Novel Microsatellite Detection, Microsatellite Based Biomarker Discovery in Lung Cancer and The Exome-Wide Effects of a Dysfunctional DNA Repair Mechanism

Karthik Raja Velmurugan

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Harold R. Garner, Co-chair David R. Bevan, Co-chair Christopher B. Lawrence Pawel Michalak

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ABSTRACT

Since the dawn of the genomics era, the genetics of numerous human disorders has been understood which has led to improvements in targeted therapeutics. However, the focus of most research has been primarily on protein coding genes, which account for only 2% of the entire genome, leaving much of the remaining genome relatively unstudied. In particular, repetitive sequences, called microsatellites (MST), which are tandem repeats of 1 to 6 bases, are known to be mutational hotspots and have been linked to diseases, such as Huntington disease and Fragile X syndrome. This work represents a significant effort towards closing this knowledge gap. Specifically, we developed a next generation sequencing based enrichment method along with the supporting computational pipeline for detecting novel MST sequences in the human genome. Using this global MST enrichment protocol, we have identified 790 novel sequences. Analysis of these novel sequences has identified previously unknown functional elements, demonstrating its potential for aiding in the completion of the euchromatic DNA.

We also developed a disease risk diagnostic using a novel target specific enrichment method that produces high resolution MST sequencing data that has the potential to validate, for the first time, the link between MST genotype variation and cancer. Combined with publically available exome datasets of non-small cell lung cancer and 1000 genomes project, the target specific MST enrichment method uncovered a

signature set of 21 MST loci that can differentiate between lung cancer and noncancer control samples with a sensitivity ratio of 0.93.

Finally, to understand the molecular causes of MST instability, we analyzed genomic variants and gene expression data for an autosomal recessive disorder, Fanconi anemia (FA). This first of its kind study quantified the heterogeneity of FA cells and demonstrated the possibility of utilizing the DNA crosslink repair dysfunctional FA cells as a suitable system to further study the causes of MST instability.

GENERAL AUDIENCE ABSTRACT

The field of genetics has enjoyed substantial growth since the conclusion of the human genome project, which was declared complete in the year 2003. The human genome project produced the first framework for the human DNA sequence, the human genome. With the availability of this framework, the understanding of the genetic basis for a number of diseases has significantly grown, which has resulted in better methods of clinical diagnosis and treatment. While the current focus on understanding the genomic regions that are responsible for making proteins has inarguably helped, it has also created a gap in knowledge. Protein coding regions of the human genome account only for 2% of the entire human genome and a large part (47%) of the genome is occupied by repetitive DNA. DNA sequences can be complex, with the nucleotides arranged in no particular order, e.g. ATCGTACGA, or DNA sequences can be repetitive, e.g. ATATATAT. Repetitive sequences, which have repeating units of 1 to 6 bases, are called microsatellites (MST). MSTs have been shown to be unstable and they have been linked to diseases such as Huntington disease and Fragile X syndrome. This work helps to close this knowledge gap by developing molecular methods and computational tools focused on identifying MST variations. Research conducted with this aim has resulted in three major accomplishments. One, we developed novel molecular and computational methods which we used to detect 790 previously unknown sequences in the human genome. This work proved the ability of our method to uncover functional elements in the human genome that can potentially answer numerous biological questions. Two, we developed another novel method for the production of high resolution MST sequence data that not only can improve MST research in general but also shows the potential for the development of new genetic diagnostics and cancer therapeutics. We identified a signature set of 21 MST sequences that can differentiate between lung cancer patient genomes and non-cancer control genomes. These results represent the first potential validation for a proposed link between MST sequence length (genotype) variation and cancer. Three, we attempt to understand a possible molecular cause and consequences of MST instability in a disease called Fanconi anemia. The results from this work not only, for the first time, quantify the effects of this disease on the genome but also establishes Fanconi anemia as a suitable system for studying MST instability in detail.

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I dedicate this work to the existence

that never asks to be acknowledged,

that does through non-doing,

that exists beyond the paradigms of space and time,

that with its infinite wisdom has found me,

that which empowers and contains me and becomes the end of all questions.

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Chapter 1: Introduction and overview

INTRODUCTION

The genome and repetitive DNA: The human genome project was declared complete in 2004¹. Since then, a total of 3981 eukaryotic organisms have been sequenced². The human genome is approximately 3 billion base pairs long³. Protein coding genes occupy about 2% of the human genome while introns occupy 24% (Figure 1-1). About 47% of the human genome is found to be repetitive sequences. Other organisms, compared to human, have a higher percentage of their genome occupied by repetitive DNA: Mus musculus (mouse) – 55%, Gallus gallus (chicken) – 88%, Drosophila melanogaster (fruit fly) – 71%, Anopheles gambiae (mosquito) – 85% and Caenorhabditis elegans – 80%⁴. It is evident that a large percentage of most genomes is composed of repetitive DNA. Repeats can be long transposable elements (DNA sequences that can alter their position in the genome) such as DNA transposons and retrotransposons or tandem repeats such as minisatellites and microsatellites.

Microsatellites and microsatellite instability: Microsatellites (MST) are short tandem repeats of 1 to 6 bases (Minisatellites contain repeats of greater than six bases). Repetitive DNA sequences are prone to slippage (replication slippage happens when the DNA polymerase erroneously adds more nucleotides than needed) and breaks (chromosomal translocations) during DNA replication by DNA polymerase. Hence MSTs are often mutational hot spots. The mutational rates at MSTs have been shown to be higher than what is found to occur in non-repetitive DNA⁵⁻⁸. Microsatellite mutations, or instability (MSI), caused by polymerase slippage has been shown to occur at a higher rate in MSTs made up of repeating monomers, dimers and trimers. The higher rate of variability at the shorter MSTs can be explained by the greater reduction in DNA complexity (equal and more

stochastic distribution of the 4 nucleotides), compared to the repeats with longer units ⁹⁻¹¹.

Challenges in MST research: There are two reasons MSTs have been poorly studied compared to non-repeating coding regions. The first reason is that the large majority of MSTs occur in non-coding regions, which until very recently were considered "junk" DNA. Consequently, most of the programs for mapping reads from next generation sequencing were tuned to study the exome. Popular programs like Bowtie and BWA mask repeat regions in the reference genome and map sequencing reads only to the non-repetitive parts of the genome 12,13. Thus, research projects that use such codes completely ignore this part of the genome and miss any relevant genetic or clinical contributions therein. The second reason is that a microsatellite-containing sequencing read needs to include both flanking regions of the repeated sequence to be correctly mapped. However, until recently the sequencing technology for reads of sufficient length was expensive and rarely used. Without a read of sufficient length, a repeat region can map to many different locations in the genome and hence a single read that contains nothing but MST will be mapped to multiple locations in the genome. Thus, the alleles or genotype of any microsatellite-containing locus with miss-mapped reads will not be called correctly. Hence, there is an urgent need to develop dedicated DNA enrichment techniques and the accompanying computational tools to further our understanding of the repeat regions of the genome.

MST genotyping: The accepted convention for MST genotyping from next generation sequencing reads is to calculate the number of reads that contain the entire MST along with at least 5 flanking bases on both sides. The allele with the highest number of reads is considered to be the primary allele. If an allele with a read depth

larger than the half of the read depth of the primary allele is present, it is considered as the secondary allele and that MST locus is assumed to be heterozygous. If no such secondary allele is found, then the MST locus is assumed to be homozygous. After having established the genotype of an MST locus, the procedure searches any other alleles that are found with at least 3 reads, and if found the allele is assumed to be a minor allele¹⁴. While genotyping variants in the non-repetitive parts of the genome are not heavily dependent on read depth, genotyping MST variation depends both on length of the read and the depth of coverage for a given locus. The accuracy of MST genotyping is generally less than 94% for a sample coverage (read depth) of $40X^{15}$. Due to the higher possibility of allele variation and insufficient read depth, comparing MST alleles in population size studies are generally distribution oriented; beginning with defining a modal (most frequent) genotype in the control population and then looking for a significant difference in the ratio of the modal and non-modal genotypes in the disease population ^{14,16,17}.

