of TRs and structural variants ^{15,32} . We also examined the distribution of rREs
140	relative to gene features with annotatr (Fig. 2d) ³³ . The 7% of rREs labeled as exonic appeared
141	proximal to, but not within, exons, but others were in introns, untranslated regions (UTRs), and
142	splice sites. These results suggest rREs may play different functional roles in the regulation of
143	gene expression.
144	We measured the distance between rREs and candidate cis-regulatory elements
145	(cCREs) ³⁴ ; cCREs comprise approximately one million functional elements including promoters,
146	enhancers, DNase-accessible regions, and insulators bound by CCCTC-binding factor (CTCF).
147	An rRE near a regulatory element could alter the function of that regulatory element, as is
148	observed in Fragile X syndrome and Friedreich's ataxia ¹ . Interestingly, rREs are located closer to
149	cCREs than expected by chance, and we find that 47 of 160 rREs directly overlap with a known
150	cCRE (Welch's <i>t</i> -test, <i>P</i> = 6.00e-45, Fig. 2e & Extended Data Figure 7). Thus, rREs are often
151	found in or near functional regions of the genome.
152	
153	rREs with links to cancer

We mapped each rRE to the nearest genes and found that nine rREs map to Tier 1 genes
present in the census of somatic mutations in cancer (COSMIC) database (Fig. 3, Table S1). We

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156	also observed a strong correlation with cancer-related genes (Jensen disease-gene associations ³⁵).
157	That is, four of the top five diseases associated with the collection of 160 rRE are cancers (Fig.
158	3b , Table S4).

To examine whether some rREs play a role in oncogenesis, we looked at their association with previously-identified cancer risk loci. Many rREs were identified in prostate cancer, and 63 loci have previously been associated with susceptibility to prostate cancer from available genome-wide association studies³⁶. When we examined the co-localization of rREs and cancer risk loci in prostate cancer, we found that rREs are located closer to prostate cancer susceptibility loci than standard STRs or by chance (Student's *t*-test, FDR q = 0.08, **Fig. 3c & Extended Data Figure 7**).

166 We next studied the relationship between the occurrence of the census of somatic 167 mutations in cancer (COSMIC) genes to the occurrence of rREs (Fig. 3d). Interestingly, we 168 found that there are five COSMIC genes whose somatic mutations are found to occur 169 significantly more in patients' genomes with no rREs, after correcting for multiple hypothesis 170 testing. Among them, TP53 was particularly striking, as wildtype TP53 is critical for mediating 171 the pathogenic effects of repeat expansions in both Amyotrophic Lateral Sclerosis (ALS) and 172 Huntington's Disease^{37,38}. Consistent with these findings, a DNA damage repair gene in yeast, 173 *Rad53*, is phosphorylated and activated in the presence of an expanded repeat³⁹.

MSI-high cancers are often correlated with higher levels of immune cell infiltration⁴⁰. We
hypothesized that some rREs might also be associated with higher immune cell infiltration, but
we did not observe a correlation between cytotoxic activity⁴¹ and the presence of an rRE
(Extended Data Figure 9). Because there are matching RNA-seq data for only 4 of 160 rREs,

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178	this analysis warrants further investigation as more matching WGS and RNA-seq datasets
179	become available.

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181 An rRE in the UGT2B7 gene observed in RCC

182	A GAAA expansion located in the intron of <i>UGT2B7</i> was observed in 34% of RCC

- 183 samples. *UGT2B7* is a glucuronidase that clears small molecules—including
- 184 chemotherapeutics—from the body and is selectively expressed in the kidney and liver⁴².

185 With gel electrophoresis, we identified the expected TR size of ~ 26 GAAA repeats in the

186 normal kidney cell line, HK-2, corresponding closely to the length observed in the reference

187 genome (Fig. 4a). In contrast, we identified an expansion between ~63 and ~160 GAAA repeat

188 units in 5 of 8 clear cell RCC cell lines. Most expansions were heterozygous (Fig. 4a). Long-

read DNA sequencing with highly-accurate PacBio HiFi reads confirmed the PCR results and

190 revealed the precise structure of this repeat expansion at single base pair resolution for both 786-

191 O and Caki-1 (Fig. 4b). We also detected this repeat expansion in five out of 12 primary kidney

192 tumor tissue samples from patients with clear cell RCC (Extended Data Figure 8), which

showed more heterogeneity than the RCC cell lines; more heterogeneity might be expected for

194 human tumor samples compared to the clonal cell lines.

195 Given that *UGT2B7* is selectively expressed in the liver and kidney, and that it plays a 196 role in clearing small molecules from the body, we examined whether this rRE may be located 197 near any functional elements that could regulate its expression. Analysis of the chromatin 198 environment surrounding the rRE in *UGT2B7* revealed a nearby enhancer, raising the possibility 199 that this rRE alters the expression of *UGT2B7* (**Fig. 4c**). The repeat motif of this rRE, GAAA,

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200	appears similar to the pathogenic repeat motif found in Friedreich's ataxia, which is GAA. The
201	pathogenic GAA repeat expansion blocks FXN expression ³¹ . We therefore hypothesized that the
202	intronic GAAA repeat expansion might repress the expression of UGT2B; we found a modest
203	decrease in expression that was not statistically significant (Extended Data Figure 8). While
204	this rRE is also not associated with a difference in survival (Extended Data Figure 8), it is
205	associated with a significant decrease in a transcript isoform in UGT2B7 (Wald test with FDR
206	correction, $P = 0.0048$) (Fig. 4e). Interestingly, a shift in isoform usage of $UGT2B7$ has been
207	noted in cancer ⁴³ .

208

209 Repeat-targeting anti-proliferative agents

210 Do GAAA repeat expansions contribute to cell proliferation? We previously showed that 211 targeting a related TR motif, GAA, with synthetic transcription elongation factors (Syn-TEF1) 212 reverses pathogenesis in several models of Friedreich's ataxia²³. Therefore, if the GAAA rRE in 213 RCC behaves similarly, then a Syn-TEF targeting GAAA may have anti-proliferative activity. 214 We rationally designed Syn-TEF3, which contains a GAAA-targeting polyamide (PA), and a 215 bromodomain ligand, JQ1, designed to recruit part of the transcriptional machinery (Fig. 5a and 216 Fig. S2). We also included a control molecule, Syn-TEF4, which targets GGAA TRs, as well as 217 polyamides (PAs) PA3 and PA4 that lack the JQ1 domain. We have previously shown that Syn-218 TEFs and PAs localize to repetitive TRs in living cells^{23,44}.

