1 Mutational impact of chronic alcohol use on stem cells in cirrhotic liver

- 2 Myrthe Jager¹
- 3 Ewart Kuijk¹
- 4 Ruby Lieshout²
- 5 Mauro D. Locati¹
- 6 Nicolle Besselink¹
- 7 Bastiaan van der Roest¹
- 8 Roel Janssen¹
- 9 Sander Boymans¹
- 10 Jeroen de Jonge²
- 11 Jan N.M. IJzermans²
- 12 Michael Doukas³
- 13 Monique M.A. Verstegen²
- 14 Ruben van Boxtel^{1,†}
- 15 Luc J.W. van der Laan²
- 16 Edwin Cuppen^{1,#}
- 17
- 18 ¹Center for Molecular Medicine and Oncode Institute, University Medical Center Utrecht, Utrecht
- 19 University, Heidelberglaan 100, 3584 CX Utrecht, The Netherlands
- 20 ²Department of Surgery, Erasmus MC University Medical Center, Wytemaweg 80, 3015 CN
- 21 Rotterdam, The Netherlands
- 22 ³Department of Pathology, Erasmus MC University Medical Center, Wytemaweg 80, 3015 CN
- 23 Rotterdam, The Netherlands
- ^{*}Present address: Oncode Institute and Princess Máxima Center for Pediatric Oncology, 3584 CT
- 25 Utrecht, The Netherlands
- 26 [#]Corresponding author: <u>ecuppen@umcutrecht.nl</u>

27 ABSTRACT

28 Excessive alcohol consumption increases the risk of developing liver cancer, but the 29 mechanism through which alcohol drives carcinogenesis is as yet unknown. Here, we 30 determined the mutational consequences of chronic alcohol use on the genome of human liver 31 stem cells prior to cancer development. No change in base substitution rate or spectrum could 32 be detected. Analysis of the trunk mutations in an alcohol-related liver tumor by multi-site 33 whole-genome sequencing confirms the absence of specific alcohol-induced mutational 34 signatures driving the development of liver cancer. However, we did identify an enrichment of 35 nonsynonymous base substitutions in cancer genes in stem cells of the cirrhotic livers, such as 36 recurrent nonsense mutations in PTPRK that disturb Epidermal Growth Factor (EGF)-37 signaling. Our results thus suggest that chronic alcohol use does not contribute to 38 carcinogenesis through altered mutagenicity, but instead induces microenvironment changes 39 which provide a 'fertile ground' for selection of cells with oncogenic mutations.

40

41 INTRODUCTION

42 Alcohol consumption is an important risk factor for the development of various cancer types, 43 including hepatocellular carcinoma (HCC), and causes an estimated 400,000 cancer-related 44 deaths worldwide each year¹⁻³. In spite of the clear link between alcohol intake and 45 tumorigenesis, the underlying mechanism remains debated and mainly revolves around two 46 hypotheses. The first hypothesis suggests that alcohol consumption may contribute to the development of cancer through an increased mutation accumulation in the genome⁴. 47 Consistently, the first metabolite of ethanol, acetaldehyde, is highly carcinogenic⁵⁻⁷ and can 48 also contribute to the formation of mutagenic reactive oxygen species $(ROS)^{8-11}$. Analysis of a 49 large number of tumor exomes and genomes showed that alcohol intake is associated with an 50 increased mutation load and different mutational characteristics^{12–15}. The second hypothesis 51

52 suggests that an alcohol-induced change of microenvironment is an essential driver for tumorigenesis by providing a fertile ground for cells with oncogenic mutations^{16–18}. Indeed, 53 development of HCC is preceded by chronic inflammation and cirrhosis in about 80% of 54 55 patients and this cell-extrinsic damage appears a prerequisite for the formation of the majority of liver cancers^{18–20}. Additionally, Hepatitis C Virus (HCV)-induced cirrhotic livers show an 56 57 increase in the number and size of clonal patches with mutations in genes that are frequently mutated in HCC²¹. Alcohol use itself has been associated with an increased number of cancer-58 stem-cell-like epithelial cell adhesion molecule (EpCAM)-positive cells in the cirrhotic liver²², 59 60 which may be driven by epithelial to mesenchymal transition through activation of the Wnt pathway²³, confirming that cellular composition changes can be induced by alcohol use. Yet, 61 62 it is still uncertain whether an altered cellular environment is sufficient to drive the 63 development of cancer, or whether an increase in the mutation load is also required. The here 64 mentioned hypotheses are thus not mutually exclusive.

65 We have demonstrated previously that mutations accumulate linearly with age in liver 66 adult stem cells (ASCs) of healthy individuals, without controlling for lifestyle^{24,25}. Stem cells are believed to be an important cell-of-origin for several cancer types, including liver 67 cancer^{18,26-28}, although liver cancer can also originate in differentiated cells²⁹⁻³¹. Here, we 68 studied the accumulation of mutations in ASCs from non-cancerous, cirrhotic livers of patients 69 70 with a history of chronic alcohol use and compared these to the mutational patterns of healthy 71 liver donors and to mutations that accumulated in the most recent common ancestor (MRCA) cell of an alcohol-related HCC. 72

73

74 RESULTS

75 Mutation load similar in alcoholic liver

76 We sequenced the genomes of eight independent clonal organoid cultures derived from 77 biopsies of five non-cancerous, cirrhotic livers from patients with a known history of chronic alcohol intake who were undergoing a liver transplantation (further referred to as 'alcoholic 78 79 livers'; Supplementary Table 1). To gain insight into the mutational consequences of chronic 80 alcohol consumption, the somatic mutation catalogs of alcoholic livers were compared to those 81 obtained previously from whole genome sequencing (WGS) data of five healthy liver donors (further referred to as 'healthy livers') 24 . To increase the number of healthy liver donors and to 82 83 obtain age-matched healthy controls, five clonal liver organoid cultures derived from four 84 additional healthy liver donors with ages ranging from 24 to 68 years were included in the 85 analyses (Supplementary Table 1).

86 In total, we identified 42,093 base substitutions, 1,931 indels, and 5 copy number 87 alterations (CNAs) (Fig. 1; Supplementary Fig. 1; Supplementary Table 1). Consistent with previous observations²⁴, there is a positive relationship between somatic base substitutions and 88 age in healthy liver ASCs (two-tailed *t*-test, linear mixed model, P < 0.05; Fig. 1a). Healthy 89 liver ASCs acquired ~39.4 (95% confidence interval (95% CI): 30.5 - 48.3) somatic base 90 91 substitutions each year. The mutation load in alcoholic liver ASCs (Fig. 1a) was similar to, and 92 within the 95% CI of the slope estimate of, age-matched healthy liver ASCs. Alcohol 93 consumption did not affect the number of tandem base substitutions acquired in the genomes 94 of liver ASCs either (Supplementary Fig. 1a). Furthermore, indels also accumulated with age 95 at a comparable rate in healthy and alcoholic liver ASCs (two-tailed *t*-test, linear mixed model, P < 0.05; Supplementary Fig. 1b). Finally, a minority of the healthy liver ASCs and none of 96 the assessed alcoholic liver ASCs acquired a CNA, although few CNAs were detected 97 (Supplementary Table 1)²⁴. At the chromosomal level we observed trisomy 22 in a healthy 98 liver ASC from a 68-year-old healthy female donor and chromosome Y gain in an alcoholic 99 100 liver ASC from a 67-year-old male donor (Supplementary Fig. 1c). This suggests that

aneuploidies may occur in liver ASCs of older individuals, but this seems to be unrelated to
alcohol consumption. Taken together, these results strongly suggest that the induction of HCC
by chronic alcohol consumption is not caused by an altered base substitution, indel, or CNA
accumulation in liver ASCs prior to oncogenesis.

