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# Supplementary Materials for

# **Germline genomic patterns are associated with cancer risk, oncogenic pathways, and clinical outcomes**

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

Supplementary Materials and Methods Figs. S1 to S4 Tables S1 to S6 Legends for data S1 to S4

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

(available at advances.sciencemag.org/cgi/content/full/6/48/eaba4905/DC1)

Data S1 to S4

# **Supplementary Materials**

## **Supplementary Materials and Methods**

#### **The impact of germline variant calling methods on genomic pattern discovery**

Variant calling method plays an important role in genomics. Here we examined two distinct variant calling setups, either using HaplotypeCaller or MuTect, to determine whether the genomic pattern discovery methodology was tolerant of this technical difference. We further tested two calling modes of HaplotypeCaller and found them comparable as for this study's purpose.

(1) MuTect v119 versus HaplotypeCaller. Using the same criteria for variant read depth and VAF described in the Materials and Methods, we examined VCF files of a set of a non-redundant set of 9,930 individuals provided by the TCGA legacy archive, where variants were called using MuTect (v119 as indicated in the file headers). Mutational catalogs generated from both datasets closely resembled each other (Supplementary Fig. S4B). Major discoveries derived from HaplotypeCaller's results reported in this study, including the CGGPs, the correlation between CGGP\_E and smoking sensitivity, and the clinical outcomes between germline-variant-defined subgroups, were reproducible. These findings indicated that variant calling methods would not significantly affect the reported discoveries in this study.

(2) On HaplotypeCaller's two variant calling modes. HaplotypeCaller has two main setups: the Single Sample Mode, which processes each given sample separately, and the Jointed Mode. The Jointed Mode of the HaplotypeCaller provides more normalizations and normal-panel-based filters during variant calling. However, it requires unpractically large storage and computational resources for cohorts as large as the TCGA germline dataset (n=9,712) and non-cancer dataset (n=16,670) we used.

Alternatively, we examined if the Single Sample Mode and the Jointed Mode would generate similar mutational catalogs that would be the direct source input of germline genomic pattern discovery (see Materials and Methods for the definition of mutational catalogs). A total of 1,543 of 9,712 patients were randomly selected and processed using the HaplotypeCaller (GATK version 4.0.6.0; a different version was used due to un-fixed bugs in the implementation of parallel and data production in HaplotypeCaller 3.x's Jointed Mode) in either Jointed Mode or Single Sample Mode, generating two mutational catalogs. The two mutational catalogs closely resembled each other: For more than 98% of the patients, cosine similarities between their two mutational catalogs, defined as a vector of length 192, were higher than 0.995. All such cosine similarities were higher than 0.974 (Supplementary Fig. S4A). More importantly, our study focused on genomic patterns that represented enrichment of context-dependent variant sets, and mutational catalogs and germline genomic patterns were found more tolerant than the identification of individual variants. The genomic pattern discovery methodology showed its robustness for up to 30% disturbance of data points (see below, simulation tests). Based on these observations, we believed that Single Sample Mode and Jointed Mode could be considered equivalent with respect to our purpose.

#### **Germline Variants of cancer patients: statistics of variant annotation**

We annotated the germline variants obtained to provide an overview of the dataset, although variants were not discriminated based on their positional or functional annotations. Germline variants called using the HaplotypeCaller and then filtered with germline variant criteria (see Materials and Methods in the main text) were further annotated by the Variant Effect Predictor (VEP) from the Ensemble Tool (perl /path/to/bin/ensembl-vep/vep --offline --input\_file /path/to/data/FILENAME -o /path/to/output/FILENAME.cadd --assembly GRCh38 --force\_overwrite). VEP reported that 43.6% of all germline variants were missense mutations, whilst 54.5% were synonymous. 19.1% and 6.3% variants resided in 3' UTR regions and 5' UTR regions, respectively. Based on the annotation, we found 0.26% of the variants were stop-gaining mutations, 0.042% of the variants were stop-retaining, and 0.079% of the variants caused a loss of stop codon. Up to 0.27% of the variants were associated with splicing functions (0.14% were annotated to be splice acceptor variants, and 0.13% of the splice donor variants), while about 15.2% of the variants resided in splice regions. Note that none of these annotations affected our choice of germline variants (see Materials and Methods for germline variant criteria).

