

Article

Temporal Dissection of Altered Pathways during the Evolution of Cancer

Johanne Ahrenfeldt^{1,2#}, Ditte S. Christensen^{1,2,3#}, Mateo Sokac^{1,2}, Judit Kisistok^{1,2,4}, Nicholas McGranahan^{5,6} and Nicolai J. Birkbak^{1,2,4*}

¹ Department of Clinical Medicine, Aarhus University, Aarhus, Denmark.

² Department of Molecular Medicine, Aarhus University Hospital, Aarhus, Denmark.

³ Department of Clinical Oncology, Aarhus University Hospital, Aarhus, Denmark.

⁴ Bioinformatics Research Center, Aarhus University, Aarhus, Denmark.

⁵ Cancer Research UK Lung Cancer Centre of Excellence, University College London Cancer Institute, Paul O'Gorman Building, London, United Kingdom.

⁶ Cancer Genome Evolution Research Group, University College London Cancer Institute, University College London, London, United Kingdom.

⁷ Department of Molecular Medicine, Aarhus University Hospital, Aarhus, Denmark.

Contributed equally.

* Correspondence: nbirkbak@clin.au.dk

Simple Summary: Early-stage primary cancer, where the tumour has not yet spread from its site of origin, is commonly curable through surgery alone. Conversely, metastatic cancer, where the tumour has spread beyond its site of origin, is almost invariably lethal and is the main cause of cancer death. Given that primary cancer is often curable, it is likely that the ability to metastasise is acquired late in the development of cancer. To investigate if specific cancer gene mutations or pathways are subject to selection at different time points during the life-history of cancer, we compared genomic data from primary and metastatic cancer and timed the acquisition of genomic alterations. The results presented here supports the view that certain events are selected for late in the evolution of cancer. However, we observed no difference in the type or timing of events between primary and metastatic cancer. Taken together, our results suggests that the ability to metastasise is not acquired through evolution solely at a genomic level.

Abstract: Cancer metastasis is the lethal developmental step in cancer, responsible for the majority of cancer deaths. To metastasize, cancer cells must acquire the ability to disseminate systemically and to escape an activated immune response. Here, we endeavoured to investigate if metastatic dissemination reflects acquisition of genomic traits that are selected for. We acquired mutation and copy number data from 8,332 tumours representing 19 cancer types acquired from The Cancer Genome Atlas and the Hartwig Medical Foundation. A total of 827,344 non-synonymous mutations across 8,332 tumour samples representing 19 cancer types were timed as early or late relative to copy number alterations, and potential driver events were annotated. We found that metastatic cancers had significantly higher proportion of clonal mutations and a general enrichment of early mutations in p53 and RTK/KRAS pathways. However, while individual pathways demonstrated a clear time-separated preference for specific events, the relative timing did not vary between primary and metastatic cancers. These results indicate that the selective pressure that drives cancer development does not change dramatically between primary and metastatic cancer on a genomic level, and is mainly focused on alterations that increase proliferation.

Keywords: metastasis; cancer evolution; bioinformatics; cancer biology; cancer genomics

1. Introduction

Metastatic disease is the most common cause of cancer related deaths [1] which is usually considered the last step in evolution of lethal cancer. When diagnosed early, cancers are often curable by surgery or radiotherapy, but once the cancer cells have disseminated to distant organs the disease has become systemic and leave most patients incurable. It is therefore of critical importance to understand the evolutionary process of achieving metastatic potential in a primary tumour in order to improve the treatment of cancer. The majority of our understanding of cancer biology comes from studies investigating primary tumours, and while recently more studies exploring metastatic tumours have been published[2]–[7], many fundamental questions about the metastatic cancer biology still remain unanswered[8].

Metastasis is a multi-step process, which is referred to as the metastatic cascade[9], [10], and includes the steps from local tissue invasion through intravasation into blood vessels and finally colonisation to a distant organ. This process has been described as highly inefficient, with most cells failing to colonise distant locations [10]. The metastatic process has therefore been suggested to depend on both the primary tumour's ability to shed tumour cells into the blood circulation and the cancer cells' ability to survive outside of the primary tumour.

Mutations that promote growth and increase cancer cells fitness, are referred to as driver mutations[11]. Classical oncogenes and tumour suppressor genes improve cancer cell fitness through either increased cell proliferation, or decreased cell death[12]. However, it remains unknown if specific driver mutations or pathway alterations may be linked to metastatic potential [13]. It is possible that there exist specific phenotypic traits that in the primary tumour that increase the risk of dissemination or may even act as gatekeeper events that are required for successful metastatic dissemination[12], [13].

In the MET500 project by Robinson et al more than 500 metastatic cancer samples from 20 different cancer types were analysed[4]. Here they found an increased tumour mutation burden compared to primary tumour samples from The Cancer Genome Atlas (TCGA), and found that on a gene transcription level the metastatic samples had increased global dysregulation. However, they were unable to identify defining characteristics of metastatic development, neither on gene nor pathway level[4]. Similar results were found by Hartwig Medical Foundation (HMF), where 2,520 metastatic tumours were whole genome sequenced and analysed[3]. Here they reported a lack of metastasis-specific driver mutations, again indicating limited metastasis specific evolution. Likewise, a follow-up study by HMF, with paired samples from 250 patients, where the focus was on clinically relevant genomic biomarkers, de Haar and colleagues found full concordance between paired biopsies for 99% of all patients. In a recent study[2] we found that when investigating 174 genes across 40,000 patients with primary or metastatic disease, the main evolutionary driver of metastatic cancer is resistance mutations to treatment. No single mutation or genomic event has been found to be the basis for metastatic potential, and to this day the metastatic gatekeeper event remains a hypothesis.

More recently, genomic data from unpaired primary and metastatic tumours have been analysed from large cohorts using gene panels. In a study by Nguyen and colleagues, the authors reported a correlation between chromosomal instability and higher metastatic burden[5]. They also observed that specific genomic alterations and signalling pathways are enriched in metastatic samples, but in their gene panel no differences was observed between the type of alterations reported, and the timing of individual events were not performed. In similar work published by us[2], we presented an analysis of 174 common cancer genes based on the GENIE dataset (Genomics Evidence Neoplasia Information Exchange)[14], demonstrating in a larger cohort of more than 40,000 samples how treatment was the dominant evolutionary pressure in metastatic cancer.

With this study we investigate when during the evolution of cancer metastatic potential is acquired. Using two publicly available data sets, we performed a temporal analysis of more than 4,000 primary tumours with whole exome sequencing data, and

close to 4,000 metastatic tumours with whole genome sequencing data. These datasets were analysed to compare mutations and copy number alterations between the primary and metastatic samples. Furthermore, we divided the mutations into early and late defined by their occurrence relative to copy number alterations in order to explore temporal effects of individual mutation events.