105

106 Mutation type similar in alcoholic liver

It has been shown that genome-wide patterns of base substitutions reflect past activity of 107 mutational processes in cells³². Previously, alcohol consumption was reported to be associated 108 109 with a modest increase of Catalogue Of Somatic Mutations In Cancer (COSMIC) signature 16 110 mutations, which is characterized by T:A>C:G mutations³², in esophageal and liver cancer¹²⁻ 111 ¹⁵. To identify if excessive alcohol consumption changed the mutational profiles in non-112 cancerous liver ASCs, we performed in-depth mutational analyses. The mutational profiles of 113 healthy liver ASCs were characterized by a high contribution of C:G>A:T, C:G>T:A, and 114 T:A>C:G mutations (Fig. 1b-c; Supplementary Fig. 2). The mutational profiles of alcoholic 115 liver ASCs were highly similar to the mutational profiles of healthy liver ASCs (cosine 116 similarity = 0.99), indicating that chronic alcohol use does not alter the mutational processes in liver ASCs. 117

To determine whether chronic alcohol use changed the contribution of the known COSMIC mutational signatures^{32–34}, we calculated the contribution of these signatures to the mutational profiles of all ASCs and, subsequently, performed a bootstrap resampling method to identify potential significant differences between healthy and alcoholic liver ASCs, similar as described in Zou *et al.* ³⁵. COSMIC signatures 5 and 40 could explain the majority of the accumulated base substitutions in both healthy and alcoholic liver (Supplementary Fig. 3). However, we did not observe a significant change in signature contributions between alcoholic

125 liver ASCs and healthy liver ASCs (bootstrap resampling method, see Methods;126 Supplementary Fig. 3).

127 A possible explanation for the absence of a correlation between alcohol consumption and mutational patterns is that the cells that we have sequenced are too early in the precancerous 128 129 state. Therefore, we also sequenced five biopsies across a 13 cm HCC of a 60-year-old male 130 donor with a history of chronic alcohol use and identified mutations that were shared by all biopsies (Fig. 2a; Supplementary Fig. 4). This approach allowed for the identification of all 131 132 mutations in the MRCA and thus provided insight into the mutational process that had been 133 active prior to tumor formation and in the early to intermediate stages of tumor development 134 (Fig. 2a). As a control sample, we sequenced a non-tumorous biopsy adjacent to the tumor, to 135 identify and exclude germline mutations. In total, we identified 19,200 unique somatic base 136 substitutions across all five HCC biopsies (Supplementary Table 2; Supplementary Fig. 4b).

137 Analysis of the base substitutions shared by all biopsies (trunk mutations) revealed that 138 the MRCA of these biopsies accumulated 7,203 base substitutions (Supplementary Table 2; 139 Supplementary Fig. 4b). The mutational profile of the trunk mutations in the HCC was highly 140 similar to healthy and alcoholic liver ASCs (Fig. 2b; cosine similarity = 0.97 and 0.98, 141 respectively). These results were in line with our initial observations in ASCs that alcohol itself 142 does not introduce specific mutations in the genome of liver cells. The high mutation load 143 suggests that the MRCA already evolved significantly from the cell-of-origin (Fig. 2a) and that 144 a clonal sweep occurred after a substantial amount of mutations already accumulated. Consistently, the MRCA already acquired two CNAs (Supplementary Table 3) and several 145 chromosomal aneuploidies (Fig. 2c; Supplementary Fig. 4c). 146

147

148 Cancer driver mutations

149 Previously, alcohol intake has been shown to accelerate the expansion of clones with cancer driver mutations in the esophagus³⁶. To identify whether chronic alcohol consumption induces 150 151 similar changes in the selection of liver cells, we analyzed the genomic distribution of the 152 acquired base substitutions. If chronic alcohol use would affect cellular selection, the frequency of somatic mutations in active functional genomic elements would differ between alcoholic 153 154 and healthy liver. Base substitutions were, however, depleted to a similar extend in regions 155 such as genes and enhancers in healthy liver ASCs and alcoholic liver ASCs (Fig. 3a). Furthermore, unlike previous observations³⁷, we did not observe an enrichment of base 156 substitutions in H3K36me3 regions, associated with active transcription^{38,39}, in alcoholic liver 157 ASCs in comparison to healthy liver ASCs (Supplementary Fig. 5). The normalized ratio of 158 159 nonsynonymous to synonymous base substitutions (dN/dS) was also ~1 in all assessed cell 160 types (Fig. 3b). Taken together, these results suggest that there is no general change in selection 161 against more deleterious base substitutions.

162 However, we observed a small enrichment of potential driver mutations in alcoholic 163 liver ASCs (Fig. 3c; Table 1), although the number of mutations was low. Only one in three 164 healthy liver ASCs acquired a nonsynonymous base substitution in a COSMIC cancer census 165 gene. In alcoholic liver ASCs, on the other hand, we observed a total of seven nonsynonymous 166 base substitutions in these cancer genes across eight ASCs. Two alcoholic liver ASCs even 167 acquired multiple nonsynonymous hits in cancer genes (Fig. 3c; Table 1), while only an 168 estimated four nonsynonymous base substitutions in cancer genes is sufficient to drive the development of liver cancer¹⁶. Consistent with this idea, we identified four nonsynonymous 169 170 base substitutions in cancer genes in the MRCA of the HCC (Fig. 3c; Table 1). The modest 171 increase in nonsynonymous base substitutions in cancer genes observed in alcoholic liver ASCs 172 suggests that alcohol may cause clonal outgrowth of cells with putative oncogenic mutations, similar to alcohol-exposed esophagus³⁶ and HCV-induced liver cirrhosis²¹. 173

174 Notably, we found that the cancer gene *PTPRK* was hit by a heterozygous nonsense 175 base substitution in two alcoholic liver ASCs of independent patients, which is significantly 176 more than expected based on the background mutation rate adjusted for the mutational profile (Table 1; likelihood ratio test, FDR correction; q = 0.02)¹⁶. None of the healthy liver ASCs 177 acquired a nonsynonymous base substitution in *PTPRK*, nor did we identify nonsynonymous 178 base substitutions in this gene in healthy ASCs from small intestine or colon²⁴. RNA-179 180 sequencing of the organoids revealed that the heterozygous nonsense base substitutions in *PTPRK* resulted in a significantly reduced expression (Fig. 4; P < 0.05, negative binomial test), 181 182 indicating a gene dosage effect due to nonsense-mediated decay of the mutated allele. PTPRK can modulate EGF-signaling through dephosphorylation of tyrosine residues of the EGFR⁴⁰. 183 Western blot analysis showed that alcoholic *PTPRK*^{WT/*} cells had increased pERK levels in the 184 185 absence of EGF, indicating that the PTPRK mutations indeed disturb EGF-signaling (Fig. 4). 186

187 DISCUSSION

188 In this study, we aimed to identify the mutational consequences of chronic alcohol intake in cirrhotic livers, prior to the development of liver cancer. In contrast to previous studies^{12–15,37}, 189 190 we did not observe specific mutational signatures associated with alcohol consumption in stem 191 cells from non-cancerous cirrhotic livers. This observation can indicate that chronic alcohol 192 use may only impact directly on mutation accumulation after tumor initiation or it may reflect 193 very effective negative selection of cells with DNA damage. Alternatively, it should be noted 194 that tissue-specific liver ASCs may not be the direct cell-of-origin for HCC. Nevertheless, as 195 the cancer-initiating cells are exposed to the same mutagenic damage as the liver ASCs (and 196 show the same mutational signatures), our results suggest that alcohol-induced cancer risk is 197 not caused by altered mutagenesis.