Recent advances in MST research: Figure 1-2 shows a few allele variations of a CAG trimer. Such variations in a CAG MST have been linked to Huntington's disease¹⁸. Figure 1-3 shows the expansion of one CAG motif to three, adding two extra glutamines to the HTT protein. Now that the association between MST allele variations and diseases is well established, efforts are being made to comprehensively examine MST regions of the genome. While typical genotyping methodologies have a less than 20% accuracy in identifying MSTs, newer computational techniques have been developed to increase the accuracy of the MST genotyping to 94% ^{15,19}. MST genotyping, since then, is becoming an important part of genomic variant detection¹⁹. Taking advantage of these newer MST genotyping methodologies, including our methodology described below, several studies have shown the connection between MSI and diseases. For example, a set of 55 MST loci

was found to distinguish normal and breast cancer germline exomes with a sensitivity of 0.88^{14} . Tumor grade specific signatures that can differentiate glioblastoma and lower-grade glioma were identified by comparing MST alleles from normal germline samples from the 1000 Genomes Project (1kGP) with two grades of gliomas and glioblastoma from The Cancer Genome Atlas^{20,21}. Forty-eight glioblastoma specific MST loci and 42 lower-grade glioma specific MST loci were identified, and 29 MST loci were identified that can differentiate between these two cancer types¹⁷. Further, a set of 60 MST loci that can differentiate normal germline samples and ovarian cancer germline samples were identified at a high sensitivity of 0.90^{16} . Recently, an extensive study was done to analyze 18 types of cancer using 5930 cancer exomes. Surprisingly, 14 of the 18 cancer types were identified as having MSIs²².

MSTs and mismatch repair: The process of copying DNA, replication, often adds the incorrect nucleotide and thereby introducing an error into the genome. As MSTs are particularly vulnerable to replication slippage, understanding the following topics in detail is critical: 1. Occurrence of mismatch between DNA strands, 2. the cellular mechanisms that are in place to correct an erroneous nucleotide introduction and 3. the effects of an uncorrected mismatch. While erroneous extensions in a MST monomer leads to MST allele variation, extensions in a trimer MST can also form loop structures that have been shown to cause diseases²³. When a mismatch is introduced by the polymerase, the proofreading mechanism that follows the polymerase enzyme attempts to correct the error. Two mismatch repair complexes exist to deal with mismatch²⁴. Depending on the length of the mismatch, one of two mismatch repair (MMR) mechanisms is activated. Analogs of MutS protein, that is found in prokaryotic systems, are the two MMR complexes. Short mismatches of 1-

2 bases are handled by the MSH2/MSH6 complex while longer insertions and deletions are dealt by the MSH2/MSH3 complex^{25,26}.

Since MSTs are prone to slippage and breaks, incorrect MMR result in MSI. Recently, it has been shown that nucleotide excision repair and the cross-link repair complex also can affect the instability of MST trimers²⁷⁻²⁹. One of the projects described below explores these mechanisms in further detail.

Fanconi Anemia: Fanconi anemia (FA) is a congenital autosomal recessive disorder found predominantly in Jewish populations^{30,31}. An autosomal recessive disorder is when the offspring inherits a mutated copy of the gene from both parents. FA cells have been found to be enriched with chromosomal aberrations that are caused by unrepaired DNA crosslinks³²⁻³⁴. Thirteen genes/proteins have been reported to form the core ingredients of the FA pathway involved in repair. They are also called complementation groups and they are identified as A, B, C, D1, D2, E, F, G, I. J. L, M and N³⁵⁻⁴⁵. DNA crosslinking agents such as mitomycin have been used to disrupt the cell division in cancer but the cell's response to inter-strand crosslinks has not been understood⁴⁶. The FA pathway is known to gather crosslink repair proteins but it is also suspected to be involved in general upkeep for genomic stability⁴⁷. Hence comprehensive understanding of the FA pathway and its full range of functionalities is important. Thus, exploiting this disease will give us important insights into mismatch repair. One of the projects below studies the role of microsatellite instability on FA.

Overview of the 3 projects, hypothesis and approach

1. Novel MST detection and the possibility of completing the human genome:

The human genome project was focused on the completion of the euchromatic portion of the genome and the first completed framework contained about 94% of the euchromatin^{3,48}. Earlier attempts have been made to complete the last 1% of the incomplete reference genome. One such recent effort found 309 missing sequences in the human reference genome and also confirmed about 76% of these sequences to be commonly present in primate genomes⁴⁹. Other researchers and we believe that the last 1% of the euchromatic DNA could be embedded in the repeat rich regions of the genome which are usually ignored during sequencing due to the technical reasons that were previously discussed⁵⁰. Equipped with the necessary experience and tools to deal with challenges of studying the repeat regions of genome, our hypothesis is that the last 1% of the euchromatin (possibly including protein coding genes and/or functional elements) could be found hidden in the usually ignored MST regions of the genome. To accomplish this, we developed a novel target enrichment system to specifically sequence repeat regions genome-wide, and developed the necessary computational tools to extract possible novel MSTs and functional elements embedded within repeat rich regions.

A previous attempt to complete the genome by Liu *et al.* was done entirely on the exome data acquired from the 1000 genomes projects (1kGP)⁴⁹. The exome data downloaded from the 1kGP are sequenced using baits (hybridizing sequence adapters that can pull down target sequences in a given sample) that are designed to capture the known exome regions and genomic regions that are found to flank these exomic sequences. It should be noted that these baits do not capture the repeat regions and by that have no access to pull down and enrich any possible functional

element/complex DNA that is embedded within the repeat rich regions of the genome. To overcome this hurdle, we generated, through computational means, a set of baits that will specifically hybridize to the repeat regions of the genome.

To overcome the inefficiency of mapping MST reads, we performed analysis only on the reads that were found to be unmapped to the reference genome. The computational pipeline specifically designed to extract possible novel MSTs and hidden functional elements utilizes the paired-end sequencing method and advances in sequence assembling algorithms to overcome the technical issues related to MST computation.

MST based biomarker discovery in non-small cell lung cancer: The relevance of the MST instability in diseases such as Huntington's disease is well established 18. A normal HTT gene (gene that codes for the huntingtin protein) contains 35 or fewer CAG repeats while a gene with 36 or more CAG repeats has been linked to the onset of Huntington's disease. An array of other neurological diseases, such as Fragile X syndrome, have been established as trinucleotide repeat disorders⁵¹. The Garner lab has worked on MST instability and its influence on cancer for two decades. The lab has provided comprehensive computational insight into the positive influence of MST allele variability and cancer occurrences 14,16,17. For example, McIver et al present a set of 55 MST markers that correlate positively with breast cancer and any patient with 76% or more of the 55 MST loci with the cancer genotype will be determined as cancer-like, or at enhanced risk of developing breast cancer. These research projects take full advantage of publically available genomic datasets such as The Cancer Genome Atlas (TCGA) and 1kGP. While utilizing publically downloaded datasets come with the challenge of low depth of coverage, appropriate statistical methods of using genotype distributions have been employed to counter this challenge¹⁴. These comprehensive computational projects have established statistical models that demonstrate the potential power of MST markers as risk, subtyping and companion diagnostics.

To validate this research, it is necessary to study the consistency of these findings with high depth sequencing. As mentioned earlier, research conducted through public datasets are usually limited by their depth of coverage. The ultra-high-depth genotyping of the MST markers will validate MST genotyping, thus confirming the value of MST biomarker research. For the purpose of this project we focused on non-small cell lung cancer⁵². We developed a target enrichment system to enrich a set of 300 disease related MST loci along with 90 control MST loci and sequenced 30 lung cancer samples and 90 1kGP samples. Recent studies show highly convincing results connecting MST instability with a large (14 out of 18) varieties of cancers²². This large-scale study, again, emphasizes the need of further validation of the influence of MSI on cancer.

About 85% of the lung cancer cases are non-small cell lung cancer⁵². The well-established fact that never smokers are susceptible to lung cancer too, makes genetic biomarker screening a priority⁵³. More importantly, recent studies show that 20% of people who get lung cancer are non-smokers⁵⁴. This not only emphasizes the need for a comprehensive understanding of genetic biomarkers in lung cancer but in all other cancer types. For this project, we also try to identify genetic biomarkers for prescreening those at risk of lung cancer (including never smokers) through the development of the target specific MST enrichment kit.

Exploring the molecular sources of MST instability: MST instability is primarily caused by slippage during replication^{27,28}. The proofreading mechanism that follows

the DNA polymerase-driven replication initiates one of two mismatch repair pathways depending on the length of the error that has been introduced by the polymerase enzyme²⁴⁻²⁶. It has been largely known that MST instability is caused by mismatch repair mechanism dysfunction, but recent studies show that nucleotide excision repair and inter-strand crosslink repair also contributes to MST instability^{28,29}.

The Garner lab has studied MSTs extensively: 1. Understanding Mendelian inheritance in MST, 2. Exploring MST genotyping from 1kGP samples, 3. Developing computational tools to improve accuracy of MST genotyping, 4. Developing diagnostic models and statistical methods to understand the influence of MST instability on breast, ovarian, brain and lung cancers ^{14-17,19,55}. This project builds on this work by exploring the mechanisms that cause MST instability.