2. Materials and Methods

2.1. Cohort overview

To identify metastasis-specific cancer driver events, we acquired two patient cohorts, the Cancer Genome Atlas (TCGA), 4,435 samples, representing primary tumours, and the Hartwig Medical Foundation (HMF), 3,897 samples, representing metastatic tumours (Figure 1A). These cohorts shared 19 cancer types with an average of 225 (range 21-861) metastatic and 251 (range 25-820) primary samples. Hypermutated samples were removed, these were defined as TCGA (whole exome sequenced) samples with more than 1,000 mutations, and HMF (whole genome sequenced) samples with more than 60,000 mutations. These cutoffs were defined based on a plot of ascending number of mutations per patient, and the cut off was set approximately where the number of mutations started to rise exponentially (Figure S1).

2.2. Relative timing of mutations

All mutations were timed relative to copy number events affecting the same genomic location using the method from McGranahan et. al 2015[15]. The copy number was estimated for each mutation, and then compared to the copy number of the allele. Only regions with at least two copies of the major allele were timed. If the copy number of the mutation was 1 then it was considered late, and if it was above 1 it was considered early. Furthermore, if a mutation was subclonal, it was considered late. To avoid gender bias, only autosomes were used in the analysis.

The Cancer Cell Fraction (CCF) represents the fraction of cancer cells carrying a given mutation. To determine CCF, variant allele frequency (VAF) is integrated with tumour purity and the local copy number, as described[15], according to the formula below:

$$CCF = VAF * 1/Purity * ((Purity * CN_t) + CN_n * (1 - Purity)), \quad (1)$$

Here, CN_t is the mutation copy number, and CN_n is the diploid copy number state.

2.3. Annotation of driver events

For both TCGA and HMF all somatic mutations were annotated by ANNOVAR[16] with hg19 as the reference genome. Driver mutations were defined as frameshift indels in tumour suppressor genes (TSG) and Non-frameshift indels in oncogenes, with an occurrence in the COSMIC v90[17] database of at least 3 times. Also, deleterious variants in TSGs, predicted as either “deleterious” by SIFT, “probably damaging” by PolyPhen or if the mutation is a stop gain mutation or splice mutations they were defined as driver mutations. Finally, we included any specific mutation which was found more than 10 times in the Cosmic database in the definition of driver mutations. For somatic copy number alterations (SCNA) TSGs with deletions and oncogenes with amplifications were classified as driver events.

To evaluate potential driver events in genes not annotated in the COSMIC cancer gene census, we defined driver events in these genes as variants either predicted “deleterious” by SIFT, “probably damaging” by PolyPhen or if the variant was a stop gain mutation, frameshift deletion or insertion. Finally, any specific variant which was found more than 10 times in the Cosmic database was deemed a likely driver.

2.4. Copy number alterations

The weighted genome integrity index (wGII) was calculated on the segmented copy number data, as described previously[18]. The loss of heterozygosity (LOH) was defined as a segment where the minor allele had a copy number of 0 and the major allele had a copy number of 1 or more. A genome was said to have undergone genome doubling (GD) if at least half the genome had a major allele copy number of at least 2.

2.5. Enriched and depleted genes and pathways

For the enrichment analyses genes were considered altered if they harboured a driver event, as described above. A two-sided Fisher's exact test was used to compare primary to metastatic samples, on the number of patients with or without altered genes, per cancer type. False discovery rate (FDR) was used to correct p-values and considered significant if the corrected p-values were below 0.05. All gene driver event were mapped to the cancer specific pathways from Sanchez-Vega et al.[19] And a similar enrichment analysis as above was performed on a pathway level.

2.6. Hotspot mutations

To identify genomic positions with mutation hot-spots, we counted mutated positions for each cancer type in primary and metastatic patients separately. We then used Fisher's exact test to determine if a significant enrichment or depletion was found for a specific variant.

2.7. Statistical analysis

All analysis was performed in R version 3.6.3 [20], using Tidyverse [21] and ggpubr[22], scales[23], ggrepel[24] for visualisations. Wilcoxon test was used to test for significance, unless otherwise mentioned.

3. Results

3.1. Metastatic tumours have a higher number of driver mutations

In order to compare the number of driver mutations between primary and metastatic tumours, we defined driver mutations based on pathogenic exonic mutations in cancer genes (methods). For the TCGA cohort, we identified 15,349 likely driver mutations from a total of 427,237 non-synonymous mutations from 4,435 tumours. Similarly, for the HMF cohort, we identified 15,390 driver mutations from a total of 400,107 non-synonymous mutations from 3,897 tumours. Overall, we observed that metastatic tumours harboured a slightly higher mean number of driver mutations (mean TCGA= 3.25, mean HMF = 3.65, p value < 2×10^{-16}) (Figure S2A).

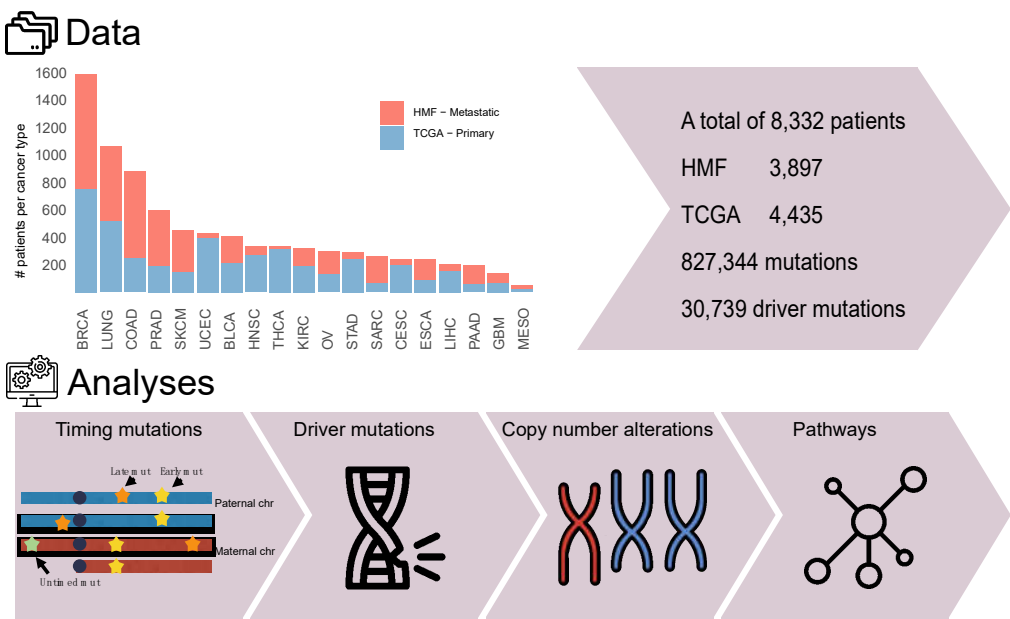


Figure 1. Overview of data and workflow. A) Barplot of number of patients per cancer type. B) Overview of number of mutations. C) Workflow for data analysis.