198 We propose that chronic alcohol consumption creates an inflamed, cirrhotic liver tissue 199 environment, which in turn provides a fertile ground for cells with specific oncogenic 200 mutations to clonally expand. Chronic damage to the liver due to chronic alcohol consumption 201 causes apoptosis and necrosis of various cells in the liver, such as the hepatocytes, leading to liver inflammation⁴¹. As a consequence, tissue-specific ASCs, which are normally quiescent, 202 will proliferate to aid in the regeneration of the damaged liver⁴². Oncogenic mutations that have 203 accumulated randomly in ASCs through normal mutational processes could provide a 204 205 proliferative advantage under these inflamed conditions at the expense of 'normal' ASCs that 206 do not carry such mutations, while there is too little proliferation under normal conditions for 207 ASCs with oncogenic mutations to outcompete normal ASCs. In the damaged liver, the 208 enhanced proliferation of such potential cancer progenitor cells could subsequently result in an 209 increasing number of mutations that drive tumorigenesis further, as long as inflammation 210 persists.

211 An illustrative example of this potentially altered selection process in the current study 212 is the significant enrichment of nonsense base substitutions in EGFR phosphatase PTPRK in 213 alcoholic liver ASCs. Reduced expression of PTPRK has been reported to cause enhanced EGF-signaling and ultimately increases cellular proliferation^{40,43,44}. Single-nucleotide 214 215 polymorphisms in *EGF* that prolong the half-life of EGF increase the risk of developing HCC through continued EGF-signaling^{17,45,46} and 22% of HCCs carry mutations in genes in the EGF 216 pathway⁴⁷. Reduced EGF-signaling, on the other hand, significantly decreases tumor formation 217 218 in cirrhotic livers from rats⁴⁸. These observations underscore the importance of (disturbed) 219 EGF-signaling in HCC development. Nonsense mutations in PTPRK may thus contribute to 220 the development of HCC by changing EGF-signaling as well, although further research should 221 be conducted to identify the significance of our findings in liver cancer.

222 The liver is not the only organ in which inflammation is suggested to contribute to 223 carcinogenesis. Inflammatory diseases, such as inflammatory bowel disease and pancreatitis, increase the risk of developing cancer in various tissues⁴⁹. However, it was believed that this 224 225 increased risk was at least partially due to a direct induction of mutations in the genome⁵⁰. The 226 results presented here indicate that alteration of selective mechanisms induced by inflammation 227 could be more directly involved in the development of cancer. For liver, reversal of the 228 inflammatory phenotype that precedes cancer might aid in reducing cancer risk in patients with 229 cirrhotic liver disease due to chronic alcohol use.

230

231 METHODS

232 Human tissue material

233 All human tissue biopsies were obtained in the Erasmus MC - University Medical Center 234 Rotterdam. Liver biopsies from healthy liver donors and patients with alcoholic cirrhosis were obtained during liver transplantation procedures. All patients were negative for viral infection 235 236 and metabolic diseases. The biopsies were collected in cold organ preservation fluid (Belzer 237 UW Cold Storage Solution, Bridge to Life, London, UK) and transported and stored at 4°C 238 until use. The liver and tumor biopsies from the hepatocellular carcinoma patient were collected 239 from a resected specimen and stored at -80°C until use. The acquisition of these liver and tumor 240 biopsies for research purposes was approved by the Medical Ethical Committee of the Erasmus 241 Medical Center (MEC-2014-060 and MEC-2013-143). Informed consent was provided by all patients involved. 242

The biopsies of the HCC were cut into 6μm sections. Subsequently, the tumor
percentage of both ends of each biopsy was determined using HE staining (Supplementary Fig.
6). The tumor percentage of the biopsies was determined by averaging both values. The
remaining slices were used for long-term storage at -80°C or for DNA isolation.

9

247

248 Generation of clonal liver organoid cultures from human liver biopsies

Organoid cultures from healthy and alcoholic liver tissue material were derived as previously described^{51,52}. After 2 - 3 days, organoids started to appear in the BME. The cultures were maintained for approximately 2 weeks after isolation, to enrich for ASCs. Subsequently, clonal organoid cultures were generated from these organoid cultures as described previously²⁵. The organoid cultures were expanded until there was material for WGS.

254

255 Whole-genome sequencing and read alignment

DNA was isolated from all organoid cultures, blood samples, and tissue biopsies using the 256 257 Qiasymphony (Qiagen). Whole-genome sequencing libraries were generated from 200 ng of 258 genomic DNA according to standard Illumina protocols. The organoid cultures and control 259 samples were sequenced paired-end (2 x 150bp) to a depth of at least 30X coverage using the 260 Illumina HiSeq Xten. The HCC biopsies were sequenced paired-end (2 x 150bp) to a depth of 261 at least 60X coverage using the Illumina HiSeq Xten. A 60X depth was required to identify the somatic base substitutions in the tumor cells, as the biopsies contain $\sim 50\%$ healthy cells 262 263 (Supplementary Fig. 6). Whole-genome sequencing was performed at the Hartwig Medical 264 Foundation in Amsterdam, the Netherlands. The sequence reads were mapped to the human reference genome GRCh37 using the Burrows-Wheeler Aligner (BWA) tool v0.7.5a⁵³ 265 266 (settings -t, 4, -c, 100, -M).

267

268 Copy number alteration calling and filtering

For the healthy and alcoholic samples without HCC, CNA catalogs were obtained and filtered by using FreeC v2.7^{25,54}. Calls were excluded if the mapping quality of the split reads was 0 on either sides of the split read. BED-file of blacklist positions is available upon request. For the

HCC biopsies, structural variants were called using Manta v.1.1.0⁵⁵ with standard settings. We
only considered structural variations of at least 150 base pairs in autosomal the genome with a
manta filter 'PASS'. Subsequently, the mutation catalogs of all five biopsies were intersected
with a window of 500 bp to obtain the trunk CNAs using bedtools⁵⁶.

- All CNA calls were inspected manually in the Integrative Genomics Viewer (IGV) to exclude false-positives with no change in read-depth. The breakpoints were identified manually in IGV. Finally, the number of genes within the deletions was obtained from http://genome.ucsc.edu/.
- 280

281 Genome-wide copy number profiles

Genome-wide copy number profiles of the ASCs were estimated by using the output of the FreeC calls obtained in section 'Copy number alteration calling and filtering' prior to filtering. Subsequently, we calculated the mean copy number across 500,000 bp bins. Copy number of ≥ 2.8 was considered a gain and copy number of ≤ 1.2 a loss. Genome-wide copy number profiles of the HCC biopsies and the adjacent liver biopsy were obtained in a similar manner.