#### **Filtering of somatic mutations**

For the COSMIC signature analysis, to coordinate with the configuration of the previous study (*28*), the controlled somatic mutations called by VarScan2 were obtained from TCGA repository (current release at GDC, v12.0; https://gdc.cancer.gov/). No VAF criteria like that for the germline variants were set for tumor somatic variants. Instead, we only dropped any somatic variant that had read depth less than 20 or VAF less than 0.01 for better variant quality.

Variants were further filtered by VEP (Variant Effect Predictor) from the Ensemble Tool, using the command 'perl /path/to/bin/ensembl-vep/vep --offline --input file /path/to/data/FILENAME -o /path/to/output/FILENAME.cadd --assembly GRCh38 --filter " $DP > 19$ " --filter "AF $> 0.01$ " --force overwrite'. Then variants flagged to have germline risks were dropped (i.e., flagged as germline\_risk, panel\_of\_normals, alt\_allele\_in\_normal in `FILTER`; only the following flags were accepted: 3 prime UTR variant, 5\_prime\_UTR\_variant, NMD\_transcript\_variant, downstream\_gene\_variant, frameshift variant, inframe insertion, missense variant, non coding transcript exon variant, non coding transcript variant,

splice donor variant, splice region variant, stop gained, upstream gene variant).

It is also noteworthy that we directly used the recently updated MC3 somatic mutation dataset (v0.2.8, controlled version) without further filtration (*34*) when performing the oncogene analysis.

## **The robustness of the NMF method for the CGGP discovery**

To test the robustness of the NMF method for the CGGP discovery, we conducted the followings:

(1) Simulation test A: random removal of signals. We down-sampled the variants from the VCF files of patient germline dataset to the point where 30% of data points were randomly removed:

*(I) for each individual of patient germline dataset:*

*<i> let Ntarget be the target number of data points, and Ncurrent be the real total counts of profiles of the patient;*

*<ii> encode the patient's mutational profile to "reads": for example, profile of ACA>AAA, 100 counts will be conceived as 100 data points tagged as 'ACA>AAA'. In this way a virtual short read pool can be formed, where the number of "read s" will be Ncurrent;*

*<iii> draw Ntarget "reads" from the virtual pool, and decode the "reads" to called profiles.* 

*(II) a down-sampled mutational catalog Viteration\_i is formed;*

*(III) solve the Viteration\_i.*

The down-sampled catalogs and derived CGGPs were collected for 3,400 iterations. More than 80.2% of the resulted CGGPs closely resembled their real counterparts, measured by cosine similarities (threshold of 0.999).

(2) Simulation test B: manipulative noise. Random noise were introduced at the volume of roughly 30% of the total signal strength, modifying (i.e. substituting) the strength of affected signals. The process was implemented as below:

```
def bootstrapGenomes(X, seed=0, n=None):
normX = X/np.sum(X, axis=0) bootstrap_all = []
N = np.sum(X, axis=0) for i in range(X.shape[1]):
    tmp = normX[:, i] # 0.4 and 1.6 were chosen to achieve 30% signal strength difference
     tmp = tmp*np.random.uniform(0.4,1.6, len(tmp))
     tmp = tmp/np.sum(tmp)
     bootstrapX = np.random.multinomial(N[i], tmp)
     bootstrap_all.append(bootstrapX)
 bootstrap_all = np.asarray(bootstrap_all).T
```
 *return bootstrap\_all*

5000 simulations were done. About 97.0% of the resulted CGGPs closely resembled their real counterparts, measured by cosine similarities (threshold of 0.999). The number was 85.7% when the threshold was set to 0.9995. The algorithm acting better on manipulative simulations was not a surprise. Alexendrov et al. reported that the NMF methodology would scale along with dataset size (*21*). Loss of signals in simulation 1 possible compromised pattern discoveries of NMF methodology slightly; in simulation 2, 30% of substituting random noises would not prevent NMF from finding the actual signals, therefore demonstrating the robustness.