To investigate whether a higher number of driver mutations may be a result of increased background mutation burden in metastatic cancer, the number of driver mutations were normalised based on the total number of exonic SNVs per patient. Here we found that the distribution of the two cohorts were more similar, with a slightly higher mean in the primary cohort (4.1 versus 3.7 driver mutations per 100 exonic SNV, p value = 0.048) (Figure S2B).

When we compared the number of driver mutations per tumour between primary and metastatic samples within each cancer type, generally we found a higher number of driver mutations per tumour in metastatic samples, which was significantly higher in 8/19 cancer types, whereas for only 3/19 cancer types there was a significantly higher level in primary cancer (Figure 2A). To further explore whether this increase was caused by a general increase in mutations in metastatic tumours, we compared the mean number of drivers per tumour normalised by the exonic SNV count for each cancer type within the two cohorts, and here we found that metastatic tumours harbour significantly more driver mutations in 5/19 cancer types and primary tumours in 2/19 cancer types (figure 2B). This indicates that the acquisition of driver mutations is not solely driven by the total number of mutations.

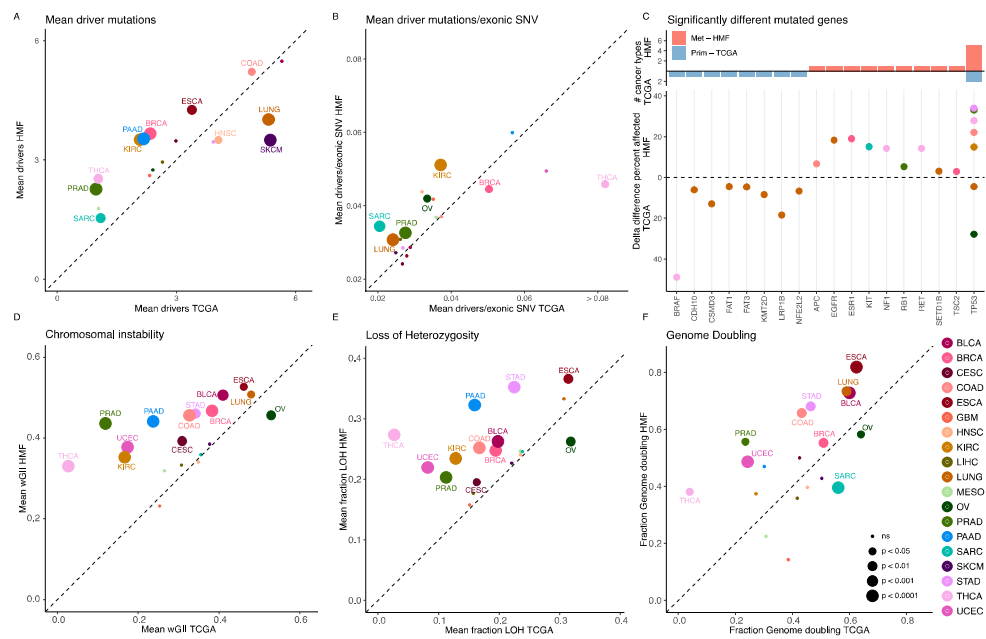


Figure 2. Quantitative analysis of mutations and copy number alterations. A) Scatterplot of the mean number of driver mutations per cancer type in primary vs metastatic cancer. B) Scatterplot of the mean number of driver mutations per 100 exonic SNV per cancer type in primary vs metastatic cancer. C) Genes significantly enriched for driver mutations in primary or metastatic mutations, and the fraction of delta differences in mutations for these genes, for each significant cancer type. D) Scatterplot of the mean value of chromosomal instability per cancer type in primary vs metastatic cancer. E) Scatterplot of the mean fraction of loss of heterozygosity per cancer type in primary vs metastatic cancer. F) Scatterplot of the fraction of patients with genome doubling per cancer type in primary vs metastatic cancer.

3.2. Most cancer genes are affected by driver mutations at the same frequency in primary and metastatic cancer

To investigate whether the prevalence of driver mutation events is higher in metastatic samples, we compared the number of driver events between metastatic and primary cancer samples, combining all cancer types. Here, we observed that most driver mutations in specific genes were found at similar frequencies in both primary and metastatic disease. Only 3 genes were found enriched or depleted at frequencies exceeding 5% (TP53 and APC, enriched 15% & 10%, PTEN, depleted 9%, Figure S2D). An additional 682 genes were significantly enriched or depleted in metastatic cancer at frequencies below 5%, with 632 showing less than 1% enrichment or depletion. To investigate if any of the genes showed stronger enrichment or depletion within cancer types, we performed a cancer type specific gene enrichment analysis. Here, we found 18 genes which were significantly enriched or depleted in metastatic cancer. TP53 was the only gene enriched in more than one cancer type, enriched in metastatic cancer in 5 cancer types (KIRC, COAD, TCHA, PRAD and STAD).

3.3. Metastatic tumours have a higher level of somatic copy number alterations

To investigate the chromosomal instability and the overall level of differences in copy number alterations between metastatic and primary cancer, we determined the weighted genome integrity index (wGII)[18], the fraction of Loss of Heterozygosity (LOH) and the fraction of patients with genome doubling. We found that metastatic tumours had a higher level of copy number alterations relative to primary tumours, with the amount of chromosomal instability, as determined through wGII, was significantly higher in metastatic cancer in 12/19 cancer types. Only in ovarian cancer (OV) did we observe significantly higher levels of wGII in primary tumours (Figure 2D). LOH was also significantly more frequent in metastatic cancer, found increased in 11/19 cancer types.

Again, OV stands out as the only cancer type where the frequency of LOH was significantly higher in primary cancer (Figure 2E). The fraction of patients with genome doubling was significantly higher in metastatic cancer, in 9/19 cancer types. For two cancer types significantly more tumours had genome doubling in primary cancer (Sarcoma (SARC)) and OV, Figure 2F).

3.4. Metastatic tumours are more clonal than primary tumours

To investigate the clonality of the mutations and how clonality differs between primary and metastatic cancer, we determined cancer cell fraction (CCF) for all mutations. CCF describes the fraction of cancer cells that carry a given mutation. Thus, for a clonal mutation, a mutation present in all cancer cells in the tumour sample, the CCF value is 1. Likewise, for a subclonal mutation present only in a subset of the cancer cells, the CCF value is below 1. We found that across all cancer types a lower level of subclonal mutations was observed in metastatic tumours compared to primary (figure 3A). The mean CCF values for all mutations in a sample were significantly higher in metastatic cancer in 15/19 cancer types. This was also true when we investigated driver mutations, here the fraction of subclonal driver mutations was higher in primary tumours across all cancer types, and significantly so in 10/19 cancer types (figure 3B). We investigated if any genes had more clonal or subclonal driver mutations than average, by calculating the mean CCF per gene, performed for primary and metastatic cancer within the individual cancer types. This was only performed for genes with at least 5 driver mutations per cancer type. We identified genes with a mean CCF more than two standard deviations from the mean per cancer type, and here we find that CYLD has a CCF significantly below average, which means that it is more subclonal, in metastatic cancer in 6 cancer types (BLCA, BRCA, COAD, LUNG, PRAD and SKCM). When we further investigated CYLD, we found that there were only 12 timed driver mutations of CYLD across all primary cancers (4 early, 8 late), whereas there were 98 across metastatic tumours (6 early, 92 late). ARID1B also has a CCF below average in two types (BRCA and LUNG), the same goes for TSC2 (BRCA and PAAD). In primary cancer we find that CDKN2A is above average clonal in three cancer types (BLCA, HNSC and LUNG). LRP1B and KMT2C are subclonal in two primary cancers (UCEC and BRCA, UCEC and LUNG respectively) (Figure 3C).