287

288 Base substitution calling and filtering

289 For the organoid cultures, base substitution catalogs were obtained by filtering GATK v3.4-290 46⁵⁷ variant calls as previously described²⁵, with additional removal of variants with a sample-291 specific genotype quality < 10 in the control sample, and positions with a sample-specific 292 genotype quality < 99 in the organoid clone sample. The callable regions, used to define regions 293 with high confidence base substitutions, were obtained by using the GATK CallableLoci tool $v3.4.46^{58}$ as previously described²⁵. BED-file of blacklist positions is available upon request. 294 295 All organoids showed a peak at a base substitution VAF of 0.5, confirming that the organoid samples are clonal (Supplementary Fig. 7). Publicly available variant call format (VCF) files 296

and surveyed bed files of healthy liver ASCs were downloaded from donors 14 - 18 from
 https://wgs11.op.umcutrecht.nl/mutational_patterns_ASCs/ to allow the comparison between
 healthy and alcoholic liver ASCs.

300 For the HCC biopsies, base substitutions were called by using Strelka v1.0.14 with settings 'SkipDepthFilters = 0', 'maxInputDepth = 250', 'depthFilterMultiple = 3.0', 301 302 'snvMaxFilteredBasecallFrac 0.4', 'snvMaxSpanningDeletionFrac = 0.75', 303 'indelMaxRefRepeat = 1000', 'indelMaxWindowFilteredBasecallFrac 0.3', = 'indelMaxIntHpolLength = 14', 'ssnvPrior = 0.000001', 'sindelPrior = 0.000001', 'ssnvNoise 304 305 = 0.0000005', 'sindelNoise = 0.000001', 'ssnvNoiseStrandBiasFrac = 0.5', 'minTier1Mapq = 20', 'minTier2Mapq = 5', 'ssnvQuality LowerBound = 10', 'sindelQuality LowerBound = 306 307 10', 'isWriteRealignedBam = 0', and 'binSize = 25000000'. We only considered variations 308 with a filter 'PASS'. Subsequently, the mutation catalogs of all five biopsies were intersected to obtain the trunk mutations using bedtools⁵⁶. We only considered base substitutions on the 309 310 autosomal genome that did not overlap with an indel call. Positions that were detected at least 311 5 times in 1,762 Dutch individuals were removed from these catalogs using the Hartwig Medical Foundation Pool of Normals (HMF-PON) version 2 (available upon request), to 312 313 exclude Dutch germline variations. Only 138 base substitutions are found in four out of five 314 biopsies, whereas we detect 7,203 base substitutions in all five biopsies (Supplementary Fig. 315 4), indicating that the majority of the trunk mutations were identified successfully.

To exclude that the observed similarities/differences in base substitution load and type are a consequence of the differences between the filtering pipelines, we also applied the filtering steps of the HCC samples to the base substitutions in the alcohol liver ASCs. We observe no obvious differences in base substitution load or type between the alcoholic liver samples using both filtering pipelines (Supplementary Fig. 8).

321

322 Tumor adjusted allele frequencies

The VAFs of the shared base substitutions (the trunk mutations) were calculated for each biopsy. Subsequently, we calculated the tumor-adjusted variant allele frequency (TAF) per biopsy, in which the VAF is divided by the tumor-fraction. Chromosome 1 and chromosome 8 were excluded from these analyses, as these chromosomes deviate from a copy number of two in the majority of the biopsies (Supplementary Fig. 4). Most biopsies showed a peak around a TAF of 0.5 (Supplementary Fig. 9), confirming that these base substitutions are clonal in each sample and that the biopsies share a recent common ancestor.

330

331 Indel calling and filtering

332 WGS data of previously published samples was obtained from EGAD00001001900. Indels 333 were called using GATK v3.4-46⁵⁷. We only considered indels that were callable/surveyed on autosomal chromosomes with one alternative allele and a GATK filter 'PASS'. To remove 334 335 false positive calls, indels with a GATK quality score < 250 and/or with a mapping quality < 336 60 were excluded. Additionally, only indels with a coverage of at least 20X and a GATK sample-specific quality score of at least 99 in both control and organoid clone sample were 337 338 considered. Subsequently, variants with a cosmic and/or a dbSNP id (dbSNP v137.b3730) and 339 indels that were found in three unrelated control samples (BED-file available upon request) 340 were excluded. To obtain a catalog of somatic indels, we excluded indels with any evidence in 341 the reference sample, and that were located within 100 base pairs of an indel that was called in 342 the reference sample. Finally, we only considered variants with a VAF of > 0.3 in the organoid 343 clone sample.

344

345 (Tandem) base substitution and indel rate in liver ASCs

346 The number of base substitutions in the genomes of liver ASCs was obtained from the VCF 347 files and extrapolated to the non-N autosomal genome (2,682,655,440 bp) of GRCh37 using the callable/surveyed genome size obtained in section 'Base substitution calling and filtering'. 348 349 To identify whether the number of somatic base substitutions acquired in the genomes of liver ASCs are correlated with the age of the donor, we fitted a linear mixed-effects regression model 350 351 with the donor as a random effect in this model using the nlme R package, as described 352 previously²⁴. Two-tailed *t*-tests were performed to determine whether the correlation between 353 age and number of mutations was significant. The accumulation of base substitutions did not 354 correlate significantly with age in the alcoholic liver ASCs (~38.6 somatic base substitutions 355 per year; 95% CI: -51.8 - 128.9; two-tailed *t*-test, linear mixed model, non-significant), most 356 likely due to the fact that the age-range is much smaller in these donors. Therefore, we obtained 357 the 95% CI of the healthy liver ASCs from the output of the linear mixed-effects regression 358 model and determined whether the number of somatic base substitutions acquired in the 359 genomes of the alcoholic liver ASCs are within this 95% CI.

360 To identify tandem base substitutions, we extracted base substitutions that were called 361 on two consecutive bases in the GRCh37 human reference genome from the VCF files. Similar 362 to single base substitutions, we extrapolated this number to the non-N autosomal genome and determined whether the number of tandem base substitutions was correlated with the age of the 363 364 donor using a linear mixed effects regression model. As the number of tandem base 365 substitutions did not significantly correlate with age in the alcoholic liver ASCs (~0.04 tandem 366 base substitutions per year; 95% CI: -1.13 - 1.21; two-tailed t-test, linear mixed model, non-367 significant), we determined whether these tandem base substitution numbers are within the 368 95% CI of the healthy liver ASCs.

369 Similar to base substitutions and tandem base substitutions, the number of indels was370 extracted from the filtered VCF files and extrapolated to the non-N autosomal genome. Using

14

a linear mixed effects regression model with the donor as random effect, we assessed whether
the number of indels was correlated with the age of the donor. Two-tailed *t*-test were performed
to determine whether the correlation was significant for both alcoholic liver ASCs and healthy
liver ASCs.

375

376 Mutational pattern analysis

Mutation types of the base substitutions were extracted from the VCF files and the mutational profiles were generated by retrieving the sequence context of each base substitution. For the healthy and alcoholic liver ASCs, we calculated an 'average' mutational profile. Pairwise cosine similarities of these average mutational profiles and of the mutational profile of the trunk mutations of the HCC were calculated, to identify the similarity between these profiles.