(3) Germline genomic pattern discovery in the non-cancer dataset

Our algorithm performed robustly in the non-cancer dataset according to results from simulation tests (same procedures as described above). Germline patterns except CGGP\_E were reproduced (cosine similarities were: 0.99, 0.98, 1.00, 0.97, 0.93 and 1.00, receptively, for CGGP A, B, C, D and F). Given that the non-cancer cohort mainly

recruited individuals in a healthy state or with ails other than cancer, we think non-perfect reproduction is acceptable.

(4) Reproducibility of the CGGPs in the merged dataset of the non-cancer dataset and TCGA patient germline dataset. To further test the robustness of the NMF method, we applied it to the dataset which was the combination of the non-cancer dataset and patient germline dataset. All the 7 CGGPs were reproducible with cosine similarities of 1.00, 0.99, 1.00, 0.96, 1.00, 1.00, and 1.00, respectively. As it was suggested by the silhouette method for the germline dataset (see Materials and Methods), here k=7 were the best hyperparameter before overfitting.

In previous studies (*21, 23, 28*), the comparisons of somatic signatures were mainly examined for their strongest signal peaks or clusters of peaks, while a single peak alone was not of much interest. We considered the same rationale would hold for the germline genomic patterns. To capture both local and global features of genomic patterns, we pooled each germline pattern based on sequential contexts, rendering each (192, 1) vector to (24, 1) before calculating a cosine similarity. The cosine similarities reported in this study were very significant according to randomization tests. For each CGGP, we permutated their elements (a.k.a. the signal peaks) and calculated the similarity between the resulted vector and the original germline genomic pattern for 10,000 iterations. In randomization test, the average cosine similarity between permutations of each CGGP and their ground truth counterparts were 0.20, 0.090, 0.46, 0.25, 0.19, 0.09 and 0.35, respectively. Standard deviations were 0.058, 0.066, 0.039, 0.055, 0.058, 0.067 and 0.047, respectively. Compared to the randomization test results, cosine similarities between CGGPs reported in this study were significantly higher.

#### **Examining the robustness of CGGPs by considering potential sequencing artifacts**

Sequencing artifacts such as WES coverage depth, batches in library preparation and sequencing, and so on could become confounding factors for CGGPs. To rule out potential confounding factors, we tested the robustness the CGGPs using alternative sets of variants, samples, and conditions including:

(a) Removing variants in repeats and outlier samples that are likely to be associated with batch effects according to previous studies (named as the *DP20maksed conditio*n here): The genomic coordinates of repeats identified by RepeatMasker were from http://hgdownload.cse.ucsc.edu/goldenpath/hg38/database/rmsk.txt.gz, and the variants settled on the repeats regions were removed. Following the idea of Buckley et al. (25), the outlier samples for each self-reported ancestry in the principal component analysis (PCA) plots of common variants were deemed as the samples that were significantly influenced by batch effect and thus could be excluded. Firstly, the 1000 genome germline variants were downloaded from https://www.cog-genomics.org/plink/2.0/resources#1kg\_phase3, and the variants with minor allele frequency  $> 0.01$  were considered as common variants (filtration was done by vcftools). The PCA analysis of these common variants were performed by PLINK2 (version 20200314, with linkage disequilibrium flag of --indeppairwise 50 10 0.2; using alternative  $r^2$  thresholds like 0.1 or 0.5 produced fewer outliers). The eigenvectors of the first two principal components were extracted, and samples showing a 3-fold standard deviation from the center point of each ancestry sample set were considered as the outliers. As a result, 25 European ancestry samples and 3 Asian ancestry samples were excluded.