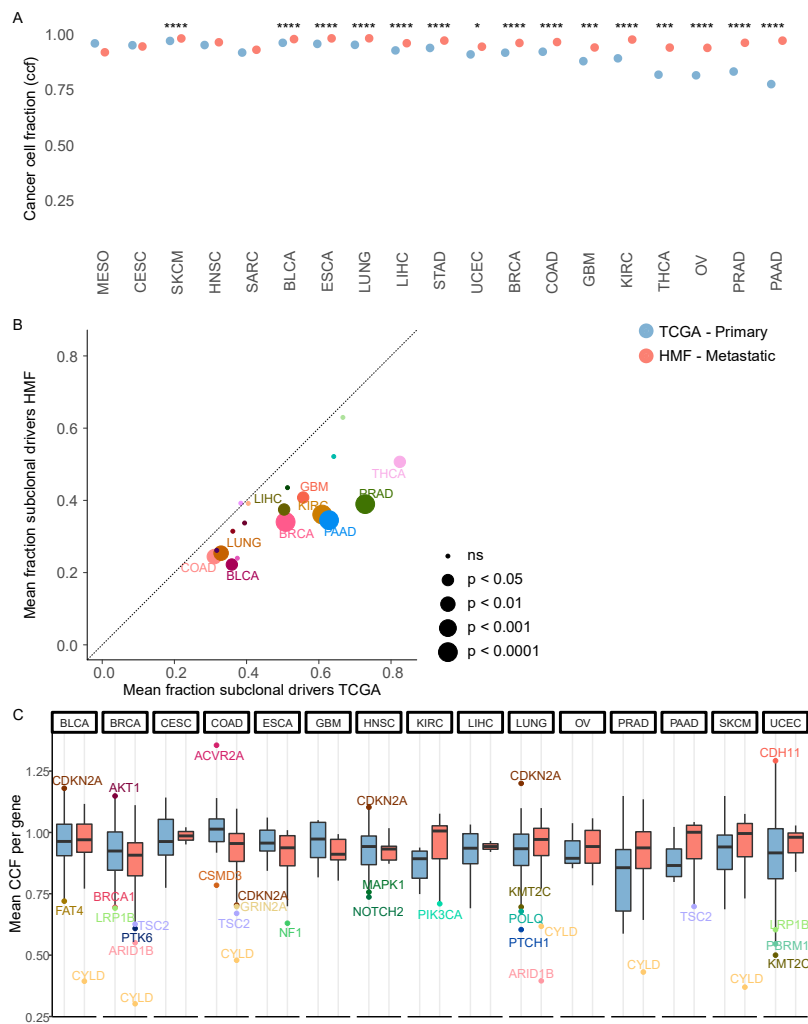


Figure 3. Subclonal mutations. A) Dot plot of the mean cancer cell fraction per patient per cancer type for primary and metastatic cancer. B) Scatterplot of the mean fraction of subclonal driver mutations per cancer type in primary vs metastatic cancer. C) A boxplot of the mean CCF per gene for all driver genes that have more than 5 hits per cancer type. The outliers are genes that have a mean that is more than two standard deviations from the mean for the entire cancer type. .

3.5. Driver mutations outside common cancer genes

We recently found that in a core set of 174 established cancer genes, metastatic cancer showed limited selection for driver mutations, with metastatic evolution primarily driven by treatment[2]. To investigate if metastatic cancer may select for or against mutations in genes not commonly associated with cancer, we specifically explored if other genes were significantly enriched for mutations in primary or metastatic cancer, outside of these 174. We only found 5 genes enriched (CSMD3, LRP1B, KMT2D, FAT1, FAT3), all showing enrichment of mutations in primary lung cancer (Figure S3B). To take this analysis further, we analysed whether metastatic cancer may select for genes found outside of the COSMIC cancer gene census. For this analysis, we applied a wider definition of driver mutations, including any pathogenic mutations (methods). With this definition, each cancer type harboured a high number of mutations, ranging from 5 to 125 mutations per cancer type (Figure S3C). Enrichment analysis identified 51 genes enriched in primary cancer, and 6 genes enriched in metastatic cancer. Genes enriched in primary cancer were particularly found in melanoma and lung cancer, while 6 genes were enriched in metastatic breast cancer (MUC6, FSIP2, OBSCN, PLEC, IGFN1, CACNA1H, Figure S3D). Notably, all of these genes are very long. The 5 enriched genes in primary lung cancer (Figure S3B) are all longer than 98% of all human genes, and the 6 enriched in metastatic breast cancer

(Figure S3D) are all longer than 84% of all human genes, with one being longer than 99.88 %. All 5 genes enriched in primary lung cancer are more than two standard deviations longer than the median for all human genes, 3 of the metastatic breast cancer genes are (Figure S3E). This suggests, that the extra mutations in these genes could be a reflection of gene size lengths, as longer genes have a higher probability of being mutated simply because of the length.

3.6. Timed driver mutations show similar patterns in primary and metastatic tumours

We hypothesised that acquisition of specific driver mutations might give rise to a more aggressive tumour, and essentially function as gate-keepers events. Especially, we wished to explore, whether the metastatic potential and thus a more aggressive tumour occurs at a specific step during cancer evolution. To explore this, all mutations were timed relative to copy number events occurring at the same segment. Here we found 26% of the mutations were early, 25% late, 18% subclonal in primary tumours. In contrast, we found 26% early, 35% late, 11 % subclonal in metastatic tumours. 31% and 29% could not be timed in primary and metastatic tumours respectively. When we investigated the driver mutations specifically, 65% could be timed in primary tumours. Of these, 49% were early mutations, 25.5% were late and 25.5% were subclonal mutations. Among metastatic tumours, 68 % of the driver mutations could be timed. Of these 58 % were early, 28% were late and 14% were subclonal mutations. More subclonal mutations were found in primary cancer (Figure 3A). Interestingly, there were more early mutations in metastatic cancer, this taken together with there being more timeable mutations in metastatic tumours, may be caused by increased chromosomal instability late in the evolution of cancer, which will result in more early events. To increase power in the analysis, we considered all subclonal mutations as late mutations. To investigate if any genes were enriched in early or late mutations, we performed a gene enrichment analysis of early vs. late mutations for each dataset. We then compared the results for the two datasets, to explore if the timing of the enriched genes were similar. Overall we only found 23 genes enriched, and the majority of these, 19 genes, were enriched in early mutations. 6 of these genes (TP53, KRAS, BRAF, VHL, PIK3CA, AKT1) were significantly enriched in both primary and metastatic cancers, and only TP53 and KRAS in more than one cancer type, 8 and 2, respectively (Figure S4).