382 We reconstructed the mutational profiles of the average mutational profiles and the 383 trunk mutations using the 60 known SBS signatures (Supplementary Fig. 3; https://cancer.sanger.ac.uk/cosmic/signatures v3). A bootstrap resampling method similar as 384 described in Zou et al., 35 was used to generate 120,000 (8 x 15 x 1,000) replicas of the 385 mutational profiles of the healthy and alcoholic liver ASCs. Subsequently, 8 or 15 (for healthy 386 387 and alcoholic liver ASCs respectively) replicas were randomly selected and an average mutational profile was calculated. This was repeated 10,000 times, to obtain 10,000 average 388 389 mutational profiles of the replicas for both healthy and alcoholic livers. These average 390 mutational profiles of the replicas were reconstructed using the 60 known SBS mutational 391 signatures and the Euclidean distance to the original signature contribution was calculated for each reconstructed average mutational profile. Next, the distance at which P = 0.01 was 392 393 determined for both healthy and alcoholic liver ASCs ($d_{\text{healthy}=0.01}$ and $d_{\text{alcoholic}=0.01}$, 394 respectively). The Euclidean distance (d) between the original signature contributions of

healthy and alcoholic liver ASCs was considered significant when *d* was larger than $d_{\text{healthy}=0.01}$ and $d_{\text{alcoholic}=0.01}$.

397

398 Genomic distribution of somatic base substitutions

399 The promoter, enhancer, and open chromatin regions of hg19 were obtained from Ensembl using biomaRt^{59,60} and the genic regions of hg19 were loaded from UCSC Known Genes tables 400 as TxDb object⁶¹. To determine whether the somatic base substitutions are non-randomly 401 402 distributed, we tested for enrichment and depletion of base substitutions in these regions with 403 a one-sided Binomial test, corrected for the callable/surveyed regions per sample, similar as 404 described in ²⁴. For the HCC trunk mutations, the callable regions were obtained by defining 405 callable loci per biopsy using the GATK CallableLoci tool v3.4.46⁵⁸ (optional parameters 406 'minBaseQuality 10', 'minMappingQuality 10', 'maxFractionOfReadsWithLowMAPQ 20', 407 and 'minDepth 15'). Subsequently, these files were intersected to obtain the regions that are 408 callable in all biopsies. 96.79% of the non-N autosomal genome was callable in all six biopsies. 409 Two-sided poisson tests were done to estimate significant differences in depletion/enrichment 410 in all genomic regions between the healthy liver ASCs, the alcoholic liver ASCs, and the trunk 411 mutations of the HCC. Differences were considered significant when q < 0.05 (Benjamini-412 Hochberg FDR multiple-testing correction). All mutational pattern analyses were performed using the MutationalPatterns R package⁶². 413

To obtain a generic genome-wide profile of H3K36me3, we downloaded and merged 415 40 available H3K36me3 ChIP-Seq datasets from UCSC, and determined the median 416 H3K36me3 values in regions that show H3K36me3 enrichment in at least 2 of the datasets. 417 H3K36me3 peaks were subsequently called using bdgpeakcall function of MACS2 (broad 418 peaks)⁶³. The amount of base substitutions that overlap with these peaks was calculated for all 419 base substitutions acquired in liver ASCs. These analyses were repeated for T:A > C:G

420	mutations specifically. Wilcoxon-rank tests were performed to estimate significant differences
421	in the relative amount of base pair substitutions in H3K36me3 regions between alcoholic and
422	healthy liver ASCs. Differences with $P < 0.05$ were considered significant.

423

424 dN/dS and identification of nonsynonymous base substitutions in cancer genes

dN/dS ratios were computed using the dNdScv R package¹⁶. The output of the dNdScv package
was used to identify missense, nonsense, and splice site base substitutions in cosmic cancer
genes. For this analysis, we considered all 409 'tier 1' cancer genes (genes with sufficient
evidence of being a cancer driver). The list of cosmic cancer genes was obtained from
https://cancer.sanger.ac.uk/cosmic/census.

430

431 RNA sequencing

432 Organoid cultures of three healthy donors (18-c, 21-b, and 22-a) and three alcoholic organoids, 433 of which 2 with a nonsense base substitution in PTPRK (alc3-a and alc5-a) and one without 434 any base substitutions in *PTPRK* (alc-3b), were cultured for 1 day either in presence or absence of hEGF in the culture medium. Subsequently, cells were collected in Trizol. Total RNA was 435 436 isolated using the QiaSymphony SP with the QiaSymphony RNA kit (Qiagen, 931636). mRNA 437 sequencing libraries were generated from 50 ng total RNA using the Illumina Neoprep TruSeq 438 stranded mRNA library prep kit (Illumina, NP-202-1001). RNA libraries were sequenced 439 paired-end (2 x 75 bp) on the Nextseq500 to > 20 million reads per sample at the Utrecht 440 Sequencing facility.

RNA sequencing reads were mapped to the human reference genome GRCh37 with
STAR v.2.4.2a⁶⁴. The BAM-files were indexed using Sambamba v0.5.8 Subsequently, reads
were counted using HTSeq-count 0.6.1 and read counts were normalized using DESeq v1.18.0.

444 DESeq nbinomTest was used to test for differential expression of *PTPRK* between the445 organoids with a nonsense *PTPRK* base substitution and the other organoids.

446

447 Western blot

Simultaneous to the collection of samples for RNA isolation described above, we also obtained protein samples for western blot in Laemmli buffer. 20 ug of protein was run on a 10% SDS page gel and blocked for 1 hour using 5% ELK in TBS-T after transfer to a nitrocellulose membrane. Subsequently, the membrane was incubated overnight with primary antibody (pERK AB50011, abcam; ERK AB17942, abcam; Actin A2066, sigma-aldrich) and for 1 hour at room temperature with secondary antibody. We visualized the proteins with the Amersham ECL Western blotting analysis system (GE Healthcare, RPN2109).

455

456 Data availability

The whole-genome sequencing and RNA sequencing data generated during the current study are available at EGA (https://www.ebi.ac.uk/ega/home) under accession number EGAS00001002983. Filtered VCF-files, metadata, BED-files with callable regions, and RNA-Seq counts generated during the current study are available at Zenodo under DOI 10.5281/zenodo.3295513 (https://doi.org/10.5281/zenodo.3295513). Data analysis scripts used during the current study are available at <u>https://github.com/UMCUGenetics/Liverdisease</u>, <u>https://github.com/UMCUGenetics/IAP</u> and <u>https://github.com/hartwigmedical</u>.

464

465 **REFERENCES**

- 466 1. Stewart, B. W. & Wild, C. P. World Cancer Report 2014. (2014).
- 467 2. Boffetta, P., Hashibe, M., La Vecchia, C., Zatonski, W. & Rehm, J. The burden of
- 468 cancer attributable to alcohol drinking. *International Journal of Cancer* **119**, 884–887

- 469 (2006).
- 470 3. World Health Organization. *Global Status Report on Alcohol and Health*. (World Health
 471 Organization, 2014).
- 472 4. Mizumoto, A. et al. Molecular Mechanisms of Acetaldehyde-Mediated Carcinogenesis
- 473 in Squamous Epithelium. Int. J. Mol. Sci. 18, (2017).
- 474 5. Obe, G. & Ristow, H. Mutagenic, cancerogenic and teratogenic effects of alcohol.
- 475 *Mutat. Res.* **65**, 229–259 (1979).
- 476 6. Helander, A. & Lindahl-Kiessling, K. Increased frequency of acetaldehyde-induced
- 477 sister-chromatic exchanges in human lymphocytes treated with an aldehyde
- 478 dehydrogenase inhibitor. *Mutat. Res. Lett.* **264**, 103–107 (1991).
- 479 7. Matsuda, T., Kawanishi, M., Matsui, S., Yagi, T. & Takebe, H. Specific tandem GG to

480 TT base substitutions induced by acetaldehyde are due to intra-strand crosslinks between
481 adjacent guanine bases. *Nucleic Acids Res.* 26, 1769–1774 (1998).