219 The effect of Syn-TEFs on cell proliferation was examined (**Fig. 5b**). Caki-1 and 786-O were

selected because they have the largest (161) and smallest (24) GAAA tracts within the first

intron of UGT2B7, respectively. In a dose-dependent manner, we observed that Syn-TEF3 led to

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222	a significant decrease in the proliferation of Caki-1 cells but had little effect on 786-O cells. Syn-
223	TEF4, which does not target a GAAA TR, did not significantly decrease proliferation in either of
224	the cell lines tested, demonstrating the requirement for GAAA-specific targeting (Fig. 5b). Two
225	additional GAAA repeat expansion cell lines as well as two additional control non-expanded
226	lines showed a similar association between Syn-TEF sensitivity and the presence of the repeat
227	expansion (Extended Data Figure 10). Consistent with this finding, Caki-1 cells treated with
228	Syn-TEF3 exhibited a significant increase in cell death compared to DMSO control, as measured
229	by propidium iodide staining (Fig. 5c,d and Extended Data Figure 10). In contrast, 786-O cells
230	treated with Syn-TEF3 showed no significant difference in propidium iodide-positive cells
231	compared to DMSO (Fig. 5c,d and Extended Data Figure 10). Importantly, the Syn-TEF4,
232	PA3, and PA4 control agents exhibited no significant effect on cell death in either cell line
233	compared to vehicle control (Fig. 5c,d and Extended Data Figure 10). These results suggest
234	that GAAA repeat expansions may represent a genetic vulnerability in RCC and provide a proof-
235	of-principle study for the functional role of rREs in cancer.

236

237 Discussion

Here, for the first time, we conduct a genome-wide survey of recurrent repeat expansions (rREs) across cancer genomes, distinct from MSI. Our data identified (i) 160 rREs in 7 human cancers and revealed that (ii) most (155 of 160) rREs are cancer subtype-specific; (iii) amongst diseases, rREs are enriched in human cancer loci and tended to occur near regulatory elements; (iv) recurrent repeat expansions do not correlate with MSI status; and (v) targeting a GAAA repeat expansion in RCC with a small molecule leads to cancer cell killing. Taken together, our

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results uncover an unexplored genetic alteration in cancer genomes with important mechanisticand therapeutic implications.

246 Cancer cells evolve and adapt in response to environmental or pharmacological 247 perturbations, but the mechanisms supporting these changes are still being uncovered. One 248 source of genetic variation that may enable genetic adaptations is TR DNA sequences. Mutations 249 in repeat length of TRs can occur up to 10,000 times more frequently than single nucleotide 250 variants (SNVs) or insertions and deletions (INDELs)¹. Repeat expansions may provide a source 251 of genetic variation to enable cancer cells to adapt to changes in the environment⁴⁵. Indeed, 252 colorectal cancers acquire mutations in STRs in response to targeted therapy just 24 hours 253 following treatment, suggesting that mutations in these regions may associate with rapid 254 evolution⁴⁶. In future studies, it will be particularly valuable to study repeat expansions in the 255 genomes of cancer cells that face changing environments, including metastasis and 256 chemotherapy.

257 Historically, MSI has been the focus of efforts to profile changes in STRs in cancer 258 genomes because specific cancer-causing genetic alterations in repair genes can promote 259 widespread STR alterations. Interestingly, we find little to no correlation between rREs and MSI. 260 These results are consistent with previous findings in which the correlation between MSI and 261 repeat instability at larger TRs is not definitive⁴⁷. MSI may contribute to a subtype of rREs that 262 we have not yet uncovered, or rREs may arise from a mutation process that is distinct from that 263 of MSI. There are several different DNA cellular repair systems, and presumably the rREs that 264 we observed are due to very specific loci-associated mechanisms or activities. Some of these 265 repeat expansions may be due to cis-regions with interesting DNA or chromatin configurations

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that are prone to expansion at distinct loci, rather than gene mutations that cause global transeffects, as occurs in MSI.

268 There are numerous mechanisms by which a repeat expansion can alter cellular function. 269 Known pathogenic repeat expansions can alter the coding sequence of a protein, such as in the 270 case of Huntington's disease. However, there are several repeat expansions that occur in non-271 coding regions that alter gene expression¹. In other instances, the repeat expansion can lead to a 272 pathogenic RNA molecule (myotonic dystrophy) or protein (ALS)¹. Finally, repeat expansions in 273 MSI-associated cancers, which are too small to detect by EHdn, can disrupt DNA replication⁴⁸. 274 Thus, our catalog represents a powerful resource to explore the mechanisms by which rREs alter 275 cellular function in cancer.

276 The identification of repeat expansions would benefit from improved sequencing 277 coverage and increased cohort sizes. Like other tools that identify repeat expansions, we cannot 278 distinguish zygosity from sample heterogeneity or obtain precise lengths of repeats. Our 279 independent experimental validation showed that some repeat expansions are heterogeneous 280 (Extended Data Figure 8). We suspect that tumor heterogeneity may lead to an underreporting 281 of rREs. Furthermore, this study focuses on somatic mutations, but repeat expansions that occur 282 in the context of normal development will be another important area of study⁴. Furthermore, 283 germline events that predispose an individual to cancer would also be worthwhile to study; there 284 is evidence that a TR in the androgen receptor gene is associated with prostate cancer onset, 285 tumor stage, and tumor grade⁴⁹. Finally, we only detected changes in repeat length that were 286 greater than sequencing read length. In future studies, it will be important to explore recurrent 287 changes that are smaller in length. Finally, it is important to acknowledge that rREs could be 288 mediators of phenotypes or passengers that result from genetic instability and clonal selection. In

289	the one instance where we targeted the rRE in RCC, cell proliferation was reduced, consistent
290	with a mediator role for this rRE. Distinguishing between these two possibilities for each rRE is
291	an important line of work in the future.
292	To our knowledge, this is the first genome-wide survey of repeat expansions beyond a
293	neurological or neurodegenerative disorder. Thousands of high-quality whole genome sequences
294	exist for many diseases, and our data provide evidence that repeat expansions should be explored
295	beyond the classical bounds of neurodegenerative diseases where they have been most
296	investigated.
297	A careful dissection of repeat expansions in human disease may reveal their role as
298	causative or contributory. We show here that repeat expansions can be targeted by tandem
299	repeat-targeting precision molecules ²³ . Thus, our results set the stage for a new class of
300	therapeutics to be deployed in cancer and other diseases.
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405		adjacent normal tissues. Proc. Natl. Acad. Sci. 116, 16987 LP – 16996 (2019).