3.7. Driver events in cancer specific pathways show near identical timing in primary and metastatic cancer

We know genes act in synergy and are connected in different signalling pathways. Hence, we did only observe limited genomic differences between primary and metastatic cancer, we wanted further to investigate whether a specific pattern of the affected pathways in primary and metastatic cancers could be observed. Therefore we mapped the driver mutations to established cancer pathways[19]. On a Pan-cancer level we observe that metastatic cancer has a significantly higher number of mutated pathways compared to primary cancer (TCGA mean = 1.68, HMF mean = 1.99, p-value < 2×10^{-16}) (Figure 4A). We performed a pathway enrichment analysis to explore the timed pathways, and if there were any remarkable difference in timing on a pathway level. As we did for driver genes, we performed an enrichment analysis for early vs. late pathway hits for each dataset, and then we compared the results of the two. When we compared the significantly enriched timed pathways in primary cancer to metastatic cancer, we found that pathway timing were highly concordant, i.e. if a pathway was significantly enriched in early mutations in primary, it was never found significantly enriched for late mutations in metastatic and vice versa (Figure 4B). We observed that the odds ratios for the pathways of two datasets were highly correlated (pearson = 0.79, $P = 1.82 \times 10^{-10}$). As no shift was observed between primary and metastatic cancer, where events found late in primary cancer became early in metastatic cancer through further selection, this indicates that evolution in the metastatic setting may play a minor role in development of lethal metastatic cancer. The p53 pathway was overall the pathway most enriched in early

mutations across cancer types (Primary: 13/19 cancer types, Metastatic: 14/19 cancer types), consistent with a defining role in cancer development. Only CESC, KIRC, MESO, SKCM and THCA were not enriched for early p53 pathway hits, while in PAAD it was only enriched in metastatic tumours. The KRAS and Cell cycle pathways were also highly enriched in early mutations, RTK/KRAS in 7 metastatic and 4 primary cancer types, and Cell cycle in 6 metastatic and 2 primary cancer types (Figure 4B). Conversely, while early pathway hits were quite consistently enriched in p53, RTK/KRAS and Cell cycle pathway genes, late pathway hits affected more pathways. These included Hippo (Primary: 4/19, Metastatic: 3/19) in BRCA and COAD for both and STAD and UCEC for primary and PAAD for metastatic, Notch (Primary: 4/19, Metastatic: 4/19) in COAD and OV for both and UCEC and SKCM in primary and BRCA and PRAD in metastatic, Wnt (Primary: 3/19, Metastatic: 3/19) in BRCA and UCEC for both and STAD for primary and COAD in metastatic (Figure 4B).

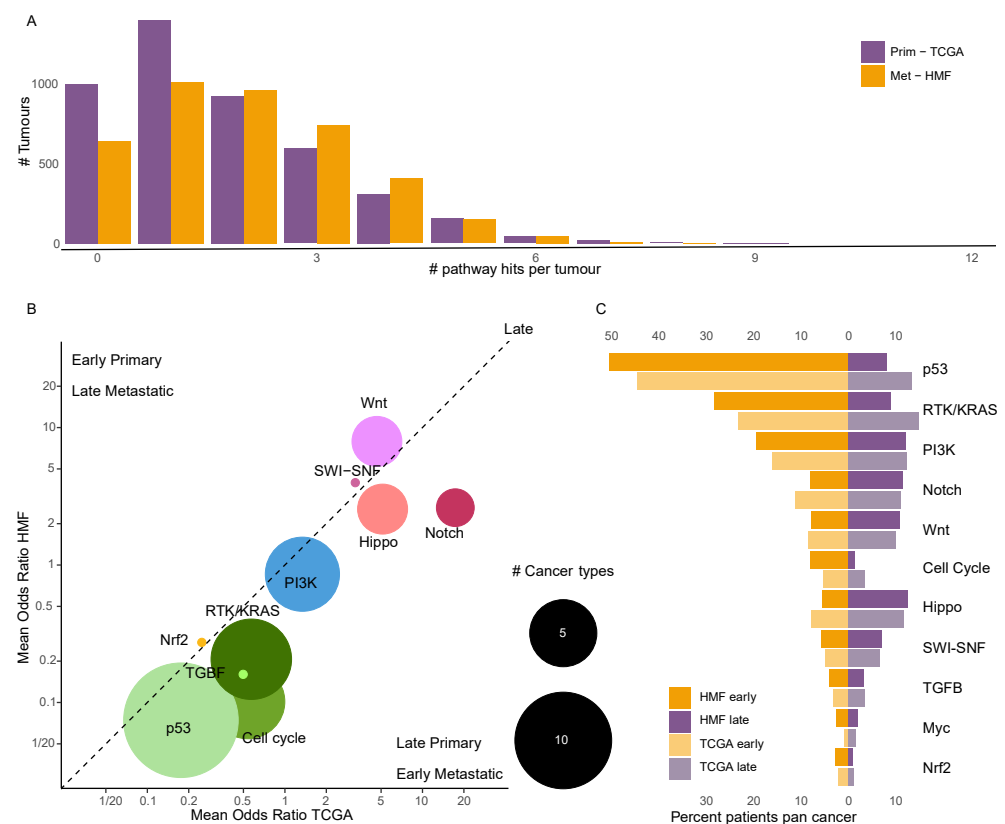


Figure 4. Enriched timed pathways. A) A histogram showing the distribution of affected specific cancer pathways by driver mutations. B) A bubble plot of the mean odds ratio for enrichment of early or late pathway hits in primary vs metastatic cancer. The size of the bubble shows the number of significant cancer types. C) A mirror plot showing the percentage of patients pan-cancer which have been affected by early and late driver mutations in each of the 11 cancer specific pathways.

3.8. Mutational hotspots indicate treatment resistance as driver for metastatic evolution

Hotspots are defined as specific genomic positions mutated at higher-than-expected frequency across cancer patients. Across the genome, 11 variants were specifically enriched in metastatic samples. Three variants in the EGFR gene were significantly enriched in patients with Non-Small Cell Lung cancer, consistent with acquired resistance to anti-EGFR treatment in this cancer type. Likewise, we identify a specific variant in the ESR1 gene in Breast Cancer, consistent with resistance to anti-hormone treatment. Interestingly, we found significant enrichment of a variant in the MUC6 gene in Breast Cancer and in Colon cancer, both of which are of unknown effect. In Thyroid cancer we found a variant in RET which has previously been linked to worse survival for

patients[25]. We also observed two variants that were significantly enriched in primary cancer, both BRAF variants with known targeted treatments, most likely a sign that targeted treatment against these two mutations work well, as they do not re-emerge in metastatic cancer. Rather, while metastatic tumours are also enriched in chromosomal instability and driver events involved with cell proliferation, both known drivers of aggressive cancer, another dominant driver of metastatic cancer evolution appears to be anti-cancer therapy.