(b) Similar to the DP20masked condition, but further removing variants in low mappability regions. The low mappability regions were defined as genomic regions with the CRG-36 alignability score  $\leq 0.1$ . Because there were no pre-computed CRG-36 alignability scores for the hg38 genome, we re-calculated the scores using the GEM tool (version Linux-x86  $64$ -core 2-20130406-045632) with following commands: gemindexer -T 20 -c dna -i hg38 -o hg38 index --max-memory 'force-slow-algorithm'; gemmappability -T 20 -I hg38 index.gem -l 36 -o hg38 k36; gem-2-wig -I hg38 index.gem -i hg38\_k36.mappability -o hg38\_k36; wigToBigWig hg38\_k36.wig hg38\_k36.sizes hg38 k36.bw. The germline variants overlapped with low mappability regions were detected by bwtool and discarded in this experiment condition.

(c) Similar to the DP20masked condition, but using an alternative read depth threshold. The alternative read depth thresholds (based on DP field annotation in VCF files) of 10, 15, and 25 were considered.

(d) Removing low-quality variants. Two variant quality filters based on VCF file information were considered: requiring QD>2 or requiring GQ>20.

(e) Considering subsets of samples from different sequencing centers, whole genome amplification protocol, or exome capture array platform. Following subsets of samples were considered: 1) those sequenced in Broad Institute (BI) sequencing center (6,018 samples); 2) those sequenced in other sequencing centers (3,694 samples (because the algorithm for identifying genomic patterns requires a large number of samples, we combined the samples from these centers); 3) those did not adopt whole genome amplification protocol before sequencing (8,512 samples); 4) those applied the most common 'Custom V2 Exome Bait, 48 RXN X 16 tubes' exome capture array (5,978 samples); 5) those did not apply this exome capture array (3,734 samples; we combined the samples from other platforms due to the same sample size requirement of the algorithm).

(f) Following the implication from Harris and Pritchard (*27*), splitting the dataset by population ancestry. 7,214, 898, 593, 1007 samples from European, African, Asian, and Other/Unknown ancestries were obtained, respectively. Because the NMF approach requires several thousands of samples to obtain stable results, we here only re-examined the samples from European ancestry.

(g) Using exon-defined strand-specific mutational profiles. The exon annotation of known genes was obtained from the UCSC genome browser. The strand attribution of a variant was in line with the strand annotations of the exon it overlapped with. Only the trinucleotide mutational profiles on the exons' strand were considered in this experiment.

(h) Using the germline variants called by TCGA (Huang et al. (*16*)). All germline variants called by Huang et al. were included. To ensure the sample sets between two studies were comparable, only 9,521 samples which were also presented in the sample set of this study were considered.

For each of the above experiment conditions, in addition to the cosine similarity (i.e., between a resulted CGGP and its corresponding-original CGGP) of each individual CGGP, two combined cosine similarities were also provided. The first approach was the collapsed cosine similarity, in which the resulted CGGPs and the corresponding-original CGGPs (i.e. the first matrix in Supplementary Data S1) were flattened into 192 dimensional vectors and then compared by calculating a cosine similarity of the two vectors. The second approach was the average cosine similarity, which simply took the average of the cosine similarities of individual CGGPs. Besides, to take care of sample

variability and outliers, 1,000 bootstrap sample sets have been used to solve the CGGPs, and the resulted CGGPs were clustered by using affinity propagation algorithm in the scikit-learn Python package with default parameters, and the outliers distal to the cluster centers were removed (by requiring collapsed cosine similarity >0.98 to the cluster centers) before finding the best match to the original CGGPs. This step removed about 15% to 20% samples as the potential outliers. The cosine similarity with CGGPs obtained in the DP20masked condition was assessed in the same approach.