- 482 8. Tamura, M., Ito, H., Matsui, H. & Hyodo, I. Acetaldehyde is an oxidative stressor for
 483 gastric epithelial cells. J. Clin. Biochem. Nutr. 55, 26–31 (2014).
- 484 9. Novitskiy, G., Traore, K., Wang, L., Trush, M. A. & Mezey, E. Effects of ethanol and
- 485 acetaldehyde on reactive oxygen species production in rat hepatic stellate cells. *Alcohol*.
- 486 *Clin. Exp. Res.* **30**, 1429–1435 (2006).
- 487 10. Grollman, A. P. & Moriya, M. Mutagenesis by 8-oxoguanine: an enemy within. *Trends*488 *Genet.* 9, 246–249 (1993).
- 489 11. van Loon, B., Markkanen, E. & Hübscher, U. Oxygen as a friend and enemy: How to
 490 combat the mutational potential of 8-oxo-guanine. *DNA Repair* 9, 604–616 (2010).
- 491 12. Chang, J. et al. Genomic analysis of oesophageal squamous-cell carcinoma identifies
- 492 alcohol drinking-related mutation signature and genomic alterations. *Nat. Commun.* **8**,
- 493 15290 (2017).

494	13.	Schulze, K. et al. Exome sequencing of hepatocellular carcinomas identifies new
495		mutational signatures and potential therapeutic targets. Nat. Genet. 47, 505-511 (2015).
496	14.	Fujimoto, A. et al. Whole-genome mutational landscape and characterization of
497		noncoding and structural mutations in liver cancer. Nat. Genet. 48, 500-509 (2016).
498	15.	Letouzé, E. et al. Mutational signatures reveal the dynamic interplay of risk factors and
499		cellular processes during liver tumorigenesis. Nat. Commun. 8, 1315 (2017).
500	16.	Martincorena, I. et al. Universal Patterns of Selection in Cancer and Somatic Tissues.
501		<i>Cell</i> 171 , 1029–1041.e21 (2017).
502	17.	Hernandez-Gea, V., Toffanin, S., Friedman, S. L. & Llovet, J. M. Role of the
503		Microenvironment in the Pathogenesis and Treatment of Hepatocellular Carcinoma.
504		Gastroenterology 144, 512–527 (2013).
505	18.	Zhu, L. et al. Multi-organ Mapping of Cancer Risk. Cell 166, 1132–1146.e7 (2016).
506	19.	Seitz, H. K. & Stickel, F. Molecular mechanisms of alcohol-mediated carcinogenesis.
507		Nat. Rev. Cancer 7, 599–612 (2007).
508	20.	Desai, A., Sandhu, S., Lai, JP. & Sandhu, D. S. Hepatocellular carcinoma in non-
509		cirrhotic liver: A comprehensive review. World Journal of Hepatology 11, 1-18 (2019).
510	21.	Zhu, M. et al. Somatic Mutations Increase Hepatic Clonal Fitness and Regeneration in
511		Chronic Liver Disease. Cell (2019). doi:10.1016/j.cell.2019.03.026
512	22.	Khosla, R. et al. EpCAM+ Liver Cancer Stem-Like Cells Exhibiting Autocrine Wnt
513		Signaling Potentially Originate in Cirrhotic Patients. Stem Cells Transl. Med. 6, 807-
514		818 (2017).
515	23.	Chen, D. et al. Epithelial to mesenchymal transition is involved in ethanol promoted
516		hepatocellular carcinoma cells metastasis and stemness. Mol. Carcinog. 57, 1358-1370
517		(2018).
518	24.	Blokzijl, F. et al. Tissue-specific mutation accumulation in human adult stem cells

- 519 during life. *Nature* **538**, 260–264 (2016).
- 520 25. Jager, M. *et al.* Measuring mutation accumulation in single human adult stem cells by
- 521 whole-genome sequencing of organoid cultures. *Nat. Protoc.* **13**, 59–78 (2018).
- 522 26. Barker, N. *et al.* Crypt stem cells as the cells-of-origin of intestinal cancer. *Nature* **457**,
- **523**608–611 (2009).
- 524 27. Adams, P. D., Jasper, H. & Rudolph, K. L. Aging-Induced Stem Cell Mutations as
- 525 Drivers for Disease and Cancer. *Cell Stem Cell* **16**, 601–612 (2015).
- 526 28. Lee, J.-S. *et al.* A novel prognostic subtype of human hepatocellular carcinoma derived
- 527 from hepatic progenitor cells. *Nat. Med.* **12**, 410–416 (2006).
- 528 29. Tummala, K. S. et al. Hepatocellular Carcinomas Originate Predominantly from
- Hepatocytes and Benign Lesions from Hepatic Progenitor Cells. *Cell Rep.* 19, 584–600
 (2017).
- 30. Holczbauer, Á. *et al.* Modeling pathogenesis of primary liver cancer in lineage-specific
 mouse cell types. *Gastroenterology* 145, 221–231 (2013).
- 533 31. Mu, X. *et al.* Hepatocellular carcinoma originates from hepatocytes and not from the
 progenitor/biliary compartment. *Journal of Clinical Investigation* 125, 3891–3903
 535 (2015).
- 32. Alexandrov, L. B. *et al.* Signatures of mutational processes in human cancer. *Nature*537 500, 415–421 (2013).
- 538 33. Nik-Zainal, S. *et al.* Landscape of somatic mutations in 560 breast cancer whole-genome
 539 sequences. *Nature* 534, 47–54 (2016).
- 540 34. Alexandrov, L. B. *et al.* The Repertoire of Mutational Signatures in Human Cancer.
- *bioRxiv* 322859 (2018). doi:10.1101/322859
- 542 35. Zou, X. *et al.* Validating the concept of mutational signatures with isogenic cell models.
- 543 *Nat. Commun.* 9, 1744 (2018).