While nucleotide excision repair and crosslink repair mechanisms have been shown to affect MST instability, this project will investigate the mechanism by which crosslink repair results in MSI. To understand inter-strand crosslink caused MSI, the Fanconi anemia system has been chosen. PD20 cells are a cell line that have a dysfunctional Fanconi anemia (FA) pathway gene called FANCD2. PD20 cells which are retrovirally corrected for FANCD2 expression have also been obtained to study and compare the effects of a functional and dysfunctional FA pathway and their corresponding effects of MST instability.

While a list of 16 genes have been linked to the dysfunction of the FA pathway, very little is known about the downstream effects of a FA pathway affected by the failure to repair inter-strand crosslinks. DNA lesions causing chromosomal translocations have been identified to occur in FA patients⁵⁶. This work aims to address the need

to explore in detail the effect of crosslink repair and its effect on MST instability and the urgent demand to quantify and understand the types and amount of genomic damage that is caused by a dysfunctional FA pathway.

Figure 1-1: Composition of the human genome. About 47% of human genome is composed of a variety of repetitive DNA of which microsatellites have known to significantly change DNA complexity and thereby are mutational hot spots.

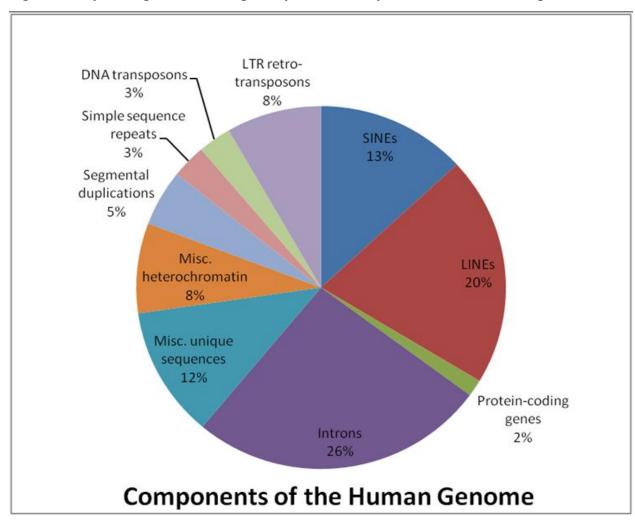
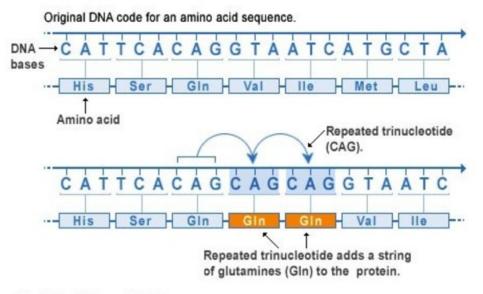


Figure 1-2: MST allele variation. This figure illustrates a few of the many possibilities of allele length variation of the MST shown as reference. It should be noted that without the flanking region, this CAG microsatellite can be placed in the genome in at least a thousand locations, making the identification of a single MST impossible. By considering the flanking regions, the genotyping programs identify a MST from the unmapped reads that are correctly mapped to the appropriate locus.

Reference:ATCTG-CAGCAGCAGCAGCAG-TGCTG	5 repeats
Alleles:ATCTG-CAGCAGCAGCAGCAG-TGCTGATCTG-CAGCAGCAGCAGCAGCAG-TGCTGATCTG-CAGCAGCAGCAG-TGCTGATCTG-CAGCAGCAGCAGCAGCAGCAG-TGCTG	5 repeats 6 repeats 4 repeats 7 repeats

Figure 1-3: CAG repeat expansion causes Huntington's disease. Huntington's disease is one of the diseases that is caused by a CAG repeat expansion. Huntington's disease is not caused when the MST contains 35 or fewer repeats while 36 or more has been shown to be strongly associated with the disease condition.

Repeat expansion mutation



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Chapter 2: Genomic leftovers: identifying novel microsatellites, over represented motifs and functional elements in the human genome
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ABSTRACT

The human genome is 99% complete. This study contributes to filling the 1% gap by enriching previously unknown repeat regions called microsatellites (MST). We devised a Global MST Enrichment (GME) kit to enrich and nextgen sequence 2 colorectal cell lines and 16 normal human samples to illustrate its utility in identifying contigs from reads that do not map to the genome reference. The analysis of these samples yielded 790 novel extra-referential concordant contigs that are observed in more than one sample. We searched for evidence of functional elements in the concordant contigs in two ways: (1) BLAST-ing each contig against normal RNA-Seq samples, (2) Checking for predicted functional elements using GlimmerHMM. Of the 790 concordant contigs, 37 had an exact match to at least one RNA-Seq read; 15 aligned to more than 100 RNA-Seq reads. Of the 249 concordant contigs predicted by GlimmerHMM to have functional elements, 6 had at least one exact RNA-Seq match. BLAST-ing these novel contigs against all publically available sequences confirmed that they were found in human and chimpanzee BAC and FOSMID clones sequenced as part of the original human genome project. These extra-referential contigs predominantly contained pentameric repeats, especially two motifs: AATGG and GTGGA.

INTRODUCTION

In April of 2003 the Human Genome Project was declared complete, and from it we gained a framework to build the reference genome upon which the majority of analyses are anchored. The scope of the Human Genome Project was focused on the 94% of the genome that is euchromatin¹, now sequenced to 99% completion². Attempts are being made to complete the 1% of the incomplete "complete" human reference³, however we and others have hypothesized that some genomic sequence regions (which may contain functional elements, genes) may be missing from the human reference because they are embedded in refractory repetitive DNA sequence, e.g. microsatellites (MSTs)⁴. MST sequences, regions of repeated 1- to 6-mer DNA motifs, are abundant throughout the genome and are a source of significant genomic variation⁵. However, to date, analysis of microsatellite-containing loci has been limited because standard exome enrichment and whole genome sequencing uses software to mask out repeats⁶, focuses on capturing non-repetitive DNA, or is designed to capture only a small subset of the known MST loci⁷. In this paper we present a novel target enrichment strategy specifically designed to enrich for all microsatellite loci based on the repeat motif, rather than the flanking sequence, as baits, and have paired this technique with our recently developed method for analysis of unmapped reads⁸. Our analysis has revealed: 1) assembly of contigs from unmapped genome sequences and high-depth sequences from this novel target enrichment system that specifically selects for repetitive elements enables the quantification and characterization of these regions; 2) concordant contigs, those that appear in multiple samples, contain new structural elements (potential genes/pseudogenes, etc.), a subset of which have high similarity to expressed mRNAs; 3) these extra-referential genome regions are dominated by 5-mer repeats, in particular, an AATGG and a GTGGA centromeric repeat. This platform technology has the potential to extend "reference genomes" and identify new functional elements.

METHODS

Standard exome enrichment sequencing is designed using a bait set that contains the sequence of the known high complexity exomic regions. However, portions of the human genome remain unknown and as such are not captured and evaluated by current enrichment technologies. In addition, whole genome sequencing, which can be used to sequence these additional unknown regions is limited in its ability to evaluate these regions because sequencing reads are aligned to the known reference genome, and they lack sufficient sequencing depth for reliable assembly. Although these methods (WGS and exome enrichment) are excellent for evaluating a large portion of the genome, they are not optimal for identifying and aligning novel genomic sequence (i.e. gap filling, finishing genomes containing highly repetitive regions). Similarly, only reads in RNA-Seq data that are aligned to known reference genes are quantified, thus, an incomplete reference genome also impacts expression studies. One potential reason that sections of the human genome remain unknown, or are not included in the reference, is that they contain highly repetitive DNA that makes it difficult to sequence and align properly. We have created a referenceindependent enrichment method that is designed to specifically enrich for repetitive DNA. This global microsatellite enrichment (GME) assay uses a bait design in which each 120 nt bait is composed of 4 x 30nt segments, selected to minimize the potential for intra-bait hairpin formation. Every possible 1-6 nt repetitive motif is represented within the bait set.

Design of global microsatellite enrichment (GME) bait set: We designed a custom bait set that target all 1- to 6-mer microsatellite motifs. Each120nt bait is broken into four 30nt regions, each of which targets a different motif sequence. We programmed and ran a custom PERL script to design the baits to maintain

approximately a 40% G/C content along the full length of the bait (across all four motifs on each bait). The custom script also evaluated the potential for hairpin formation of the baits and selected motifs for each bait to have a lower probability of internal hairpin formation. The baits were uploaded into Agilent's eArray.