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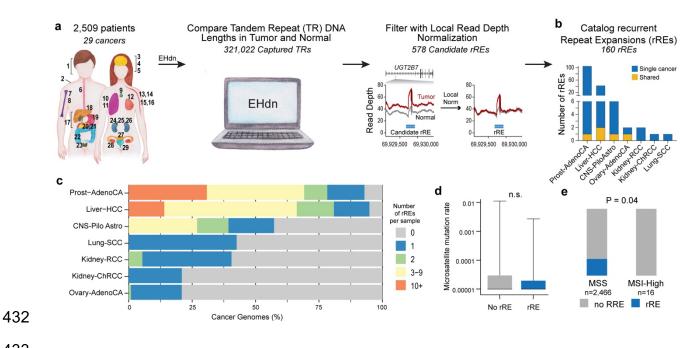
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410

411	Figure 1. Genome-wide detection of recurrent repeat expansions (rREs) in cancer genomes.
412	a) Scheme of method to identify rREs in 2,509 patients across 29 human cancers. 1, head and
413	neck squamous cell carcinoma (Head-SCC); 2, Skin-Melanoma; 3, glioblastoma (CNS-GBM);
414	4 medulloblastoma (CNS-Medullo); 5, pilocytic astrocytoma (CNS-PiloAstro); 6, esophageal
415	adenocarcinoma (Eso-AdenoCA), 7, osteosarcoma (Bone-Osteosarc); 8, leiomyosarcoma
416	(Bone-Leiomyo); 9, thyroid adenocarcinoma (Thy-AdenoCA); 10, lung adenocarcinoma
417	(Lung-AdenoCA); 11, lung squamous cell carcinoma (Lung-SCC); 12, mammary gland
418	adenocarcinoma (Breast-AdenoCA); 13, B-cell non-Hodgkin lymphoma (Lymph-BNHL); 14,
419	chronic lymphocytic leukemia (Lymph-CLL); 15, acute myeloid leukemia (Myeloid-AML); 16,
420	myeloproliferative neoplasm (Myeloid-MPN); 17, biliary adenocarcinoma (Biliary-AdenoCA);
421	18, hepatocellular carcinoma (Liver-HCC); 19, stomach adenocarcinoma (Stomach-AdenoCA);
422	20, pancreatic adenocarcinoma (Panc-AdenoCA), 21, pancreatic neuroendocrine tumor
423	(Panc-Endocrine); 22, colorectal adenocarcinoma (ColoRect-AdenoCA); 23, prostatic
424	adenocarcinoma (Prost-AdenoCA); 24, chromophobe renal cell carcinoma (Kidney-ChRCC);
425	25, renal cell carcinoma (Kidney-RCC); 26, papillary renal cell carcinoma (Kidney-pRCC); 27,
426	uterine adenocarcinoma (Uterus-AdenoCA); 28, ovarian adenocarcinoma (Ovary-AdenoCA);
427	29, transitional cell carcinoma of the bladder (Bladder-TCC). b) Distribution of rREs across
428	cancer types. c) Proportion of cancer genomes with rREs. d) STR mutation rate for cancer
429	genomes with and without a rRE. Two-tailed Wilcoxon rank sum test. e) Distribution of rREs
430	across microsatellite stable (MSS) and microsatellite instability high (MSI-high) cancers. Chi-
431	square test with Yates' correction.

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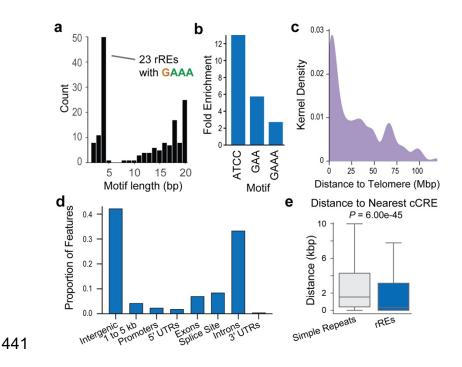
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436 Figure 2. Features of rREs. a) Distribution of the repeat unit (motif) for rREs. b) Motifs

- 437 enriched in the catalog of rREs. c) Distance of rREs to the end of the chromosome arm. d)
- 438 Proportion of genic features that overlap with rREs. UTR, untranslated region. e) Distance of
- 439 simple repeats and rREs to the nearest ENCODE candidate cis-regulatory element (cCRE).
- 440 Center values represent the median. Welch's *t*-test.

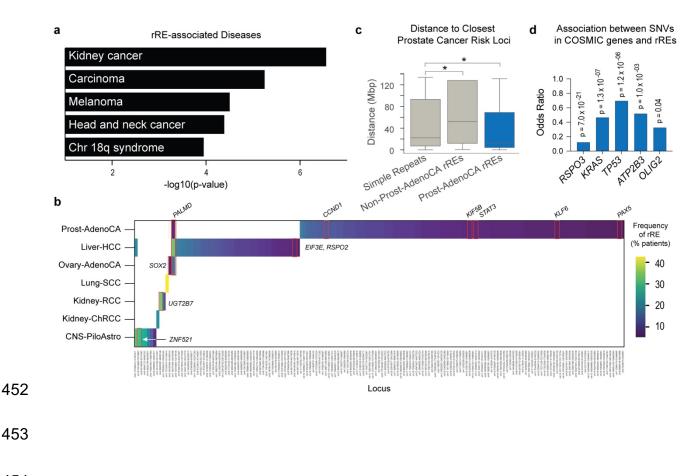


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445 Figure 3. Association of rREs with cancer features. a) Association of rREs with human

- 446 diseases. b) Frequency of rREs in genes of interest, including the nine COSMIC genes, are
- 447 highlighted. c) Distance of simple repeats, non-prostate cancer rREs, and prostate-cancer rREs to
- the nearest prostate cancer risk locus. Center values represent the median. Statistical significance
- 449 was measured with Welch's *t*-test (* q < 0.10). d) Association between SNVs in genes in the
- 450 census of somatic mutations in cancer (COSMIC) Tier 1 genes and the presence of rREs.
- 451 Student's *t*-test with FDR correction by Benjamini-Hochberg.