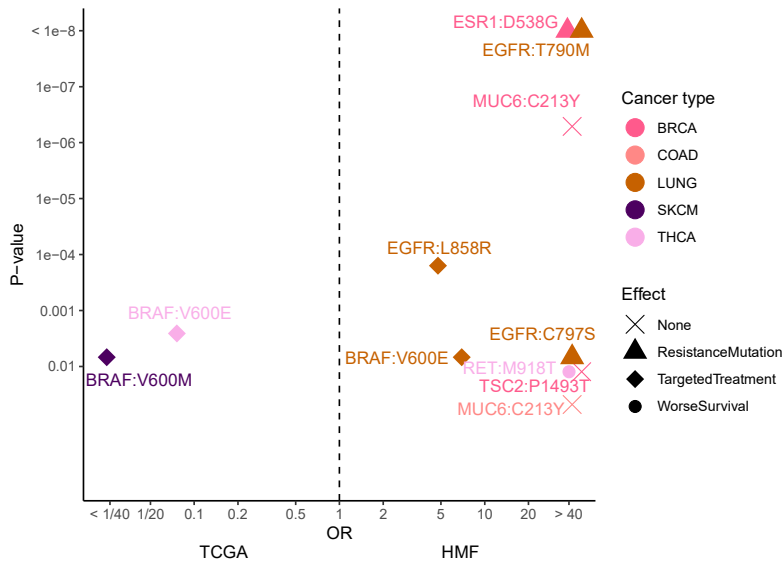


Figure 5. Enrichment of specific variants. A volcano plot showing the variants that are enriched in primary or metastatic cancer. The shape of the dot represents the effect of the mutations.

3.9. Loss of Heterozygosity and driver mutations primes for additional mutations

We observed a significantly larger frequency of LOH in the metastatic samples. Tumour suppressor genes are commonly affected by a driver mutation that disables a gene copy, followed by a copy number loss event that disables the remaining allele though LOH. However, single copy loss may in this manner provide a first hit to several tumour suppressor genes found within the same genomic region, which may now be limited to a single functioning copy. To investigate if LOH may act as a catalyst for multiple driver mutations acting on tumour suppressor genes, we investigated if areas of LOH with a driver mutation also contained other driver mutations. We did this by exploring pairs of driver mutations on segments with LOH. We found that TP53 was by far the gene occurring most commonly in pairs across cancer types, found in gene pairs in 12 cancer types. Commonly, TP53 loss and LOH co-occurred with MAP2K4 and NCOR1, occurring together with TP53 and LOH 31 and 21 times respectively, each in 6 different cancer types (Figure 6A-B). This may support that a mutation combined with LOH in TP53 leaves the area vulnerable to additional driver mutations. For KIRC we observed loss of tumour suppressor genes VHL, BAP1, PBRM1 and SETD2 often occurring in pairs (Figure 6A-B). These genes are all found on chromosome 3p, and has previously been reported as co-occurring through sequential loss, where initial mutation and copy number loss of VHL drives further selection of loss of tumour suppressor genes on the same chromosome arm[26]. Some gene pairs were only found in metastatic samples, including KEAP1, SMARCA4, STK11, all found together on chromosome 19, which occurred together in pairs in metastatic BRCA, LUNG, HNSC, COAD and MESO.

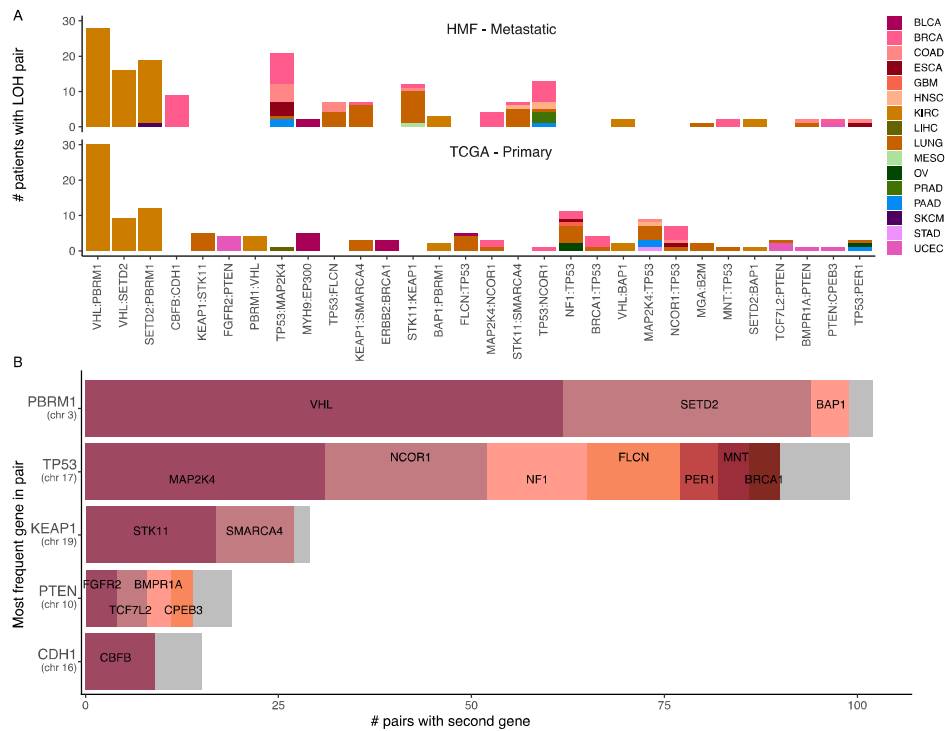


Figure 6. Driver gene pairs in areas of LOH. A) a Bar plot showing the pairs of driver genes found in areas of LOH. B) The five most frequent genes in the LOH gene pairs. Colored by the least frequent gene in the pair.

4. Discussion

With this study we have demonstrated how the relative timing of mutations can give additional information on the mutation patterns of primary and metastatic tumours. Our analysis included data from more than 8500 tumour samples from 19 different cancer types. Cancer driver mutations classically affect tumour suppressor genes and oncogenes, and drive the cancer phenotype through selection for increased proliferation, longevity, chromosomal instability and immune escape[27]. Consistent with previous work we found that metastatic tumours harboured more cancer driver mutations and increased levels of chromosomal instability[5], [28], including higher wGII scores, increased fraction of LOH and higher genome doubling rates (Figure 2). However, when we corrected the number of driver mutations with mutation burden, we found that only 5/19 cancer types had significantly higher levels in metastatic cancer. We further investigated whether the acquisition of metastatic potential may be driven by mutations acquired in genes outside of established cancer genes (Figure S3), yet we found no evidence of mutations in specific genes enriched in metastatic cancer. Taken together, this supports the notion that the acquisition of genetically defined cancer driver mutations later in tumour evolution plays a relatively minor role in the development of traits supporting metastatic dissemination[2].