Enrichment and Sequencing: Agilent exome enrichment, and our custom enrichment were performed according to the manufacturer's directions. For the combined GME + Exome enrichment, the bait sets were combined in house. All enrichments were sequenced using the 150bp Illumina HiSeq Rapid-Run.

Cell culture: DLD1 (ATCC® Number: CCL-221TM) and SW403 (ATCC® Number: CCL-230TM) human cell lines were purchased from ATCC (http://www.atcc.org Date of access: 01/06/2014). Cells were grown to confluence in DMEM + 10% FBS at 37C with 5% CO2 (DLD1) or Lebovitz media at 37C with no CO2 (SW403). Genomic DNA was isolated using Qiagen DNA Blood and Tissue kit according to the manufacturer's protocol. DNA for the 16 normal samples was purchased from Coriell.

Novel microsatellites prediction from unmapped reads: Sequenced reads of all samples were obtained in the form of fastq files. The sequenced reads were pairedend with a sequence length of 150 bases. The reads were quality checked and trimmed using Trimmomatic. The program uses sliding windows to check for the quality and a window of 10 bases was used. A quality score threshold of 20 was used; a 20 quality score means an error probability of 1 in 100 bases. The length threshold was set to 70 bases so any sequence read that is shorter than 70 bases after the quality trimming will be filtered out.

The BWA aligner was used to align the paired-end reads to the human reference genome, Hg19. A custom written python program was used to extract the unmapped reads from the sam files and output them in fasta format. The SAMTOOLS view and index programs were used to sort the sam files and convert sam file to bam format. The 'add-read-groups' program in the Picard software suite was used to add read groups to the bam files. The GATK program was used for indel realignment. The bam file that was indel realigned was then used to collect the unmapped reads in fasta format using a custom written PERL script for further processing.

The fasta file with unmapped reads was passed on to a shell program to check and remove recurring "N"s in the unmapped reads. Any read shorter than 50 bases after the removal of "N"s was discarded. The "N" filtered unmapped reads were used to form contigs using the Velvet program. The kmer length (hash length) used for the velveth program was 71. The choice of an odd number for hash length is a requirement of the program so as to avoid palindromes. The resultant contig file is then passed on to the Tandem Repeat Finder (TRF) program for microsatellites identification. Note that there are a total of 1811360 known microsatellite loci in the Hg19 reference genome as identified by TRF. The match weight, mismatch penalty, indel penalty, match probability, indel probability, minimum alignment score and period size used are 2, 7, 5, 80, 10, 14 and 6, respectively. The '-h' parameter was used to suppress HTML output. A custom written PERL program was used to extract the predicted microsatellite list from binary output provided by TRF. In order to check if there are known microsatellites in the list generated by TRF, the TRF identified microsatellites are BLASTed against known genomes. For this purpose, a PERL program was written to add flanking regions (30 bases on each side) to the microsatellite list by referring back to the contigs file generated by Velvet. The microsatellites with flanking sequences are then BLASTed using the blastn program against the blast formatted nucleotide sequence database and the human genome database downloaded from https://ncisf.org/software-databases/blast-databases (Date of access: 08/09/2014). An e-value of 0.001 was used for the blastn program. A PERL program was written to separate the microsatellites that were either found in the human or the nucleotide sequence database hence leaving only novel microsatellites.

Read number calculation: The read depth is calculated from the contig depth using the formula provided by Velvet. For a given contig the information about the contig provided the ID the Velvet is contig by program (e.g. NODE 35 length 226 cov 17.079645). Using this information the contig coverage can be converted into read depth: C=Ck*L/(L-k+1). C is the read depth, Ck is the contig coverage, L is the average read length, and K is the read kmer length used.

Identifying novel contigs/MSTs: Any assembled contig that has 100% identity match with a human or a NT database sequence for more than half the length of the query sequence, then the contig is considered known. The remaining contigs are considered novel. All TRF predicted MSTs in the novel contigs are considered to be novel MSTs.

Kmer calculation: The kmers are divided into six categories: 1-mer, 2-mer, 3-mer, 4-mer, 5-mer and 6-mer. The main input file to calculate kmer frequency information is the final output from the previous section that contains a predicted novel microsatellite list. The kmers were grouped into families. A kmer is added to a family if a) they are cyclically same or b) they are cyclical reverse complements. For example, if AACT is a family name, then TAAC, CTAA and ACTA belong to the

same family. According to reverse complementarity, AGTT, TAGT, TTAG and GTTA also belong to the AACT family. So an N-mer family has N*2 possible family members. All the read depths in a family are summed and hence each family has one kmer read depth value. To aid in the comparison of kmer families across samples, the name of the kmer families are kept similar. After grouping the cyclical kmers and cyclical reverse complements kmers, measures were taken to unify the family names across samples. The entire kmer calculation procedure was done using a series of custom python scripts.

Concordant contig calculation: The novel contigs from all the 16 + 6 samples were pooled together to find contigs that are observed in two or more samples, i.e. concordant. The pooled contigs were converted into a fasta file and was formatted into a BLAST database. All the individual contigs were then BLASTed against the database. Alignments that are more than 70% of the query length and aligned with 0 or 1 mismatch (to allow for potential individual variation) were considered for further analysis. A python script was written to generate two lists (with no mismatch and 1 mismatch) of concordant contigs that were found in more than one sample. The contigs in each concordant group were assembled into one contig sequence using the CAP3 program.

Evaluation of contigs for gene-like structure: All concordant contigs were fed into the GlimmerHMM program for Gene-Like Structure (GLS) prediction. The program was trained using the human training data provided with the GlimmerHMM package. The program can predict one or more exons in a given contig. The predicted exons in a GLS can be of three types; initial, internal and final. All the GLS with more than one exon were considered for further processing.

Comparison of putative cDNA to RNA-seq data: The start and end positions of the exons were obtained from the GlimmerHMM output to extract putative cDNA sequences. The cDNA sequences of all concordant contigs from all the samples were combined to make a single cDNA database. Ten lymphoblastoid RNA-Seq samples obtained of files were in the form **FASTQ** (http://www.ebi.ac.uk/arrayexpress/experiments/E-GEUV-1/samples/ Date ofaccess: 15/01/2015) and were BLAST searched against the cDNA database. A cDNA query sequence that aligned to an RNA-Seq read with an identity of 100% and with an alignment length longer than 70% of the query length was considered to be a highly similar match. The RNA-Seq reads evaluated in this study were on average 75 bases long. The results of the both the BLAST searches were combined and are provided in Extended Data Table 7. Analysis of the BLAST search output was done using custom written python scripts.

Similar to the paragraph above, the concordant contigs were searched against RNA-Seq sample reads. The results of this BLAST search are provided in Extended Data Table 5.

Whole genome analysis: The k-mer analysis graph presented in Figure 1 contains the k-mer distribution of all the 22 samples along with the human reference genome and a whole genome sample. The whole genome sample was added to compare the k-mer levels of the six samples with a sample where the entire genome is sequenced without enrichment bias and not just the exome.

A B-Lymphocyte whole genome DNA sequencing sample (HG00106) was downloaded from the 1000 genomes project for this purpose. The paired-end sequencing reads were downloaded in the form of a FASTQ file. The reads were N

filtered and mapped to the human reference genome (Hg19) using BWA. The unmapped reads were separated from the SAM file. The unmapped reads, in the form of a FASTA file, was used as the input for the TRF program to predict MST loci. The same parameters used for the other samples for TRF was used here too. A custom written PERL program was used to analyze a list of known MSTs and the TRF output data file to generate a list of predicted MST loci along with their read depths. This list of MST loci was used in the preparation of Figure 1.