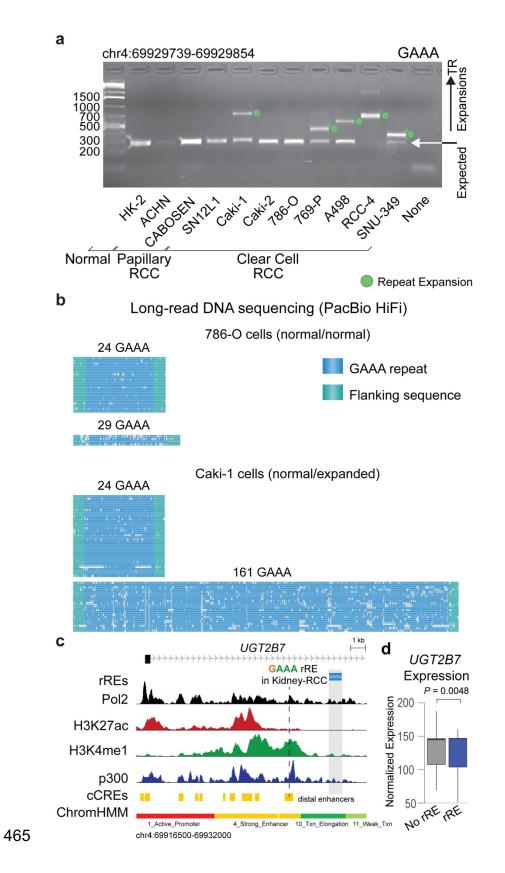
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455 Figure 4. An rRE in Renal Cell Carcinoma (RCC). a) Gel electrophoresis of the GAAA

- 456 tandem repeat in RCC samples. This analysis was performed in duplicate and the gel is
- 457 representative of the results. For gel source data, see Fig. S1. b) Visualization of long-read
- 458 sequencing of GAAA rRE in the intron of *UGT2B7*. Data are from PacBio HiFi sequencing. c)
- 459 The locus surrounding the rRE detected in the intron of *UGT2B7*. Signal traces of Pol2,
- 460 H3K27ac, H3K4me1, and p300 in HepG2 cells are shown. Candidate cis-regulatory elements
- 461 (cCREs) and chromatin states (ChromHMM) are also depicted. d) Expression of UGT2B7
- 462 isoform ENST00000508661.1 in RCC samples as a function of the detection of the rRE in
- 463 UGT2B7 (Normalized Expression, Counts). Center values represent the median. Significance
- 464 was measured by Wald test with FDR correction (Benjamini-Hochberg).

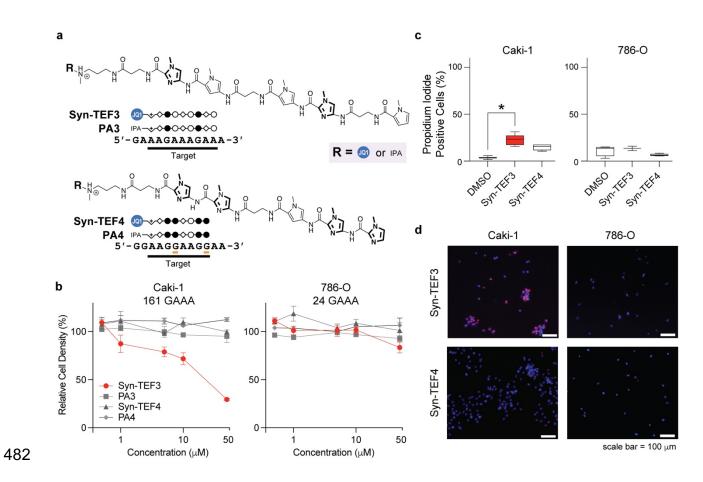
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466

467	Figure 5. The design and characterization of GAAA-targeting molecules in RCC. a)
468	Chemical structures of Syn-TEF3, PA3, Syn-TEF4 and PA4. Syn-TEF3, and PA3 target 5'-
469	AAGAAAGAA-3'. Syn-TEF4* and PA4 target 5'-AAGGAAGG-3'. The structures of N-
470	methylpyrrole (open circles), N -methylimidazole (filled circles), and β -alanine (diamonds) are
471	shown. N-methylimidazole is bolded for clarity. The structure of JQ1 linked to polyethylene
472	glycol (PEG ₆) is represented as a blue circle. The structure of isophthalic acid and linker is
473	represented as IPA. Complete chemical structures are depicted in Fig. S2. The asterisk indicates
474	the site where the R group attaches to the polyamide. Mismatches formed with Syn-TEF4 and
475	PA4 are indicated with orange. b) Relative cell density of RCC cell lines Caki-1 and 786-O
476	following treatment (72 h) with compounds, as indicated. Relative cell density was measured
477	with CCK-8 assay (see Methods). Results are mean \pm SEM ($n = 4$). c) Quantitation of the
478	percentage of propidium iodide-positive cells. Whiskers are minimum and maximum values. * p
479	< 0.05. P values are from a one-way ANOVA with multiple comparisons. d) Live cell
480	microscopy of Caki-1 and 786-O cells stained with propidium iodide (red) and Hoechst 33342
481	(blue). Scale bars, 100 μm. See also Extended Data Figure 10.

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484 Methods

485 **Data curation**

- 486 We obtained white-listed data from the International Cancer Genome Consortium (ICGC) and
- 487 The Cancer Genome Atlas (TCGA) pan-cancer analysis of whole genomes (PCAWG) dataset.
- 488 Data were accessed through the Cancer Genome Collaboratory. We used the aligned reads
- 489 (BAM files), which were aligned to GRCh37 as described previously²⁵. These data are available
- 490 through the PCAWG data portal (<u>https://docs.icgc.org/pcawg</u>). A list of samples included in the
- 491 analysis is available in **Table S2**.
- 492

493 Identification of somatic recurrent repeat expansions

494 We analyzed tumor and matching normal samples for each cancer type independently. 495 We executed ExpansionHunter Denovo (EHdn) (v0.9.0)¹⁵ with the following parameters: --min-496 anchor-mapq 50 --max-irr-mapq 40. To prioritize loci, we developed a workflow termed Tandem 497 Repeat Locus Prioritization in Cancer (TROPIC). We included loci from chr1-22, X, and Y for 498 downstream analysis. We removed loci where >10% of Anchored in-repeat read (IRR) values 499 were >40, which is the theoretical maximum value. The p-value (a non-parametric one-sided 500 Wilcoxon rank sum test) for each locus was used to calculate a false discovery rate (FDR) q-501 value. Loci with FDR < 0.10 are reported. We selected loci where >5% of samples had an 502 Anchored in-repeat read (IRR) Outient > 2.5. For a repeat expansion to be detected by EHdn, 503 the tandem repeat must be larger than the sequencing read length. A somatic repeat expansion 504 was defined as having an FDR q-value < 0.05 between tumor and normal samples. To call repeat 505 expansions in individual cancer samples, we analyzed the distribution of tumor and normal

