

## SUPPLEMENTARY METHODS

### Datasets and samples

A systematic search was performed in January 2018 to identify publicly available datasets that included gene expression profiles of malignant pleural mesothelioma (MPM) tumor samples. To perform this search, several platforms were used: Gene expression omnibus (GEO)[1] using the query “(("pleura"[MeSH Terms] OR pleural[All Fields]) AND ("mesothelioma"[MeSH Terms] OR mesothelioma[All Fields])) AND "Homo sapiens"[porgn] AND ("gse"[Filter] AND "Expression profiling by array"[Filter])”); and ArrayExpress[2] using the query “pleural mesothelioma” and filtered by organism “Homo sapiens”, experiment type “rna assay”, and enabling the filter AE only to show results from within ArrayExpress. Moreover, we also used PubMed to search for datasets related with known biomedical literature studies.

To increase the accuracy and reproducibility of the analyses performed along this study, we included datasets that had at least 30 samples, and covered most of the transcriptome. As a result, eight datasets remained, yet one of them[3] was discarded to avoid potential sample redundancies due to same authorship and nearby publication period, we kept the dataset with higher sample size. Therefore, seven gene expression datasets were included in this study,[4–10] constituting a total of 516 MPM tumor samples.

### Data downloading and processing

#### *Data downloading*

RNA-seq and whole exome sequencing raw data from Bueno et al. dataset was downloaded from the European Genome-Phenome Archive[11] upon request to the data access committee. Data from Hmeljak et al. dataset was downloaded from GDC data portal[12] for somatic variants (MAF file with MuTect2 algorithm from data release 10.0). Copy number alterations was downloaded from cBioPortal/GDAC Firehose (level 3 data; GISTIC2 lesions). Finally, gene expression quantification was downloaded from TCGA2BED FTP repository[13] in transcripts per million (TPM).

Gene expression profiles from Lopez-Rios et al. dataset were downloaded from the link supplied in supplementary materials and those of the remaining four datasets (Suraokar et al., De Reyniès et al., Bott et al., and Gordon et al.) were downloaded from GEO and ArrayExpress repositories. When available, raw data was prioritized to process all samples homogenously.

#### *RNA-seq data processing and quantification*

To obtain gene expression profiles from Bueno et al. dataset, raw reads were processed using the pipeline described hereafter. First of all, multiple quality control

checks on raw sequenced data were performed to check any potential issues using FastQC version 0.11.4 ([Simon Andrews, 2010](#)). Adapter removal and trimming of low-quality quality reads ( $Q < 25$ ) was then performed using Trimmomatic version 0.32.[14] Furthermore, a custom Python script (run with Python version 2.7.13) was used to remove reads with undetermined bases. Alignment of processed reads was performed using STAR version 2.5.3a[15] using GENCODE release 26 (GRCh38.p10)[16] as the reference genome. Quantification of aligned reads to TPM was done with RSEM version 1.3.0.[17]

### *Expression array processing*

When raw expression data from Affymetrix platforms was available, datasets were processed using robust multiarray average algorithm[18] implemented in the affy package version 1.56[19] available through the Bioconductor software project.[20] Probe-set to gene mapping was done using BioMart web services via biomaRt R package version 2.34,[21] selecting the most expressed probe as representative of gene expression when multiple mapping probes occurred to avoid duplicated genes.

### *Somatic variant calling*

In order to have a homogenous set of somatic variants between Bueno et al. and Hmeljak et al. study, Bueno et al. reads were reprocessed from raw sequencing data. Like for RNA-seq data, low-quality ( $Q > 25$ ) reads filtering, adapter trimming, and malformed reads removal was performed. Then, following Broad Institute's best practices,[22,23] variant discovery analysis was done using Genome Analysis Toolkit (GATK) version 3.7-0.[24] Processed reads were aligned using the reference genome from NCBI (GRCh38) and BWA-MEM algorithm from Burrows-Wheeler Alignment tool version 0.7.15.[25] SAMtools version 1.3[26] was used to convert file from SAM to BAM format and the set of command line tools Picard release 2.9.2 (<http://broadinstitute.github.io/picard>) were used to sort, index, and mark duplicate reads. In order to detect and avoid systematic errors in base quality scores, a base quality score recalibration was performed using GATK. Then, using the MuTect2 tool from GATK, somatic variants were called via local re-assembly of haplotypes.[27] In more detail, StrandOddsRatio, DepthPerAlleleBySample, BaseQualitySumPerAlleleBySample, TandemRepeatAnnotator, and OxoGReadCounts annotations were added to the MuTect2 results and were used for variant filtering in a subsequent step.

To get a set of high confidence somatic variants and reduce false positive calls due to technical artefacts, a set of filters were applied as described hereunder. Regarding allele frequency, only somatic variants having 0% in normal samples and more than 5% in tumor samples were kept. Moreover, the variants must be supported by at least 10 reads in either normal and tumor samples and at least 5 reads with the alternative

allele in tumor samples. SQSS quality score is the sum of base quality scores for each allele divided by its allele depth, and we required score of at least 25 in the alternative allele in tumor samples to consider the variant. A filter to detect strand bias was also set using the symmetric odds ratio test implemented in MuTect2, and variants with a score greater than 3 in the test were discarded. Finally, variants with oxidative DNA damage during sample preparation were discarded, following authors' recommendations.[28] The final set of variants were functionally annotated with the web server tool wANNOVAR.[29]

## Genomic analyses

### *Mutational signatures*

Mutational signatures are patterns in the occurrence of somatic single-nucleotide variants that can reflect underlying mutational processes. The R package *deconstructSigs* (v.1.8.0)[30] was used to infer the mutational signatures from exonic single-nucleotide variants data in Bueno et al. and Hmeljak et al. datasets.

### *Neoepitope prediction*

Four-digit HLA types were determined for each sample with raw exome sequencing data available, using OptiType version 1.3.1.[31] Variants from genes with low expression levels (i.e.,  $\log_2(\text{TPM}) < 4$ ) were excluded from the input VCF file. Mutant peptide sequences of 15 amino acids were obtained using Ensembl protein sequence file from release 93 (GRCh38). NetMHCcons[32] was used with default parameters to assess binding affinity of mutant peptides according to HLA-types.

### *Methylation data*

$\beta$  values from Illumina's Infinium HumanMethylation450K BeadChip were downloaded from GDC Data Portal.[12] Probes were summarized to gene level using the median beta value and according to probe location surrounding transcription start sites up to 200 bp upstream.[33] Analysis of variance was performed for each gene adjusting for sex, age, stage, and histology covariates. FDR was applied to correct for multiple testing.

All downstream statistical analyses were done with the free software environment R version 3.5.0.[34]

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