RESULTS AND DISCUSSION

To verify the performance of our GME, we selected two colorectal cell lines: MST stable SW403 cells, and MST unstable DLD-1 cells^{9,10} (Extended Data Table 1). For each cell line, DNA isolated from cells grown as a single large cell culture was split and enriched using: (1) the Agilent exome enrichment kit; (2) our GME enrichment kit; or (3) an admixture of exome and our enrichment where the baits were combined prior to the enrichment. This enabled us to quantify the relative enrichment of repetitive regions for each enrichment system. Once enrichment performance was optimized and verified, we then sequenced 16 additional normal human DNA samples (Extended Data Table 1) from the 1000 Genomes Project using this enrichment system, and then processed the data to identify novel contigs that reproducibly appear in multiple samples. These concordant contigs were then analyzed for potential functional elements, as predicted by GlimmerHHM and supported by high similarity to RNA-Seq reads found in a variety of tissues. All enrichments, on average, had 99% of the high-quality reads map to the known human reference Hg19 (Table 1), consistent with what is expected given that 99% of the genome is "complete". A substantial fraction of the reads from our GME enrichment, as opposed to those reads from exome enrichment, fell outside the exome (Table 1, Exome Overlap %), consistent with our goal of global enrichment for genomic microsatellite loci. On average, 0.45% of the total reads were found to be unmapped in the GME and the combined samples while only 0.1% of the exome enrichment samples were unmapped (Table 1). This is, again, consistent with the GME system specifically targeting repetitive regions. The GME of the DLD-1 cell line and the SW403 cell line were both enriched for microsatellite loci, but in different manners. DLD-1-GME captured a greater fraction of the known MSTs (identified from the Hg19 reference genome using Tandem Repeat Finder (TRF)¹¹), whereas SW403GME captured fewer of the known MSTs (Table 1) but had greater depth for a greater fraction of the MSTs that were captured (Extended Data Fig. 1). That this was due to variation in hybridization temperature is supported by an increase in C/G nucleotide sequences captured in this sample (Extended Data Fig. 2). While the MST loci amounts in the colorectal samples varied, the additional normal samples processed at the optimum temperature produced consistent results. On average, 87% of the mapped reads in the normal samples contained MST loci. (Table 1)

Any reads containing novel DNA/MST sequences are by definition unmapped relative to the reference genome, therefore we analyzed the content of the unmapped reads using our unmapped read analysis pipeline (8 and methods). We built contigs from those reads that did not align to the reference (Table 2), and then re-aligned these contigs to the reference to further eliminate any contigs with known sequence from further analysis. Not only were a higher number of contigs built from the unmapped read analysis on the GME samples, but there were also a higher number of contigs containing MSTs (Table 2), as expected. We identified between 162 and 1469 novel contigs per enrichment, of which between 8% and 56% contained MSTs (Table 2). These MST-containing loci were found to be covered at a significant read depth. On average, 65% of MSTs found in novel contigs of the normal samples and the colorectal cell lines were supported by more than 10 reads (Extended Data Fig. 1 and 3). The analysis of all 20 independent GME samples (2 colorectal GME only, 2 colorectal GME combined with exome, and 16 normal) has yielded 790 concordant contigs (283 bp average length) that were observed in more than one sample (on average, each contig is seen in 5.6 samples, Extended Data Table 2). The concordant contigs were observed in as many as all 20 samples (Extended Data Table 3). This high reliability data (as confirmed in multiple samples) can reveal robust new MSTcontaining loci and high complexity sequence in unmapped regions. The distribution

of the lengths of all the concordant contigs and those that contain a MST (Extended Data Fig. 4) shows that more than 90% of concordant contigs are shorter than 500 nt. As nextgen raw read lengths grow, longer contigs in these repeat-containing regions could be assembled.

Extended Data Fig. 5 shows that the GME approach can capture MST-containing loci of varying length; as short as 10nt, but also longer than 150nt (i.e. as observed in assembled contigs). Given that 14% of the known MSTs identified in Hg19 using TRF are >50nt, our approach of enrichment plus contig building will, as raw read lengths grow, give access to longer MST loci.

To assess the potential value of these novel contigs, we searched the 790 concordant contigs for functional elements by aligning the contigs to 10 normal Lymphoblastoid RNA-Seq samples (Extended Data Table 4). We found that 37 concordant contigs aligned to at least one RNA-Seq read (Extended Data Table 5); and 22 of these 37 were supported by at least 10 RNA-Seq reads. BLASTing these 37 concordant contigs against the all known sequences in GenBank confirmed that the vast majority of these novel sequences (i.e. less than 50% identity to any portion of the known human reference) appear to be in human and chimpanzee subclones sequenced as part of the earliest human genome sequencing efforts, but not mapped to the current human genome reference, again confirming they are part of the missing human genome reference. This raises the possibility that sequences that had been relegated to the unaligned or pre-nextgen clone sequence trash heap may eventually be captured at a depth and with a reliability that allow them to be integrated into the reference. Table 3 illustrates the top 10 concordant contigs aligned to at least 235 RNA-Seg reads. Interestingly, the contig with the most hits to RNA-Seg reads was confirmed by BLASTing against GenBank to have 99% identity to abundant Ribosomal RNA sequences which may indicate a coding region for a new rRNA family member.

We also examined the 790 concordant contigs for the presence of gene-like structures (GLS) (e.g. putative exon, intron followed by another in-frame exon) using GlimmerHMM¹² (Table 2). We found that 249 concordant contigs contained potential GLSs (Table 2). The majority of the contigs with GLS had 2-3 exons with no contig identified as having over 8 exons (Extended Data Table 6). Extended Data Fig. 4 shows that there was no significant difference in average contig length for contigs containing a MST and/or GLS. We then generated putative cDNAs from the concordant contigs identified as having GLS and compared them to 10 RNA-Seq data sets discussed above. Six of these putative cDNAs matched to the RNA-Seq data with between 1 and 90 RNA-Seq reads aligned to each GLS (Extended Data Table 7), demonstrating that these novel contigs not only have potential GLS, but some were identified as low abundance mRNAs. It further indicates that many new potential coding regions that robustly align to RNA-Seq reads contain functional elements not recognized by GlimmerHHM.

Analysis of the microsatellite motifs represented in the unmapped reads containing novel MSTs revealed an over-abundance of reads containing pentameric repeats (Fig. 1). A comparison of the relative abundance of the MST-containing contigs to the expected "known" motif ratios present from the human reference (Hg19) identified with Tandem Repeat Finder (TRF) and those present in a whole genome sequenced sample from the 1000 genomes project shows that the abundance of pentameric MST loci repeats are >3.5 fold more abundant in the whole genome sample than expected from the known reference (Fig. 1). Pentameric MSTs were present in the exome enrichment at a similar abundance as in the whole genome

sequenced sample, however, in our GME the fraction of novel pentameric MSTs that were captured was an average of 9.2 fold greater than the fraction found in the known reference and 2.6 fold greater than the whole genome sequenced sample (a list of the top 5 most abundant motifs is given in Extended Data Table 8), consistent with these pentameric MSTs being localized extra-referentially.

Examination of the specific sequences of the MST containing loci revealed that the motifs AATGG and GTGGA were abundant in all samples, including the analysis of the whole genome sample, but not in the known human reference data (Extended Data Table 8). AATGG has been identified as a human centromeric ^{13,14} sequence motif and therefore the overabundance of this sequence in the data, but its absence from the human reference assembly, is consistent with it being a component of centromeric heterchromatin. The motif GTGGA differs from AATGG by one nucleotide, and based on its similarity to a known centromeric repeat and overabundance in the data also makes it a candidate centromeric repeat as well. The overabundance of reads that contain the AATGG sequence was unexpected, and an average of 53% of unmapped reads with MSTs contained the AATGG motif, whereas, reads were devoid of the often-studied telomeric repeat, GGGTTA.

CONCLUSION

Our GME provides the possibility for discovery of new/non-reference DNA sequence through the non-specific (i.e. not linked to a single reference locus) capture of repetitive DNA. Applying this target enrichment strategy broadly and pairing it with our algorithmic approach for identifying novel concordant contigs from unmapped reads can drive the human genome towards true completion; identify and annotate new potential functional elements therein; finish genomes containing even more repetitive sequence, such as plants; and be key to quantifying and comprehending the importance of telomeric and centromeric structure.

FIGURES

Figure 2-1: Frequency of MSTs motif classes in unmapped reads relative to those found in the reference genome (HG19) and the whole genome. The majority of novel microsatellite loci captured using our method contained pentameric repeats. For comparison, most loci found in the reference genome are not pentameric; and analysis of whole genome data confirms that much of the missing genome is associated with pentamer repeat regions.

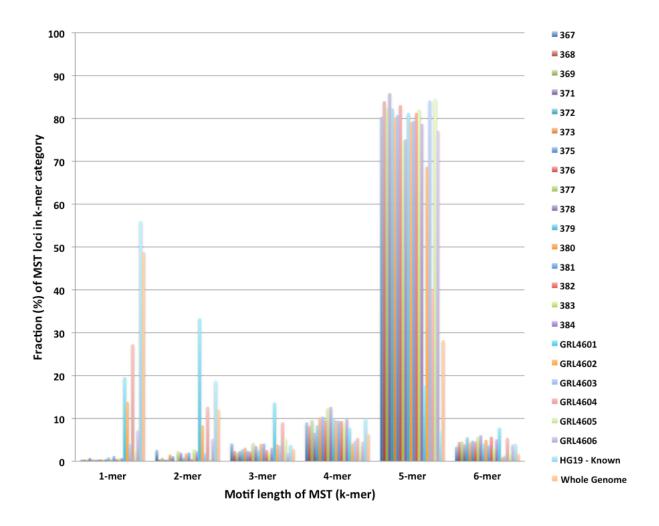


Table 2-1: Mapping of enrichment reads.