#### **Assigning the CGGPs to a genome and converting CGGP's weighing factors to binary assignments**

Weighing factors of a CGGP for an individual in their cohort (or an individual and a given set of CGGPs) can be obtained from the NMF methodology by solving the genomic patterns and converging (i.e., solving the NMF equation without updating pattern matrix), respectively. After normalization, each CGGP could be assigned to a number in the range 0 to 1, which represents an enrichment of the CGGP in the individual.

Alexandrov et al. (*22*) discovered 21 somatic mutational signatures and assigned each of them into each tumor by defining a weight threshold (by the criteria "more than 100 substitutions or more than 25% of all mutations in that sample"). Such a hard-coded threshold was not applicable for the CGGPs, because germline variants were due to not *de novo* mutations but inherited genetic heterogeneity, and the arbitrary threshold would barely make sense biologically in our case. Therefore, when performing the analyses based on the presence/absence partition of CGGPs, as described in the main text, we utilized the non-cancer cohort as a background to determine the weight thresholds for the CGGPs: for a given germline pattern X, a patient may carry (and potentially affected by) it if, and only if, the weighing factor of pattern X appears significantly higher than the weights given by non-cancer individuals; otherwise, we would conclude that the patient does possess a certain weight for pattern X, but not necessarily affected by it. The significance was modeled by the upper 95% confidence intervals of weights given by noncancer individuals. By doing so, the numerical weights of the CGGPs were transformed into a binary format.

#### **Supplementary Figures**



## **Supplementary Fig. S1. Deciphering of germline genomic patterns from germline mutational catalogs.**

Germline variants were used to generate the germline mutational catalogs. A mutational catalog was of shape (192, number of samples), and further decomposed into pattern matrix and weight matrix of the shape (192, number\_of\_patterns) and (number\_of\_patterns, number\_of\_samples), respectively, by using the non-negative matrix factorization (NMF).



#### **Supplementary Fig. S2. The distribution of variant allele frequencies in the cancer patients' germline genomes (n=9,712).**

Expansion of hematopoietic stem cells (HSCs) could introduce somatic mutation contaminations in peripheral blood samples (i.e., buffy coats). The VAFs (variant allele frequencies) of the somatic mutations derived from HSCs were significantly departed from the main peaks around the theological VAF of germline variants (i.e.  $VAF = 0.5$  or 1.0). Therefore, the variants which have such a VAF outside the intervals covered by these main peaks were considered as HSC' somatic mutation contaminations and therefore removed from the germline mutational catalogs.



#### **Supplementary Fig. S3. Overall distribution of CGGP weighing factors between cancer and non-cancer samples.**

Weighing factors assigned for each CGGP by either germline genomes of individuals from the TCGA dataset (n=9,712) or the non-cancer dataset (n=16,670) were illustrated as violin plots to show their distributions. Weighing factors from the non-cancer population were obtained through freezing the feature matrix (i.e. not updating values of CGGPs reported in this study) while resolving NMF. See Materials and Methods for details.



**Supplementary Fig. S4. Comparison of mutational catalogs derived from different calling modes or different callers (represented by different TCGA releases).** (A) Comparison of Single Sample Mode and Jointed Mode of HaplotypeCaller. Jointed Mode and Single Sample Mode of the HaplotypeCaller produced very similar mutational catalogs in randomly selected 1,543 patients. Limited by computational resources, here we examined only Chromosome 1. However, we believed that similar results should be obtained for other chromosomes since there was no significant and systemic bias between chromosomes in both exome-sequencing and variant calling. (B) Comparison of mutational catalogs derived from HaplotypeCaller and MuTect. Mutational catalogs were not strongly affected by different variant calling methods. Comparing patients' mutational catalogs derived from the BAM files of the TCGA current release (called by HaplotypeCaller) and the legacy archive dataset (called by MuTect v119, provided as-is), little difference was observed.

#### **Supplementary Table S1. The reproducibility of germline genomic patterns against the effects of potential sequencing artefacts**





<sup>a</sup> The CGGPs were compared either to the original CGGPs (denoted as 'original' in this column) or to the CGGPs resulted from the DP20masked condition (denoted as 'DP20masked' in this column).