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506	Anchored IRR values and selected a conservative threshold for the Anchored IRR Quotient
507	((Tumor Anchored IRR – Normal Anchored IRR)/(Normal Anchored IRR + 1)) > 2.5 (Extended
508	Data Figure 4).
509	
510	Local read depth normalization
511	EHdn normalizes the number of Anchored IRRs for a given locus to the global read
512	depth. To account for chromosomal amplifications and other forms of genetic variation that
513	could alter local read depth, we performed the following normalization. For each rRE locus and
514	sample in its corresponding cancer, samtools v1.13 was used with the parameter depth -r to find
515	the read depth at each base pair within the locus and a 500 bp region surrounding the start and
516	stop positions of the TR. We calculated the average read depth at each base pair and defined this
517	as the local read depth. Finally, we calculated the local read depth-normalized Anchored IRR
518	value specific to a sample and rRE combination by dividing the unnormalized Anchored IRR
519	value from EHdn by the local read depth at the locus.
520	
521	Generation of CABOSEN cells
522	CABOSEN cells were generated from a <u>cabo</u> zantinib- <u>sen</u> sitive (CABOSEN) human papillary
523	RCC xenograft tumor grown in RAG2 ^{-/-} gammaC ^{-/-} mice, as described previously ⁵⁰ . Tumor tissue
524	was minced with a sterile blade and the cell suspension cultured in DMEM/F-12 medium
525	(Corning) supplemented with 10%(v/v) Cosmic Calf Serum (ThermoFisher). Cells were
526	expanded and cryopreserved in growth medium supplemented with 10%(v/v) DMSO and cells

527 from passage 8 were used for analysis.

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529 Analysis of rREs by gel electrophoresis

530	We performed PCR with CloneAmp HiFi PCR Mix (Takara Biosciences, Mountain
531	View, CA) and added DMSO to a final concentration of $5-10\%$ (v/v) as needed. All cell lines
532	were tested negative for mycoplasma contamination with the MycoAlert Mycoplasma Detection
533	Kit (Lonza). Cell line identities were authenticated by STR profiling by the Genetic Resources
534	Core Facility at Johns Hopkins University, with the exception of SNU-349, which did not match
535	the reported STR profile of SNU-349 or any other catalogued cell line, but has a mutated VHL
536	gene and expresses high levels of PAX8 and CA9, consistent with ccRCC origin. A list of
537	primers used to analyze the loci is available in Table S6 .
538	
539	Visualization of repeat expansions with ExpansionHunter and REViewer
539 540	Visualization of repeat expansions with ExpansionHunter and REViewer To inspect the reads supporting a repeat expansion, we annotated the repeat as described
540	To inspect the reads supporting a repeat expansion, we annotated the repeat as described
540 541	To inspect the reads supporting a repeat expansion, we annotated the repeat as described on the GitHub page for ExpansionHunter. We then profiled the region with ExpansionHunter
540 541 542	To inspect the reads supporting a repeat expansion, we annotated the repeat as described on the GitHub page for ExpansionHunter. We then profiled the region with ExpansionHunter (v4.0.2) using the default settings ¹⁴ . The resulting reads were visualized with REViewer (v0.1.1)
540 541 542 543	To inspect the reads supporting a repeat expansion, we annotated the repeat as described on the GitHub page for ExpansionHunter. We then profiled the region with ExpansionHunter (v4.0.2) using the default settings ¹⁴ . The resulting reads were visualized with REViewer (v0.1.1) using the default settings. REViewer is available at <u>https://github.com/Illumina/REViewer</u> . A
540 541 542 543 544	To inspect the reads supporting a repeat expansion, we annotated the repeat as described on the GitHub page for ExpansionHunter. We then profiled the region with ExpansionHunter (v4.0.2) using the default settings ¹⁴ . The resulting reads were visualized with REViewer (v0.1.1) using the default settings. REViewer is available at <u>https://github.com/Illumina/REViewer</u> . A repeat expansion was called when the repeat tract length for one allele of the tumor sample was

548 Validation of rREs in independent cohorts of samples

549	Twelve pairs of matching normal and tumor samples from patients with clear cell renal
550	cell carcinoma were obtained with the patients' informed consent ex vivo upon surgical tumor
551	resection (Stanford IRB-approved protocols #26213 and #12597) and analyzed. Eighteen and 15
552	pairs of matching normal and tumor samples for prostate and breast cancer, respectively, were
553	obtained from the Tissue Procurement Shared Resource facility at the Stanford Cancer Institute
554	and analyzed. Nucleic acid was isolated with either the Quick Microprep Plus kit (Catalog
555	D7005) or the Zymo Quick Miniprep Plus kit (Catalog D7003) (Zymo Research, Irvine, CA).
556	Gel electrophoresis was performed as described above. A locus was considered detected if a
557	somatic repeat expansion was identified in at least one patient tumor sample compared to a
558	matching normal sample.
559	
560	Downsampling Analysis
561	For the downsampling analysis, tumor genomes from renal cell carcinoma samples were
561 562	For the downsampling analysis, tumor genomes from renal cell carcinoma samples were downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools
562	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools
562 563	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the
562 563 564	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the Bonferroni-corrected p-value was plotted for the recurrent repeat expansion in <i>UGT2B7</i> (GAAA,
562 563 564 565	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the Bonferroni-corrected p-value was plotted for the recurrent repeat expansion in <i>UGT2B7</i> (GAAA,
562 563 564 565 566	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the Bonferroni-corrected p-value was plotted for the recurrent repeat expansion in <i>UGT2B7</i> (GAAA, chr4:69929297-69930148).
562 563 564 565 566	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the Bonferroni-corrected p-value was plotted for the recurrent repeat expansion in <i>UGT2B7</i> (GAAA, chr4:69929297-69930148). Benchmarking the Local Read-Depth Normalization (LRDN) filter
562 563 564 565 566 567 568	downsampled from their mean (52x) sequencing depth to 40, 30, 20, and 10x with the samtools view command. EHdn was run, as described above for each of the sequencing depths, and the Bonferroni-corrected p-value was plotted for the recurrent repeat expansion in <i>UGT2B7</i> (GAAA, chr4:69929297-69930148). Benchmarking the Local Read-Depth Normalization (LRDN) filter We benchmarked the local read depth filter <i>in silico</i> by observing its behavior with

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571	length of 100 bp. We artificially expanded these TRs in chromosome 1 of GRCh37 with the
572	BioPython python package (version 1.79). Next, we used wgsim (version 0.3.1-r13) to simulate
573	reads from the reference file with the command "wgsim -N 291269925 -1 100 -2 100
574	reference_file.fasta output.read1.fastq output.read2.fastq". The number of reads (specified by the
575	-N option) was calculated to achieve 30x coverage of chromosome 1. The resulting pair of files,
576	hereinafter referred to as the base fastq files, contained a copy number of 2 for all of the
577	expansions.