Sample & Enrichment	Total Reads	Mapped %	Exome Overlap %	Mapped with MST %	Known MST Loci called %	Unmapped %	Unmapped with MST%
DLD-1- Exome	107763705	99.9	53.7	7.3	44.4	0.1	1.6
DLD-1 - GME	99869840	99.6	2.9	15.7	61.7	0.4	2.8
DLD-1 - Comb	86571454	99.8	52.3	12.1	41.1	0.2	4.2
SW403 - Exome	99392535	99.9	57.3	6.8	41.2	0.1	1.8
SW403 - GME	93042396	99.1	2.3	67.4	11.7	0.9	3.8
SW403 - Comb	95846052	99.7	51.7	12.0	27.3	0.3	3.3
Normal-1-GME	107184846	99.2	1.8	86.7	33.3	0.8	1.1
Normal-2-GME	86039208	98.4	1.9	87.5	26.3	1.6	0.5
Normal-3-GME	77776824	98.1	1.9	88.6	23.3	1.9	0.4
Normal-4-GME	76888422	99.0	2.0	89.1	23.1	1.0	0.9
Normal-5-GME	88088498	97.6	2.1	87.1	26.1	2.4	0.5
Normal-6-GME	87529722	97.7	2.0	87.7	25.9	2.3	0.4
Normal-7-GME	85362982	98.8	2.0	86.5	26.7	1.2	0.7
Normal-8-GME	69912104	98.3	1.8	88.7	24.1	1.7	0.6
Normal-9-GME	89072202	99.1	1.8	83.5	36.8	0.9	0.7
Normal-10-	88599848	99.1	1.9	87.0	30.6	0.9	0.7
GME							
Normal-11-	67477542	99.1	1.9	87.1	27.0	0.9	1.1
GME							
Normal-12-	74895624	98.4	2.1	87.6	27.3	1.6	0.5
GME							
Normal-13- GME	102597820	98.3	2.0	89.1	29.3	1.7	0.5

Normal-14- GME	39497576	98.5	1.8	89.6	22.4	1.5	0.6
Normal-15-	97582298	99.3	1.8	88.1	29.3	0.7	1.3
GME Normal-16-	91613940	98.1	1.8	86.7	32.0	1.9	0.6
GME							

Table 2-2: Novel contigs and MSTs from unmapped reads.

Sample & Enrichment	Novel Contigs	% Contigs with MSTs	% Contigs with GLS	% Contigs with both MST and GLS	Total MSTs	% Novel MSTs
DLD1-Exome	224	8	16	2	48	35
DLD1-GME	1469	20	23	7	510	71
DLD1-Comb	515	36	25	9	297	79
SW403-Exome	162	19	16	3	55	62
SW403-GME	372	46	34	19	227	92
SW403-Comb	267	38	34	15	153	88
Normal-1-GME	312	52	34	20	265	78
Normal-2-GME	278	55	28	18	244	82
Normal-3-GME	261	54	30	17	239	74
Normal-4-GME	289	53	30	17	255	75
Normal-5-GME	257	54	34	18	249	70
Normal-6-GME	316	50	33	17	253	79
Normal-7-GME	275	52	36	20	250	71
Normal-8-GME	255	56	31	18	219	82
Normal-9-GME	245	52	36	18	210	74
Normal-10-GME	221	54	31	17	197	75
Normal-11-GME	248	52	33	20	219	79
Normal-12-GME	265	51	38	21	221	76
Normal-13-GME	308	51	32	18	243	79
Normal-14-GME	198	52	29	16	192	68
Normal-15-GME	351	52	34	19	279	81
Normal-16-GME	307	51	28	16	254	79

Total	7395	42	29	14	5079	77
Concordant	790	42	32	16	533	100

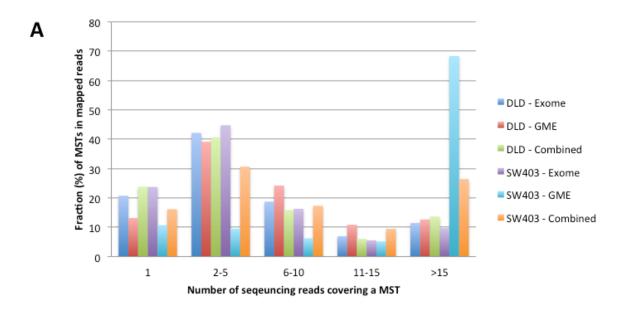
Table 2-3: Alignment analysis of concordant contigs with normal lymphoblastoid RNA-Seq samples. The top 10 out of 37 concordant contigs that had RNA-Seq hits are presented in this table. HS: Homo sapiens; PT: Pantroglodytes; Chr: chromosome.

				RN	NA-Seq	samples	3				Total	Contig	
#	1	2	3	4	5	6	7	8	9	10	aligned reads	length	BLAST hit
1	9441	17648	208	31	6957	1506 4	7134	2005	12173	7	70668	370	HS clone. Chr21
2	24	76	77	7	26	33	19	63	32	11	368	615	HS FOSMID clone. Chr7
3	24	67	75	7	21	33	20	61	32	11	351	628	HS FOSMID clone. Chr7
4	24	69	75	7	21	33	19	60	32	11	351	624	HS FOSMID clone. Chr7
5	55	38	28	11	4	48	0	48	46	26	304	531	HS FOSMID clone. Chr17
6	25	67	43	4	23	23	16	52	29	14	296	310	PT BAC clone. Chr7
7	18	25	38	5	57	36	35	7	30	24	275	303	HS BAC clone. Chr17
8	22	66	42	4	19	18	13	52	22	13	271	314	PT BAC clone. Chr7
9	21	66	41	4	16	18	13	51	21	13	264	323	PT BAC clone. Chr7
10	19	61	39	4	18	12	11	44	16	11	235	289	PT BAC clone. Chr7

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Figure S2-1: Read coverage analysis for MST motifs. For every sample >15% of known microsatellite loci (MSTs in mapped reads) (A) and >50% of novel microsatellite loci (MSTs in novel contigs) (B) were covered by more than 10 sequencing reads.



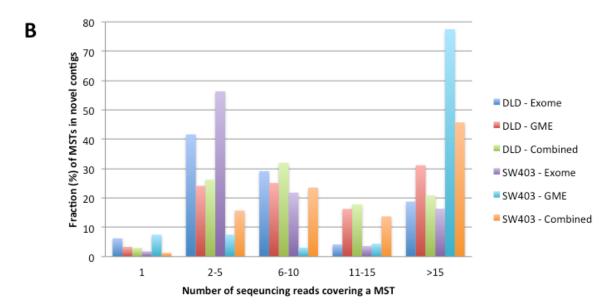


Figure S2-2: Homopolymer Nucleotide Distribution. As our GME captures repetitive motifs based on 30nt repetitive regions, it was possible that C/G nucleotides were captured in higher abundance than with standard exome capture. We found that the SW403-GME sample, but not the DLD1-GME enriched sample was enriched for C/G nucleotides. This difference in capture between the two GME samples may be due to slight differences in hybridization temperatures used while optimizing the capture process, and may indicate a use for this technology in specifically capturing C/G nucleotide regions in the future.

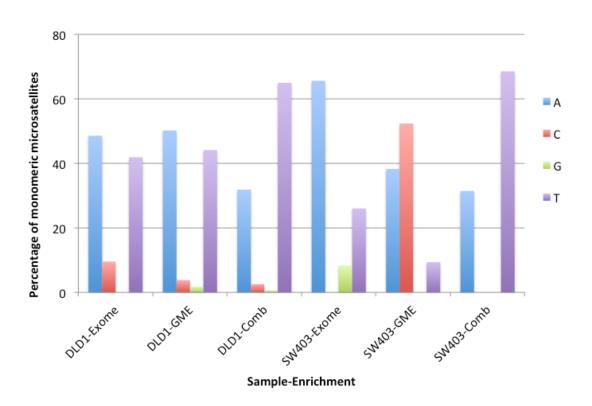


Figure S2-3: Read coverage analysis of MST motifs in normal human samples.

(A) In every individual sample more than 30% of the MSTs are covered by more than 15 reads while an equal percentage are covered by 2 to 5 reads. (B) Approximately 60% of MSTs found in the novel contigs are covered by more than 15 reads.