<sup>b</sup> The collapsed cosine similarity was calculated by concatenating 7 CGGPs into one vector before calculating the similarity, while the average cosine similarity represents the average of cosine similarities of CGGP\_A to \_G.

 $\sqrt{\text{c}}$ The condition was used to assess the influence of the sample size on solving CGGPs. The CGGPs from two conditions showed less similarities than the others: (1) TCGA samples sequenced in sequencing centers except the Broad Institute (BI),  $n = 3,694$ ; and (2) TCGA samples used exome capture platforms excluding the Agilent 'Custom V2 Exome Bait, 48 RXN X 16 tubes' exome capture array before sequencing,  $n = 3,734$ . We noted that both conditions were performed with a relatively small sample size  $(n=-3,700)$ . We were aware of that a larger sample size was necessary for obtaining stable genomic patterns. Here, to evaluate the influence of the sample size, we extended the same analysis by randomly picking 3,694 samples from TCGA samples sequenced in Broad Institute (BI) and 3,734 samples from the set of Agilent 'Custom V2 Exome Bait, 48 RXN X 16 tubes' exome capture array before sequencing, respectively. Not surprisingly, the cosine similarities between the resulted genomic patterns and the original patterns were substantially reduced after the subsampling, indicating that sample sizes rather than batch effects affected the observed lower similarities mentioned above.

# **Supplementary Table S2. CGGPs impacted on somatic mutations of key oncogenes in tumors of European patients**







<sup>a</sup> The ratio was calculated by comparing the mean of CGGP weights of the samples between a mutated gene group and the non-mutated gene group for a given gene.

<sup>b</sup> FDR-corrected p-values among each cancer type. The high confident associations whose empirical pvalue<0.05 were highlighted in boldface.



#### **Supplementary Table S3. Differential associations of CGGPs and their combinations between the germline genomes of cancer samples and those of non-cancer samples**







Note: Chi-square test (FDR < 0.25) was used to test if cancer and non-cancer samples could be distinguished by CGGPs or CGGP combinations.



#### **Supplementary Table S4. CGGPs and their combinations in the germline genomes associated with the enrichment of COSMIC somatic signatures in tumors**



Note: Chi-square test (FDR < 0.25) was used to test the associations between COSMIC somatic mutational signatures and CGGPs (or CGGP combinations) in the germline genomes.



#### **Supplementary Table S5. CGGPs and their combinations in the germline genomes associated with different cancer (sub)types**





Note: Chi-square test (FDR < 0.25) was used to test if two cancer (sub)types could be distinguished by CGGPs or CGGP combinations.

#### **Supplementary Table S6. Functional annotation of differentially expressed genes between the CGGP-defined subgroups of three cancer types**





#### **Auxiliary Supplementary Materials**

**Supplementary Data S1. Seven cancer germline genomic patterns deciphered in this study.** This file contains (a) the original CGGP, which is a float number matrix of shape (192, 7); (b) collapsed 96-component CGGPs, which is a float number matrix of shape (96, 7); (c) CGGPs derived from the DP20masked condition (i.e. removing repeats-related variants and outlier samples and keep other conditions as the same as those described for identifying genomic patterns in the main text), which is a float number matrix of shape (192,7); (d) the CGGs derived from European ancestry samples, which is a float number matrix of shape (192,7).

**Supplementary Data S2. Per-sample CGGP weighing factor matrix of the TCGA dataset.** This file contains (a) the per-sample CGGP weighing factor matrix re-solved by using the original CGGPs, which is a float number matrix of shape (9712,7); (b) the persample CGGP weighing factor matrix re-solved by using the DP20masked CGGPs, which is a float number matrix of shape (9712,7).

**Supplementary Data S3. List of genes affected by CGGP\_E.** This file contains (a) the list of genes; (b) the associated functional enrichment analysis results.

**Supplementary Data S4. Python code used to decipher germline genomic patterns.**