Previous studies have shown that primary tumours are commonly heterogeneous across cancer types[29]. Tissue biopsies may sample heterogeneous tissue containing multiple subclones, which contains both clonal and subclonal mutations and driver events[13]. Monoclonal dissemination of metastases would result in a bottleneck, where lineage-specific mutations acquired by the metastasising subclone over time would be unmasked. Consistent with this, we found that metastatic tumours harbour more driver mutations, and more genomic alterations compared to primary tumours, as previously reported [3–5], [13], [32]. Additionally, primary tumours harboured more subclonal mutations relative to metastatic tumours, while metastatic harboured more clonal mutations (Figure 3A-B). While we found higher levels of driver mutations in metastatic tumours, the number of drivers per exonic mutation were more even between primary

and metastatic tumours. This is an indication that the majority of tumours does not require additional canonical driver mutations for metastatic transition and these are therefore not positively selected for. Taken together, the increased mutation burden and increased clonality in metastatic tumours overall supports a predominantly monoclonal dissemination pattern within individual metastatic samples, driven by a small number of specific cancer driver events which were selected for in the primary tumour.

While subclonal alterations were less common in metastatic tumours, we did observe subclonal alterations. In our work we calculated the mean CCF per gene per cancer type, and here we identified 33 genes with a mean CCF that deviated more than 2 standard deviations from the mean value of each cancer type. The most commonly subclonal gene found in metastatic tumours was *CYLD*, found in 6 different cancer types (BLCA, BRCA, COAD, LUNG, PRAD and SKCM). *CYLD* is a tumour suppressor gene involved in regulation of several proliferation-associated pathways, including NF- κ B, Wnt, Notch and TGF- β , potentially suggesting that metastatic tumour heterogeneity driven by further adaptation to increased proliferative phenotypes does occur, though less ubiquitous than the heterogeneity observed in primary tumours.

From the gene enrichment analysis, we found that *ESR1* was significantly enriched in metastatic relative to primary breast cancer. This result is almost certainly induced by treatment, as ER+ breast cancer patients as standard, are treated with adjuvant anti-hormone therapy. We also observed specific enrichment of two other known resistance mutations EGFR T790M and C797S in non-small cell lung cancer, again this is almost certainly induced by treatment with EGFR inhibitors[30]. Our findings demonstrate how treatment changes the evolutionary pressures on cancer, inducing selection for resistance-associated drivers and clonal bottlenecks in metastatic cancer. In primary cancer we found two enriched variants of *BRAF*, in melanoma and thyroid cancer, these are both variants that can be targeted by treatment[31] and therefore likely are selected against in development of metastatic cancer.

It is hypothesised that acquisition of the metastatic cancer phenotypes is a late-stage event, where cancer cells acquire the capacity for systemic colonisation of distant sites[10], potentially facilitated through late driver mutations affecting relevant pathways. To investigate this, we analysed the timing of pathway alterations in metastatic and primary cancer (Figure 4). We did not find any additional driver mutations in the known cancer genes. Neither did we find that metastasis is driven by a certain order of events. Rather, we found that the relative timing of driver events in known cancer pathways are very similar between primary and metastatic tumours. Indeed, so similar that when we plot the odds ratio of the pathways being significantly enriched in late or early driver mutations, in primary vs metastatic tumours, there is a significant correlation with a Pearson coefficient of 0.79. And in no cancer type is a late primary event significant in early metastasis, or vice versa (Figure 5B).

5. Conclusions

Taken together, our results support a model where cancer driver events required for metastatic dissemination likely occur relatively early in the life-history of cancer, consistent with the notion that certain tumours are born to be bad. However, given that a large fraction of patients remains curable by surgery alone despite harbouring tumours with aggressive cancer mutations, there may be other non-genomic factors that are often required for metastatic progression. These could include transcriptomic reprogramming, development of immune-evasion phenotypes through non-genomic mechanisms, or potentially cancer-induced degradation of the host immune response through interaction with the tumour immune microenvironment.

Supplementary Materials:

Figure S1. A) Number of mutations per patient in the TCGA cohort, sorted by ascending value. Chosen cut-off for hypermutated samples shown with a black horizontal line. B) Number of

mutations per patient in the HMF cohort, sorted by ascending value. Chosen cut-off for hypermutated samples shown with a black horizontal line.

Figure S2. A) A histogram showing the distribution of driver mutations per patient. B) A histogram showing the distribution of driver mutations per 100 exonic SNV per patient. C) A violin plot showing the distribution of Exonic SNVs per patient for each cohort in each cancer type. Arranged by ascending median. D) A plot showing the delta difference in mutations between primary and metastatic cancers for the 25 most differently mutated genes in each direction.

Figure S3. A) Scatterplot of the mean number of driver mutations per cancer type in primary vs metastatic cancer outside the 174 genes investigated in a previous paper. B) A volcano plot showing the enrichment of the driver genes outside the 174 genes. C) Scatterplot of the mean number of loosely defined driver mutations per cancer type in primary vs metastatic cancer outside the well-established cancer driver genes. D) A volcano plot showing the enrichment of the driver genes outside the well-established cancer driver genes. E) A plot showing the distribution of length of genes in the human genome and cancer driver genes. The genes enriched in primary lung cancer and metastatic breast cancer, are marked specifically to compare to the distribution

Figure S4. A bubble plot of the mean odds ratio for enrichment of early or late driver mutations in primary vs metastatic cancer. The size of the bubble shows the number of significant cancer types and the shape shows if the gene is significant in one or both cohorts.

Author Contributions: Conceptualization, J.A., D.S.C., N.J.B and N.M.; software, M.S; formal analysis, J.A.; data curation, J.A. and M.S.; writing—original draft preparation, J.A., D.S.C., N.M and N.J.B.; writing—review and editing, J.A., D.S.C. and N.J.B.; visualization, J.A, D.S.C., J.K.; supervision, N.J.B; funding acquisition, N.J.B. All authors have read and agreed to the published version of the manuscript.

Funding: NJB is a fellow of the Lundbeck Foundation (R272-2017-4040), and acknowledges funding from Aarhus University Research Foundation (AUFF-E-2018-7-14), and the Novo Nordisk Foundation (NNF21OC0071483).

The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Acknowledgments: The results shown here are in part based upon data generated by the TCGA Research Network: <https://www.cancer.gov/tcga>. This publication and the underlying research are partly facilitated by Hartwig Medical Foundation and the Center for Personalized Cancer Treatment (CPCT) which have generated, analysed and made available data for this research.