- 544 36. Yokoyama, A. *et al.* Age-related remodelling of oesophageal epithelia by mutated
- 545 cancer drivers. *Nature* **565**, 312–317 (2019).
- 546 37. Supek, F. & Lehner, B. Clustered Mutation Signatures Reveal that Error-Prone DNA
- 547 Repair Targets Mutations to Active Genes. *Cell* **170**, 534–547.e23 (2017).
- 548 38. Barski, A. *et al.* High-resolution profiling of histone methylations in the human genome.
- 549 *Cell* **129**, 823–837 (2007).
- 39. Bannister, A. J. *et al.* Spatial distribution of di- and tri-methyl lysine 36 of histone H3 at
 active genes. *J. Biol. Chem.* 280, 17732–17736 (2005).
- 40. Xu, Y., Tan, L.-J., Grachtchouk, V., Voorhees, J. J. & Fisher, G. J. Receptor-type
- 553 protein-tyrosine phosphatase-kappa regulates epidermal growth factor receptor function.
- 554 *J. Biol. Chem.* **280**, 42694–42700 (2005).
- Luedde, T., Kaplowitz, N. & Schwabe, R. F. Cell death and cell death responses in liver
 disease: mechanisms and clinical relevance. *Gastroenterology* 147, 765–783.e4 (2014).
- Lu, W.-Y. *et al.* Hepatic progenitor cells of biliary origin with liver repopulation
 capacity. *Nat. Cell Biol.* 17, 971–983 (2015).
- 43. Sun, P.-H., Ye, L., Mason, M. D. & Jiang, W. G. Protein tyrosine phosphatase kappa
- 560 (PTPRK) is a negative regulator of adhesion and invasion of breast cancer cells, and
- associates with poor prognosis of breast cancer. J. Cancer Res. Clin. Oncol. **139**, 1129–
- 562 1139 (2013).
- 563 44. Flavell, J. R. et al. Down-regulation of the TGF-beta target gene, PTPRK, by the
- 564 Epstein-Barr virus encoded EBNA1 contributes to the growth and survival of Hodgkin
 565 lymphoma cells. *Blood* 111, 292–301 (2008).
- 566 45. Zhong, J.-H. et al. Epidermal Growth Factor Gene Polymorphism and Risk of
- 567 Hepatocellular Carcinoma: A Meta-Analysis. *PLoS One* 7, e32159 (2012).
- 568 46. Tanabe, K. K. *et al.* Epidermal growth factor gene functional polymorphism and the risk

- of hepatocellular carcinoma in patients with cirrhosis. *JAMA* **299**, 53–60 (2008).
- 570 47. Sanchez-Vega, F. et al. Oncogenic Signaling Pathways in The Cancer Genome Atlas.

571 *Cell* **173**, 321–337.e10 (2018).

- 572 48. Schiffer, E. et al. Gefitinib, an EGFR inhibitor, prevents hepatocellular carcinoma
- 573 development in the rat liver with cirrhosis. *Hepatology* **41**, 307–314 (2005).
- 49. Mantovani, A., Allavena, P., Sica, A. & Balkwill, F. Cancer-related inflammation.

575 *Nature* **454**, 436–444 (2008).

- 576 50. Shimizu, T., Marusawa, H., Endo, Y. & Chiba, T. Inflammation-mediated genomic
- 577 instability: roles of activation-induced cytidine deaminase in carcinogenesis. *Cancer Sci.*

103, 1201–1206 (2012).

- 579 51. Broutier, L. et al. Culture and establishment of self-renewing human and mouse adult
- 580 liver and pancreas 3D organoids and their genetic manipulation. *Nat. Protoc.* 11, 1724–
 581 1743 (2016).
- 582 52. Huch, M. *et al.* Long-term culture of genome-stable bipotent stem cells from adult
 583 human liver. *Cell* 160, 299–312 (2015).
- 584 53. Li, H. & Durbin, R. Fast and accurate short read alignment with Burrows-Wheeler
 585 transform. *Bioinformatics* 25, 1754–1760 (2009).
- 586 54. Boeva, V. *et al.* Control-FREEC: a tool for assessing copy number and allelic content
- using next-generation sequencing data. *Bioinformatics* **28**, 423–425 (2012).
- 588 55. Chen, X. *et al.* Manta: rapid detection of structural variants and indels for germline and
- 589 cancer sequencing applications. *Bioinformatics* **32**, 1220–1222 (2016).
- 590 56. Quinlan, A. R. BEDTools: The Swiss-Army Tool for Genome Feature Analysis. *Curr*.
- 591 *Protoc. Bioinformatics* **47**, 11.12.1–34 (2014).
- 592 57. McKenna, A. et al. The Genome Analysis Toolkit: a MapReduce framework for
- analyzing next-generation DNA sequencing data. *Genome Res.* **20**, 1297–1303 (2010).

594	58.	Van der Auwera, G. A. et al. From FastQ data to high confidence variant calls: the
595		Genome Analysis Toolkit best practices pipeline. Curr. Protoc. Bioinformatics 43,
596		11.10.1–33 (2013).
597	59.	Durinck, S. et al. BioMart and Bioconductor: a powerful link between biological
598		databases and microarray data analysis. Bioinformatics 21, 3439-3440 (2005).
599	60.	Durinck, S., Spellman, P. T., Birney, E. & Huber, W. Mapping identifiers for the
600		integration of genomic datasets with the R/Bioconductor package biomaRt. Nat. Protoc.
601		4 , 1184–1191 (2009).
602	61.	Carlson, M. & Maintainer, B. P. TxDb.Hsapiens.UCSC.hg19.knownGene: Annotation
603		package for TxDb object(s). (2015).
604	62.	Blokzijl, F., Janssen, R., van Boxtel, R. & Cuppen, E. MutationalPatterns:

605 comprehensive genome-wide analysis of mutational processes. *Genome Med.* 10, 33606 (2018).

- 607 63. Zhang, Y. *et al.* Model-based analysis of ChIP-Seq (MACS). *Genome Biol.* 9, R137
 608 (2008).
- 609 64. Dobin, A. *et al.* STAR: ultrafast universal RNA-seq aligner. *Bioinformatics* 29, 15–21
 610 (2013).

611

612 ACKNOWLEDGEMENTS

The authors would like to thank the Utrecht Sequencing Facility and the UBEC for sequencing and for input on the bioinformatic analyses, respectively. The UBEC is subsidized by the University Medical Center Utrecht and the Utrecht Sequencing Facility is subsidized by the University Medical Center Utrecht, Hubrecht Institute, and Utrecht University. This study was financially supported by the research program InnoSysTox (project number 114027003), by the Netherlands Organisation for Health Research and Development (ZonMw), by the Dutch

619 Cancer Society (project number 10496) and is part of the Oncode Institute, which is partly 620 financed by the Dutch Cancer Society and was funded by the gravitation program 621 CancerGenomiCs.nl from the Netherlands Organisation for Scientific Research (NWO). We 622 thank the Hartwig Medical Foundation (Amsterdam, The Netherlands) for generating, 623 analyzing and providing access to reference whole genome sequencing data of the Netherlands 624 population.

625

626 AUTHOR CONTRIBUTIONS

R.L., J.J., J.I., M.D., and M.V. collected liver biopsies. M.J., E.K., and N.B. performed
organoid culturing. N.B. isolated the RNA and protein, prepared RNA-seq libraries of the
organoid cultures and performed Western blot. M.J., M.L., B.R., R.J., and S.B. performed
bioinformatic analyses. M.J., E.K., M.V., R.B., L.L., and E.C. were involved in the conceptual
design of this study. M.J. and E.C. wrote the manuscript. All authors provided textual
comments and have approved the manuscript. R.B., L.L., and E.C. supervised this study.

634 AUTHOR INFORMATION

635 Competing interests

636 The authors declare no competing interests.

- 637
- 638 Corresponding authors
- 639 Correspondence to Edwin Cuppen.