578 To simulate copy number amplification, the read simulation process was repeated using 579 reference files that contained only the artificially expanded repeats and their surrounding 1,000 580 bp flanks. We created 10 pairs of fastq files, each with an increasing copy number. We specified 581 the copy number by multiplying the number of reads to generate (wgsim -N option) by the 582 required number. To generate the final set of fastq files, we concatenated each pair of copy 583 number-amplified fastq files with the base fastq files. The end result is 8 pairs of fastq files that 584 contain reads of chromosome 1 and a copy number amplification varying from 2 to 10 of the 585 expanded repeats.

The base fastq file with a copy number of 2, in addition to the eight copy numberamplified fastq files, were aligned to chromosome 1 of GRCh37 with bwa-mem (v 0.6) with the default options. The resulting SAM files were converted to BAM format with samtools (v 1.15) with the default options. Finally, we ran the EHdn profile command (v 0.9.0) with the minimum anchor mapping quality set to 50 and maximum IRR mapping quality set to 40. Finally, the Anchored IRR values were extracted by overlapping the STR coordinates with the *de novo* repeat expansion calls.

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594 Short-read and long-read DNA sequencing

595	We sequenced Caki-1 and 786-O with both short-read sequencing (60x sequencing
596	coverage, 150 bp paired-end sequencing on a NovaSeq 6000 instrument) and long-read DNA
597	sequencing (50x sequencing coverage, PacBio HiFi sequencing on a Sequel IIe instrument). We
598	aligned the long reads to GRCh37 with pbmm2 v1.7.0, using the parameterssortmin-
599	concordance-perc 70.0min-length 50. We aligned the short reads to GRCh37 with Sentieon
600	(v202112.01) with parameters -K 10000000 -M, an implementation of BWA-MEM, and
601	analyzed the samples with EHdn, as described above. We included loci containing at least one
602	sample with an Anchored IRR value >0 for further analysis. Anchored IRR values >0 arise when
603	the repeat length exceeds the sequencing read length. To benchmark EHdn against long-read
604	sequencing data, we manually determined the TR length of a given locus in the long-read
605	sequencing data. If the TR length in the long-read sequencing data exceeded the short-read
606	sequencing read length of 150 bp, we considered that locus confirmed.
607	The PacBio HiFi data were aligned to GRCh37 with pbmm2 v1.7.0 and visualized at the

- The PacBio HiFi data were aligned to GRCh37 with pbmm2 v1.7.0 and visualized at the
- 608 *UGT2B7* locus with Tandem Repeat Genotyper v0.2.0
- 609 (<u>https://github.com/PacificBiosciences/trgt</u>).
- 610

611 Analysis of rRE loci

To determine if rREs were associated with any human diseases, rREs were mapped to
genes with GREAT (v4.0.4, default settings)⁵¹. The resulting genes were analyzed with Enrichr
using Jensen Diseases⁵². To determine whether repeat expansions were associated with
microsatellite instability-high (MSI-High) cancers, we obtained data from Hause et al⁵. The

616	percentage of MSI-high cancers was obtained from colon adenocarcinoma (COAD), stomach		
617	adenocarcinoma (STAD), kidney renal cell carcinoma (KIRC), ovarian serous		
618	cystadenocarcinoma (OV), prostate adenocarcinoma (PRAD), head and neck squamous cell		
619	carcinoma (HNSC), liver hepatocellular carcinoma (LIHC), bladder urothelial carcinoma		
620	(BLCA), glioblastoma multiforme (GBM), skin cutaneous melanoma (SKCM), thyroid		
621	carcinoma (THCA), and breast invasive carcinoma (BRCA) and compared to the number of		
622	repeat expansions and the percentage of patients with at least one repeat expansion in the		
623	corresponding cancer type from the PCAWG dataset. We also overlapped cancer genomes		
624	containing rREs with the microsatellite mutation rate, which we term the STR mutation rate, and		
625	MSI calls from Fujimoto et al ²⁹ . The association of rREs with STR mutation rate was assessed		
626	with the two-tailed Wilcoxon rank sum test. The association of rREs with MSI calls was assessed		
627	with Chi-square test with Yates' correction.		
628	To determine whether rREs are associated with known mutational signatures, we		
629	downloaded mutational signatures from the ICGC DCC		
630	(https://dcc.icgc.org/releases/PCAWG/mutational_signatures/Signatures_in_Samples). We		
631	performed a multiple linear regression for each single-base-substitution (SBS) and doublet-base-		
632	substitution (DBS) signatures to identify predictors of the number of rREs present in a sample.		
633	To choose the predictors, we performed best subset selection on DBS and SBS signatures and		
634	included age as a possible confounding factor. We used the statsmodels v0.12.2 in Python and,		
635	specifically, the ordinary least squares model found in the statsmodels.api.OLS module to		
636	estimate the coefficients of the selected predictors in their corresponding multiple linear		
637	regression model ⁵³ .		

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638	To determine whether repeat expansions were associated with a difference in cytotoxic
639	activity, we calculated cytotoxic activity as previously described for four cancers that had
640	matching RNA-seq and WGS ⁴¹ . For each locus, we compared cytolytic activity for patients with
641	a repeat expansion to patients without a detected repeat expansion using a Welch's t-test with
642	correction for multiple hypothesis testing (Benjamini-Hochberg FDR q-value < 0.05). rREs were
643	annotated with genic elements using annotatr $(v1.18.1)^{33}$.