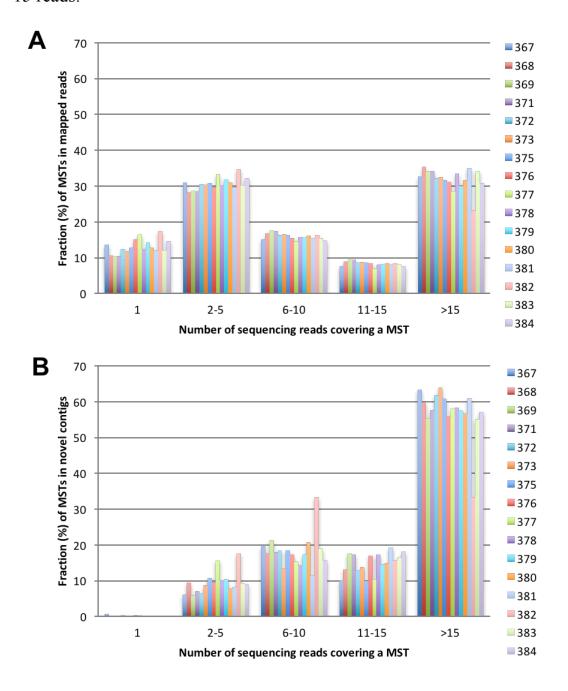


Figure S2-4: Concordant contig length distribution. This histogram shows how the concordant contigs with and without MSTs and GLS are distributed according to their lengths. Each category of contigs represents the combined information of all the samples (i.e. 16 GME sequenced normal samples, 3 DLD1 samples and 3 SW403 samples). It should be noted that except for the "less than 250 bases" bin, all other contigs contain two or more reads.

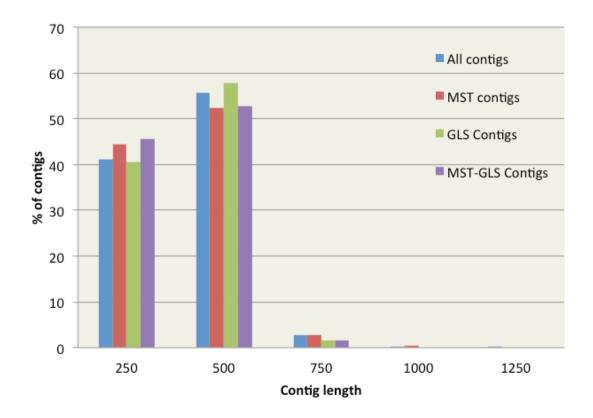
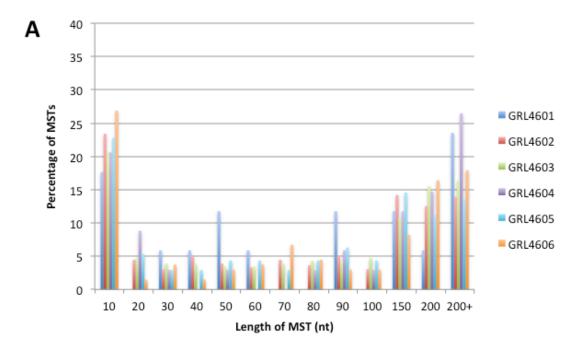


Figure S2-5: Length distribution of novel microsatellites. The following histograms show the MSTs according to their length in the colorectal cell lines (A) and in the normal samples (B).



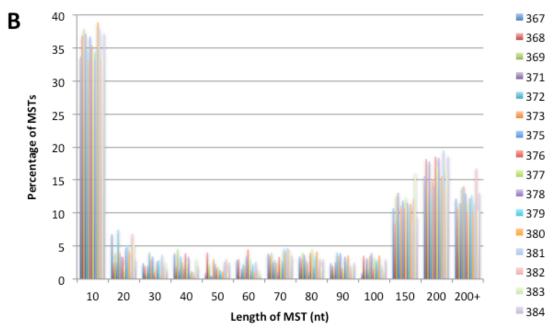


Table S2-1: Details of the samples on which GME was performed.

Sample #	Sample	Sample Type	Sample Source
1	DLD1-Exome	Colorectal	ATCC CCL-221
2	DLD1-GME	Colorectal	ATCC CCL-221
3	DLD1-Comb	Colorectal	ATCC CCL-221
4	SW403-Exome	Colorectal	ATCC CCL-230
5	SW403-GME	Colorectal	ATCC CCL-230
6	SW403-Comb	Colorectal	ATCC CCL-230
7	Normal-1-GME	Lymphoblastoid	Coriell HG00384
8	Normal-2-GME	Lymphoblastoid	Coriell HG00383
9	Normal-3-GME	Lymphoblastoid	Coriell HG00382
10	Normal-4-GME	Lymphoblastoid	Coriell HG00381
11	Normal-5-GME	Lymphoblastoid	Coriell HG00380
12	Normal-6-GME	Lymphoblastoid	Coriell HG00379
13	Normal-7-GME	Lymphoblastoid	Coriell HG00378
14	Normal-8-GME	Lymphoblastoid	Coriell HG00377
15	Normal-9-GME	Lymphoblastoid	Coriell HG00376
16	Normal-10-GME	Lymphoblastoid	Coriell HG00375
17	Normal-11-GME	Lymphoblastoid	Coriell HG00373
18	Normal-12-GME	Lymphoblastoid	Coriell HG00372
19	Normal-13-GME	Lymphoblastoid	Coriell HG00371
20	Normal-14-GME	Lymphoblastoid	Coriell HG00369
21	Normal-15-GME	Lymphoblastoid	Coriell HG00368
22	Normal-16-GME	Lymphoblastoid	Coriell HG00367

Table S2-2: The statistics of the concordant contigs are furnished in the below table. The data is divided according to the number of mismatches allowed for the concordant contig calculation to illustrate that if some mismatch is allowed (due to possible variations among individuals) the additional contigs may be further assembled. However, for further analysis, only those concordant contigs assembled using the strict 0 mismatch value were used.

Statistics	Mism	natch
Statistics	0	1
Total concordant contigs (observed in at least 2 samples)	790	747
Total sample contigs found concordant	4419	4915
Maximum # of sample contigs assembled into a concordant contig	25	29
Minimum # of sample contigs assembled into a concordant contig	2	2
Average # of samples a concordant contig was found	5.6	6.6

Table S2-3: Concordant contig sample distribution. Novel contigs that were present in multiple samples are considered to be concordant. The table groups the concordant contigs according to the number of samples in which they were found. The data is divided by mismatch 0 and mismatch 1 (Number of mismatches allowed while generating the concordant contigs).

# of	Concorda	nt contigs
samples	0mismatch	1mismatch
2	243	188
3	125	99
4	85	80
5	59	48
6	36	50
7	44	38
8	29	30
9	31	28
10	20	24
11	26	30
12	14	21
13	18	29
14	13	17
15	9	13
16	8	11
17	8	9
18	15	18
19	7	11
20	0	2

Table S2-4: Details about the RNA-Seq samples that were used to confirm that the concordant contigs contain potential functional elements.

Sample #	SampleID	Sample Type	Sample Source
1	ERR188040	Lymphoblastoid	ArrayExpress - EBI
2	ERR188231	Lymphoblastoid	ArrayExpress - EBI
3	ERR188043	Lymphoblastoid	ArrayExpress - EBI
4	ERR188280	Lymphoblastoid	ArrayExpress - EBI
5	ERR188325	Lymphoblastoid	ArrayExpress - EBI
6	ERR188327	Lymphoblastoid	ArrayExpress - EBI
7	ERR188373	Lymphoblastoid	ArrayExpress - EBI
8	ERR188313	Lymphoblastoid	ArrayExpress - EBI
9	ERR188382	Lymphoblastoid	ArrayExpress - EBI
10	ERR188359	Lymphoblastoid	ArrayExpress - EBI

Table S2-5: Thirty-seven concordant contigs aligned to at least one RNA-Seq read. As indicated in methods, a RNA-Seq hit must align with 0 mismatches to at least 70% of the length of the contig.