640 TABLES

	Entrez				q	q
Gene	gene ID	Sample type	Sample(s)	Mutation type	(missense)	(nonsense)
ATP1A1	476	Healthy liver	15-а	missense	1.00	1.00
PAX7	5081	Healthy liver	21-а	missense	1.00	1.00
PREX2	80243	Healthy liver	21-b	missense	1.00	1.00
PTPRK	5796	Alcoholic liver	alc3-a, alc5-a	nonsense, nonsense	1.00	0.02
ALK	238	Alcoholic liver	alc3-b	missense	1.00	1.00
CACNA1D	776	Alcoholic liver	alc3-b	missense	1.00	1.00
ZNF331	55422	Alcoholic liver	alc4-b	missense	1.00	1.00
CUX1	1523	Alcoholic liver	alc5-a	missense	1.00	1.00
TERT	7015	Alcoholic liver	alc5-a	missense	1.00	1.00
CD274	29126	HCC	HCC-trunk	missense	1.00	1.00
CIITA	4261	HCC	HCC-trunk	missense	1.00	1.00
KLF4	9314	HCC	HCC-trunk	missense	1.00	1.00
MUC1	4582	HCC	HCC-trunk	missense	1.00	1.00

641

642 Table 1 Somatic missense and nonsense base substitutions in cancer genes observed in healthy liver

643 ASCs, alcoholic liver ASCs, and the MRCA of an HCC. *q* values (likelihood ratio test, FDR correction)

644 indicate significant enrichment of nonsynonymous base substitutions within genes.

645 FIGURES

646

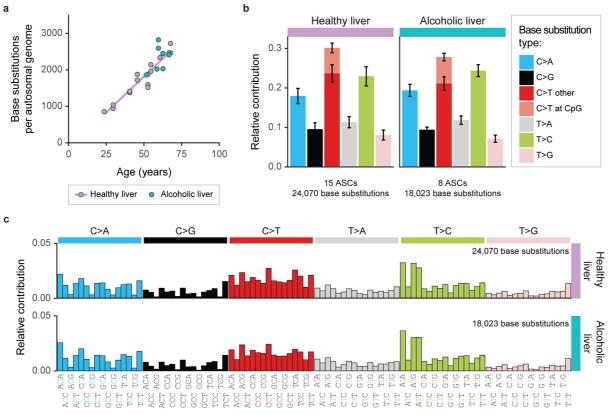
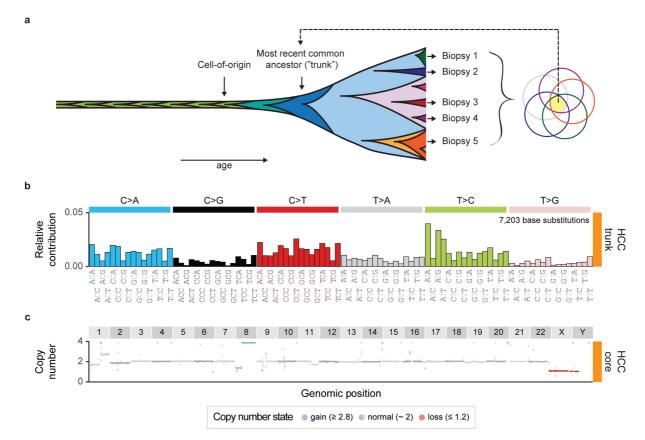


Fig. 1 Somatic base substitutions in healthy and alcoholic liver stem cells. a Number of somatic base
substitutions in the autosomal genomes of 15 healthy and 8 alcoholic liver stem cells of 9 and 5 donors,
respectively. Each stem cell is represented by a data point. A linear accumulation of base substitutions
with age was observed in healthy liver, indicated by the purple trendline. b Mean relative contribution
of the base substitution types to the mutation spectra of healthy and alcoholic liver ASCs. Error bars
represent standard deviation. c Mean relative contribution of 96 context-dependent base substitution
types to the mutational profiles of healthy and alcoholic liver ASCs.



654

Fig. 2 Somatic mutations in the most recent common ancestor of an HCC in a patient with a history of
chronic alcohol intake. a Mutations that accumulated in the most recent common ancestor ("trunk") can
be identified, by determining the mutations that are shared by multiple biopsies (in yellow). Five
biopsies across a 13cm HCC were sequenced to identify the trunk mutations. b Relative contribution of
96 context-dependent base substitution types to the mutational profile of the recent common ancestor
of an HCC. c Genomic copy number profile of one of the HCC biopsies (HCC-core), which is
representative for all biopsies (Supplementary Fig. 4c).

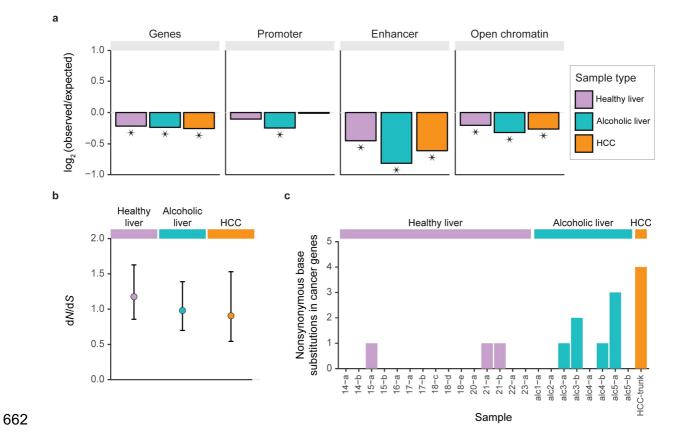
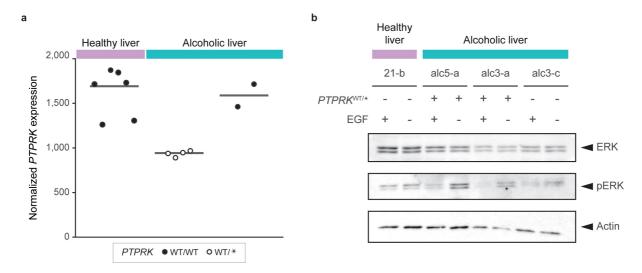


Fig. 3 Genomic distribution of the somatic base substitutions acquired in healthy liver stem cells, alcoholic liver stem cells, and the most recent common ancestor of an HCC. **a** The effect size of the depletion of somatic base substitutions in genes, promoters, enhancers, and open chromatin regions. Asterisks indicate significant depletion. **b** dN/dS of the somatic base substitutions in genes in the indicated sample types. Data points represent the Maximum-likelihood estimates and error bars represent the 95% confidence intervals. **c** Number of nonsynonymous base substitutions in cancer genes in each indicated sample.





671 Fig. 4 Functional consequences of nonsense PTPRK base substitutions. a Normalized PTPRK mRNA expression in alcoholic *PTPRK*^{WT/*}, healthy *PTPRK*^{WT/WT} and alcoholic *PTPRK*^{WT/WT} liver organoid 672 673 cultures. Normalized counts were calculated for duplicate measures of 2 alcoholic PTPRK^{WT/*}, 3 healthy PTPRK^{WT/WT}, and 1 alcoholic PTPRK^{WT/WT} organoid cultures. Each data point represents a 674 single measurement. Lines indicate median *PTPRK* expression per sample type. WT = wildtype, * = 675 676 nonsense base substitution. b Western blot of ERK, pERK and actin in organoid cultures of PTPRK^{WT/*} livers and healthy and alcoholic *PTPRK*^{WT/WT} liver cultures with and without EGF in the culturing 677 678 medium.