644 To determine if rREs were associated with regulatory elements, we downloaded

645 candidate cis-regulatory elements (cCREs)³⁴ and mapped them to GRCh37 with LiftOver

646 (UCSC)⁵⁴. We determined the distance between rREs and cCREs with the bedtools closest

647 command $(v2.27.1)^{55}$, and compared this distance to the simple repeats catalog⁵⁶. To compare the

648 distance to ENCODE cCREs, a Welch's *t*-test was performed.

To determine if prostate cancer rREs were associated with prostate cancer susceptibility loci³⁶, we calculated the distance to three sets of loci using the "bedtools closest" command. We calculated the distance between (1) rREs present in prostate cancer samples and prostate cancer susceptibility loci, (2) rREs not present in cancer samples and cancer susceptibility loci, and (3) simple repeats and cancer susceptibility loci. To compare the distances between these three associations, we performed a Welch's *t*-test with FDR correction (Benjamini-Hochberg).

To determine whether rREs were associated with replication timing, we downloadedRepli-seq replication timing data from seven cell lines from the ENCODE website (NCI-H460,

657 T470, A549, Caki2, G401, LNCaP, and SKNMC)⁵⁷. We selected regions for which all cell lines

had concordant signals for analysis (early or late replication designations agreed for each cell

659 line at a given locus). We determined whether there was a difference in the distribution of rREs

across early- and late-replicating regions compared to the simple repeats catalog with

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661	bootstrapping ($n=10,000$). We sampled 54 loci (the number of rREs that are present in a
662	concordant replication region) from rREs and simple repeats. A Welch's t-test was performed on
663	the bootstrapped samples to estimate a <i>p</i> -value. We applied FDR correction (Benjamini-
664	Hochberg) to the estimated p-values. To determine whether rRE status in UGT2B7 was
665	associated with survival outcome in clear cell RCC patients (TCGA abbreviation: KIRC), we
666	used Welch's <i>t</i> -test quartile.

667 To identify motifs enriched and depleted in the rRE catalog, we followed the same method used in the Motif-Scan python module $(v1.3.0)^{58}$. We compared our rRE catalog to 668 669 Simple Repeats (Tandem Repeat Finder, TRF) as a control. For each unique motif present, we 670 built a contingency table specifying the count of rREs and Simple Repeats with and without the 671 motif. Two one-tailed Fisher's exact tests were applied to the table to test for significance in both 672 directions, enrichment and depletion. The "stats" module in the Scipy python package (v1.7.0) 673 was used to conduct the significance test. Since multiple hypothesis tests were performed, we 674 applied FDR correction (Benjamini-Hochberg) for multiple hypothesis testing to the p-values, 675 with a cutoff (FDR) of 0.01.

676 For the comparison of SNVs in COSMIC genes to rREs, we first divided cancer genomes 677 into two categories: rRE cohort and non-rRE cohort. The rRE cohort contains all of the genomes 678 that have at least one rRE detected (n = 615) and the non-rRE cohort contains all of the genomes 679 that have no rREs detected (n = 1897). We then looked at the number of donors in the rRE cohort 680 that have at least one mutation on a given gene (COSMIC Tier 1 genes) i and the number of 681 donors in the non-rRE cohort that have at least one mutation on a given gene i with a 682 contingency table. We then calculated the p-value (Fisher's exact test) for the significance of 683 associating genes to either rRE or non-rRE cohort. This p-value calculation is repeated for all

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684 COSMIC genes and then an FDR at 0.05 significance level (Benjamini-Hochberg) was 685 employed to correct for multiple hypothesis testing.

686

Estimation of expansions in the general population 687

688	To estimate the frequency of the rREs in the general population, ExpansionHunter
689	Denovo (version 0.9.0) was run on 1000 Genomes Project samples ⁵⁹ ($n = 2,504$) (GRCh38) and
690	Medical Genome Reference Bank ⁶⁰ samples ($n = 4,010$) (GRCh37 lifted over to GRCh38).
691	The genomic coordinates of the 160 rREs (GRCh37) were padded with 1,000 bp and
692	translated to GRCh38 coordinates with the UCSC LiftOver. Then, these rRE coordinates
693	(GRCh38) were overlapped with loci from the population samples containing the Anchored IRR
694	calls. rREs that overlapped with matching motifs in the population samples were selected for
695	further analysis. We next sought to identify expanded rREs in the population samples to quantify
696	their prevalence. To do so, we converted their global-normalized Anchored IRR values to be
697	comparable to ICGC values. This step was necessary because sequencing read lengths from the
698	PCAWG dataset are generally 100 bp while the read lengths from 1000Genomes and Medical
699	Genome Reference Bank are 150 bp. The conversion follows the formula (Anchored IRR, 100
700	bp) = $0.5 + 1.5 * (Anchored IRR, 150 bp)^{15}$. A sample in the population samples was counted as
701	expanded if its Anchored IRR value was greater than the 99th percentile of Anchored IRR values
702	in the normal samples from the PCAWG dataset, a threshold that is comparable to the threshold
703	used to call expansions in tumor samples (Extended Data Figure 4). In future rRE catalogs, for
704	the rare instance where the estimated frequency of repeat expansions in the population samples is

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705	higher than expected, these data could be used to further filter rREs to improve the detection of
706	cancer-specific repeat expansions.

707	To compare the length of TRs in normal samples with and without a matching rRE in a
708	tumor sample, donors in the Prost-AdenoCA and Kidney-RCC cohorts whose data are available
709	for download through the Cancer Collaboratory were included (n=253). We used
710	ExpansionHunter (v5.0.0) with the default options to genotype prostate and kidney cancer rREs
711	in the normal samples of the selected donors. When there were two alleles of an rRE in a sample,
712	both alleles were included and treated as distinct data points. For each rRE, we tested whether
713	the distribution of genotypes from donors who have an expansion in their tumor samples differed
714	from donors who did not have an expansion. Student's t-test was used to compute p-values, and
715	FDR-correction (Benjamini-Hochberg) to adjust for multiple hypothesis testing.
716	
716 717	Association of rREs with gene expression
	Association of rREs with gene expression Matching RNA-seq and WGS data were available for Kidney-RCC, Ovary-AdenoCA,
717	
717 718	Matching RNA-seq and WGS data were available for Kidney-RCC, Ovary-AdenoCA,
717 718 719	Matching RNA-seq and WGS data were available for Kidney-RCC, Ovary-AdenoCA, Panc-AdenoCA, and Panc-Endocrine. RNA-seq data from these samples were obtained from
717 718 719 720	Matching RNA-seq and WGS data were available for Kidney-RCC, Ovary-AdenoCA, Panc-AdenoCA, and Panc-Endocrine. RNA-seq data from these samples were obtained from DCC (<u>https://dcc.icgc.org/</u>) and values were converted to transcripts per million (TPM).
717 718 719 720 721	Matching RNA-seq and WGS data were available for Kidney-RCC, Ovary-AdenoCA, Panc-AdenoCA, and Panc-Endocrine. RNA-seq data from these samples were obtained from DCC (https://dcc.icgc.org/) and values were converted to transcripts per million (TPM). Normalized gene expression (TPM) values were compared for samples with and without an rRE