Conflicts of Interest: The authors declare no conflict of interest

References

1. Z. Hu, Z. Li, Z. Ma, and C. Curtis, "Multi-cancer analysis of clonality and the timing of systemic spread in paired primary tumors and metastases," *Nat. Genet.*, vol. 52, no. 7, pp. 701–708, Jul. 2020.
2. D. S. Christensen et al., "Treatment Represents a Key Driver of Metastatic Cancer Evolution," *Cancer Res.*, vol. 82, no. 16, pp. 2918–2927, Aug. 2022.
3. P. Priestley et al., "Pan-cancer whole-genome analyses of metastatic solid tumours," *Nature*, vol. 575, no. 7781, pp. 210–216, Nov. 2019.
4. D. R. Robinson et al., "Integrative clinical genomics of metastatic cancer," *Nature*, vol. 548, no. 7667, pp. 297–303, Aug. 2017.
5. B. Nguyen et al., "Genomic characterization of metastatic patterns from prospective clinical sequencing of 25,000 patients," *Cell*, vol. 185, no. 3, pp. 563–575.e11, Feb. 2022.
6. D. R. Welch and D. R. Hurst, "Defining the Hallmarks of Metastasis," *Cancer Res.*, vol. 79, no. 12, pp. 3011–3027, Jun. 2019.
7. J. Fares, M. Y. Fares, H. H. Khachfe, H. A. Salhab, and Y. Fares, "Molecular principles of metastasis: a hallmark of cancer revisited," *Signal Transduct Target Ther*, vol. 5, no. 1, p. 28, Mar. 2020.
8. D. Hanahan and R. A. Weinberg, "Hallmarks of cancer: the next generation," *Cell*, vol. 144, no. 5, pp. 646–674, Mar. 2011.
9. J. Massagué and A. C. Obenauf, "Metastatic colonization by circulating tumour cells," *Nature*, vol. 529, no. 7586, pp. 298–306, Jan. 2016.
10. A. W. Lambert, D. R. Pattabiraman, and R. A. Weinberg, "Emerging Biological Principles of Metastasis," *Cell*, vol. 168, no. 4, pp. 670–691, Feb. 2017.
11. M. R. Stratton, P. J. Campbell, and P. A. Futreal, "The cancer genome," *Nature*, vol. 458, no. 7239, pp. 719–724, Apr. 2009.
12. J. G. Reiter, I. Bozic, B. Allen, K. Chatterjee, and M. A. Nowak, "The effect of one additional driver mutation on tumor progression," *Evol. Appl.*, vol. 6, no. 1, pp. 34–45, Jan. 2013.

13. N. J. Birkbak and N. McGranahan, "Cancer Genome Evolutionary Trajectories in Metastasis," *Cancer Cell*, vol. 37, no. 1, pp. 8–19, Jan. 2020.
14. AACR Project GENIE Consortium, "AACR Project GENIE: Powering Precision Medicine through an International Consortium," *Cancer Discov.*, vol. 7, no. 8, pp. 818–831, Aug. 2017.
15. N. McGranahan, F. Favero, E. C. de Bruin, N. J. Birkbak, Z. Szallasi, and C. Swanton, "Clonal status of actionable driver events and the timing of mutational processes in cancer evolution," *Sci. Transl. Med.*, vol. 7, no. 283, p. 283ra54, Apr. 2015.
16. K. Wang, M. Li, and H. Hakonarson, "ANNOVAR: functional annotation of genetic variants from high-throughput sequencing data," *Nucleic Acids Res.*, vol. 38, no. 16, p. e164, Sep. 2010.
17. J. G. Tate et al., "COSMIC: the Catalogue Of Somatic Mutations In Cancer," *Nucleic Acids Res.*, vol. 47, no. D1, pp. D941–D947, Jan. 2019.
18. R. A. Burrell, N. McGranahan, J. Bartek, and C. Swanton, "The causes and consequences of genetic heterogeneity in cancer evolution," *Nature*, vol. 501, no. 7467, pp. 338–345, Sep. 2013.
19. F. Sanchez-Vega et al., "Oncogenic Signaling Pathways in The Cancer Genome Atlas," *Cell*, vol. 173, no. 2, pp. 321–337.e10, Apr. 2018.
20. R Core Team, "R: A Language and Environment for Statistical Computing." R Foundation for Statistical Computing, Vienna, Austria, 2020. [Online]. Available: <https://www.R-project.org/>
21. H. Wickham et al., "Welcome to the tidyverse," *J. Open Source Softw.*, vol. 4, no. 43, p. 1686, Nov. 2019.
22. A. Kassambara, "ggpubr: 'ggplot2' Based Publication Ready Plots." 2020. [Online]. Available: <https://rpkgs.datanovia.com/ggpubr/>
23. W. Hadley and D. Seidel, "scales: Scale functions for visualization." GitHub San Francisco, 2019. [Online]. Available: <https://CRAN.R-project.org/package=scales>
24. K. Slowikowski, "ggrepel: Automatically Position Non-Overlapping Text Labels with 'ggplot2'." 2021. [Online]. Available: <https://CRAN.R-project.org/package=ggrepel>
25. R. Elisei et al., "Prognostic significance of somatic RET oncogene mutations in sporadic medullary thyroid cancer: a 10-year follow-up study," *J. Clin. Endocrinol. Metab.*, vol. 93, no. 3, pp. 682–687, Mar. 2008.
26. S. Turajlic et al., "Deterministic Evolutionary Trajectories Influence Primary Tumor Growth: TRACERx Renal," *Cell*, vol. 173, no. 3, pp. 595–610.e11, Apr. 2018.
27. D. Hanahan, "Hallmarks of Cancer: New Dimensions," *Cancer Discov.*, vol. 12, no. 1, pp. 31–46, Jan. 2022.
28. T. B. K. Watkins et al., "Pervasive chromosomal instability and karyotype order in tumour evolution," *Nature*, vol. 587, no. 7832, pp. 126–132, Nov. 2020.
29. N. McGranahan and C. Swanton, "Clonal Heterogeneity and Tumor Evolution: Past, Present, and the Future," *Cell*, vol. 168, no. 4, pp. 613–628, Feb. 2017.
30. K.-S. H. Nguyen, S. Kobayashi, and D. B. Costa, "Acquired Resistance to Epidermal Growth Factor Receptor Tyrosine Kinase Inhibitors in Non-Small-Cell Lung Cancers Dependent on the Epidermal Growth Factor Receptor Pathway," *Clin. Lung Cancer*, vol. 10, no. 4, pp. 281–289, Jul. 2009.
31. P. A. Ascierto et al., "The role of BRAF V600 mutation in melanoma," *J. Transl. Med.*, vol. 10, p. 85, Jul. 2012.
32. L. De Mattos-Arruda et al., "The Genomic and Immune Landscapes of Lethal Metastatic Breast Cancer," *Cell Rep.*, vol. 27, no. 9, pp. 2690–2708.e10, May 2019.