725 isoforms of the *UGT2B7* gene (ENST00000305231.7, ENST00000508661.1,

726	ENST00000502942.1) and performed a Wald test with FDR correction using the Benjamini-
727	Hochberg procedure (threshold q -value < 0.01).
728	
729	Design, synthesis, and characterization of Syn-TEFs and PAs
730	Synthetic transcription elongation factors (Syn-TEFs) and polyamides (PAs) were
731	designed to target a GAAA repeat (Syn-TEF3 and PA3) or a control GGAA repeat (Syn-TEF4
732	and PA4). Syn-TEF3, Syn-TEF4, PA3, and PA4 were synthesized and purified to a minimum of
733	95% compound purity by WuXi Apptec and used without further characterization. HPLC
734	conditions for chemical characterization: 1.0 mL/min, Solvent A: 0.1% (v/v) trifluoroacetic acid
735	(TFA) in H2O, Solvent B: 0.075% (v/v) TFA in acetonitrile, Gemini, Column: C18 5 μ m 110A
736	150*4.6mm. Full results of characterization can be found in Fig. S2.
737	
737 738	Treatment of RCC cell lines with synthetic transcription elongation factors (Syn-TEFs)
	Treatment of RCC cell lines with synthetic transcription elongation factors (Syn-TEFs) Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media
738	
738 739	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media
738 739 740	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media with L-glutamine (Gibco Catalog 11875093), supplemented with 10% (v/v) FBS. A498 and
738 739 740 741	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media with L-glutamine (Gibco Catalog 11875093), supplemented with 10% (v/v) FBS. A498 and ACHN cells were obtained from ATCC and grown in DMEM media with glucose, L-glutamine,
738 739 740 741 742	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media with L-glutamine (Gibco Catalog 11875093), supplemented with 10% (v/v) FBS. A498 and ACHN cells were obtained from ATCC and grown in DMEM media with glucose, L-glutamine, and sodium pyruvate (Corning Catalog 10-013-CV), supplemented with 10% (v/v) FBS. RCC-4
738 739 740 741 742 743	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media with L-glutamine (Gibco Catalog 11875093), supplemented with 10% (v/v) FBS. A498 and ACHN cells were obtained from ATCC and grown in DMEM media with glucose, L-glutamine, and sodium pyruvate (Corning Catalog 10-013-CV), supplemented with 10% (v/v) FBS. RCC-4 cells were obtained from Amato Giacca (Stanford University) and grown in DMEM media with
738 739 740 741 742 743 744	Caki-1, and 786-O, and Caki-2 cells were obtained from ATCC and grown in RPMI 1640 media with L-glutamine (Gibco Catalog 11875093), supplemented with 10% (v/v) FBS. A498 and ACHN cells were obtained from ATCC and grown in DMEM media with glucose, L-glutamine, and sodium pyruvate (Corning Catalog 10-013-CV), supplemented with 10% (v/v) FBS. RCC-4 cells were obtained from Amato Giacca (Stanford University) and grown in DMEM media with glucose, L-glutamine, and sodium pyruvate (Corning Catalog 10-013-CV), supplemented with

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748	dissolved in DMSO (vehicle) and added to cells (0.1% (v/v) DMSO final concentration). On day
749	4 (72 h later), relative metabolic activity was measured as a proxy for relative cell density, with
750	the Cell Counting Kit (CCK-8; Dojindo Molecular Technologies) per the manufacturer's
751	instructions. Absorbance (450 nm) of cells treated with molecules was normalized to DMSO
752	(0.1%(v/v)) or no treatment. Absorbance was measured with an Infinite M1000 microplate
753	reader (Tecan, Mannedorf, Switzerland).
754	For microscopy, Caki-1 and 786-O cells were plated on glass-bottom 96-well plates
755	under standard culture conditions. One day after plating, media containing either no drug,
756	0.1%(v/v) DMSO, 50 μ M Syn-TEF3, or 50 μ M Syn-TEF4 was added, and the cells were
757	incubated for 72 hours at 37°C. As a control, wells that received no treatment were incubated
758	with 70%(v/v) ethanol for 30 seconds prior to staining. Cells were then stained with propidium
759	iodide and Hoechst 33342 from the Live-Dead Cell Viability Assay Kit (Millipore Sigma,
760	Catalog CBA415) according to manufacturers' instructions and immediately imaged at 10x
761	magnification with a 0.17 numerical aperture CFI60 objective on a Keyence BZ-X710
762	microscope. Four replicates were measured for each treatment condition, and the experiment was
763	repeated three times. Quantitation was conducted using FIJI software. For statistical analyses, a
764	one-way ANOVA with multiple comparisons was conducted with GraphPad Prism.

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766 Methods References

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792				
793	Data	availability		
794		Whole-genome sequencing data (both short- and long-read DNA sequencing) from 786-		
795	O and Caki-1 cell lines are deposited in NCBI with accession PRJNA868795.			
796				
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805				

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806 Author Contributions

- 807 G.S.E. conceived the study. G.S.E., G.G., A.C.F., J.T.L., M.A.E., M.P.S., and M.G. supervised
- 808 research. G.S.E., G.G., R.A., A.S, E.D., J.P., C.M.B., K.Z., R.K.C.Y., and A.A.E. analyzed data.
- 809 G.S.E., C.R.H., L.R., A.A., A.A., K.V.K., R.A.K., D.A.S., S.M.W., and T.J.M. conducted wet
- 810 lab experiments. G.S.E. and M.P.S. wrote the manuscript with input from all the authors.

811

812 Competing Interests declaration

- 813 G.S.E. and M.P.S. are inventors on a patent application describing anti-proliferative agents. E.D.
- and M.E. are shareholders and currently or formerly employed by Illumina and Pacific
- 815 Biosciences.
- 816

817 Additional Information

- 818 Supplementary Information is available for this paper.
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