				F	RNA-Se	eq samp	les				Total	Contig	
#	1	2	3	4	5	6	7	8	9	10	aligned reads	length	BLAST hit
1	9441	17648	208	31	6957	15064	7134	2005	12173	7	70668	370	HS clone. Chr21
2	24	76	77	7	26	33	19	63	32	11	368	615	HS FOSMID
3	24	67	75	7	21	33	20	61	32	11	351	628	clone. Chr7 HS FOSMID
4	24	69	75	7	21	33	19	60	32	11	351	624	clone. Chr7 HS FOSMID
5	55	38	28	11	4	48	0	48	46	26	304	531	clone. Chr7 HS FOSMID
6	25	67	43	4	23	23	16	52	29	14	296	310	clone. Chr17 PT BAC clone.
7	18	25	38	5	57	36	35	7	30	24	275	303	Chr7 HS BAC clone.
8	22	66	42	4	19	18	13	52	22	13	271	314	Chr17 PT BAC clone.
9	21	66	41	4	16	18	13	51	21	13	264	323	Chr7 PT BAC clone.
10	19	61	39	4	18	12	11	44	16	11	235	289	Chr7 PT BAC clone.
11	21	61	37	4	18	11	9	43	15	11	230	294	Chr7 PT
11	21	61	37	4	18	11	9	43	15	11	230	294	PT uncharacteri

12	14	54	38	2	13	13	8	37	14	11	204	274	PT
													uncharacterized
13	5	11	37	2	67	4	3	7	0	2	138	327	HS clone.
14	11	18	2	0	66	13	3	12	10	0	135	242	HS rRNA gene
15	13	15	8	1	13	11	0	27	18	9	115	387	HS clone.
													Chr17
16	11	18	13	0	9	7	6	12	11	8	95	466	HS clone.
													Chr21
17	5	8	8	0	28	0	2	9	3	9	72	363	HS FOSMID.
18	7	13	13	0	22	6	1	3	1	5	71	285	PT BAC clone.
													ChrY
19	1	3	9	2	14	0	0	2	0	1	32	437	PA BAC clone.
													Chr16
20	3	11	4	0	2	0	0	6	2	1	29	324	HS clone.
													Chr21
21	0	2	0	6	0	0	2	8	3	0	21	1016	BB genome
													scaffold
22	1	5	1	4	0	0	0	1	0	3	15	512	No hits
23	0	0	1	0	1	1	0	3	0	3	9	370	HS clone.
													Chr21
24	1	2	0	2	0	0	0	0	2	0	7	368	HS FOSMID
													clone. Chr11
25	0	0	1	0	1	0	0	2	0	2	6	372	HS clone.
													Chr21
26	1	0	2	0	0	0	0	2	0	0	5	423	HS BAC clone.
27	1	1	0	0	3	0	0	0	0	0	5	495	HS clone. Chr9
28	0	0	0	0	3	2	0	0	0	0	5	346	HS clone.
													Chr21

29	0	0	0	0	0	0	0	3	0	0	3	381	PT BAC clone. Chr7
30	1	0	0	0	1	0	0	0	0	0	2	259	OF genome
													scaffold
31	0	0	0	0	0	0	0	0	0	1	1	449	PT BAC clone.
													ChrY
32	0	0	0	0	0	0	0	1	0	0	1	314	HS FOSMID
													clone. Chr7
33	0	0	1	0	0	0	0	0	0	0	1	232	No hits
34	0	0	1	0	0	0	0	0	0	0	1	364	No hits
35	0	1	0	0	0	0	0	0	0	0	1	277	HS contig.
36	0	1	0	0	0	0	0	0	0	0	1	283	HS clone.
													ChrX
37	0	0	0	0	0	0	0	0	1	0	1	295	HS clone.
													Chr17

HS: Homo sapiens; PT: Pan troglodytes; BB: Babesia bigemina; OF: Onchocerca flexuosa; Chr: Chromosome.

Table S2-6: Distribution of predicted exon number within the concordant contigs predicted by GlimmerHMM to have Gene-Like Structures (GLS).

#Exons	#GLS
2	73
3	105
4	44
5	24
6	2
8	1
Total	249

Table S2-7: Six putative cDNAs found in the concordant contigs had at least one read hit in the RNA-Seq samples.

#	Aligned RNA-Seq reads	Contig length	cDNA length	BLAST hit	
1	90	314	219	PT BAC clone. Chr7	
2	10	323	108	PT BAC clone. Chr7	
3	5	495	384	HS clone. Chr9	
4	1	370	159	HS clone. Chr21	
5	1	259	138	OF genome scaffold	
6	1	368	159	HS FOSMID clone. Chr11	

PT: Pan troglodytes; HS: Homo sapiens; OF: Onchocerca flexuosa; Chr: Chromosome.

Table S2-8: Top five pentameric and hexameric motif families. The top five pentameric and hexameric motif families are shown for the DLD-1 and SW404 samples, a representative split (50,000 unmapped reads) from a whole genome sequenced sample and the known human reference hg19 where MSTs were identified using Tandem Repeat Finder (Hg19-TRF). The telomeric repeat is underlined.

	DLD-1 Exome		DLD-1 GME			DLD-1 Combined			
	Motif	Loci	Percent	Motif	Loci	Percent	Motif	Loci	Percent
Pentamer	AATGG	2	22	AATGG	20	20	GTGGA	118	47.2
	ATATA	2	22	GTGGA	20	20	AATGG	116	46.4
	AGGGG	2	22	ATATA	6	6	GAATT	1	0.4
	GGGAT	1	11	GGGGC	4	4	GGATT	1	0.4
	TTTTC	1	11	GCCCT	4	4	GGGAT	1	0.4
Hexamer	TCCTCT	1	25	CATCAC	4	40	ccccgg	1	25
	GGGGGA	1	25	CCCTCA	2	20	AGGTCC	1	25
	CAGCAA	1	25	GGCCCA	2	20	CCTGGC	1	25
	CCTGGC	1	25	ATAAAA	2	20	CCCTCA	1	25
	SW404 Exome			SW403 GME			SW403 Combined		
	Motif	Loci	Percent	Motif	Loci	Percent	Motif	Loci	Percent
	GTGGA	8	36.4	AATGG	107	55.7	AATGG	57	48.3
πe	AATGG	5	22.7	GTGGA	64	33.3	GTGGA	55	46.6
Pentamer	ATATA	2	9.1	CCCAC	11	5.7	CCCAC	2	1.7
	CAAAA	1	4.5	ATTCG	2	1	GGATT	1	0.8
	AGGGG	1	4.5	CCTTC	1	0.5	ATTTT	1	0.8
Hexamer	TCCTCT	1	33.3	CAGCAA	1	20	CTGGGG	1	16.7
	GGCCCA	1	33.3	CAACGA	1	20	TCCTCT	1	16.7
Xa	CCTGGC	1	33.3	CTGGGG	1	20	ccccgg	1	16.7
Ĭ				AAAATG	1	20	AGGGTC	1	16.7
				CCCTCA	1	20	AAAATG	1	16.7
	H	HG19 TRI	•	WI	nole Genoi	ne			
	Motif	Loci	Percent		Loci	Percent			
Pentamer	CAAAA	51763		AATGG	2192279	82.1			
	ATTTT	39451	21.3	CAAAA	159237	6			
	TTTTC	26684		ATTTT	89791	3.4			
	ATTAA	6162	3.3	TTTTC	52059	2			
_	CTTTC	4678	2.5	GTGGA	50117	1.9			
Jer	ACAAAA	20644	17	ACAAAA	41995	25.9			
	TCTTTT	16995	14	ATAAAA	21847	13.5			
	ATAAAA	16293	13.4	GGGTTA	14626	9			
	GTATAT	4297	3.5	TCTTTT	13237	8.2			
	CATACA	3557	2.9	TGTCTC	4982	3.1			

Chapter 3: High-depth, high-accuracy microsatellite genotyping enables precision lung cancer risk classification

ABSTRACT

There remains a large discrepancy between the known genetic contributions to cancer and that which can be explained by genomic variants, both inherited and somatic. Recently, understudied repetitive DNA regions called microsatellites have been identified as genetic risk markers for a number of diseases including various cancers (breast, ovarian and brain). In this study we demonstrate an integrated process for identifying and validating microsatellite based risk markers for lung cancer using data from the cancer genome atlas (TCGA) and the 1000 genomes project. Comparing whole exome germline sequencing data from 488 TCGA lung cancer samples to germline exome data from 390 control samples from the 1000 genomes project, we identified 119 potentially informative microsatellite loci. These loci (risk markers) were found to be able to distinguish between cancer and control samples with sensitivity and specificity ratios over 0.8. Then these loci, supplemented with additional loci from other cancers and controls, were evaluated using a custom target enrichment kit and sample-multiplexed nextgen sequencing. Thirteen of the 119 risk markers were validated using high-depth (579x±315) nextgen sequencing of 30 lung cancer and 89 control samples, resulting in sensitivity and specificity ratios were 0.90 and 0.94, respectively. When 8 loci harvested from the bioinformatic analysis of other cancers are added to the classifier, then the sensitivity and specificity rise to 0.93 and 0.97, respectively. Analysis of the genes harboring these loci revealed two genes (ARID1B and REL) and two significantly enriched pathways (chromatin organization and cellular response to stress) which suggest that the process of lung carcinogenesis is linked to chromatin remodeling, inflammation, and tumor microenvironment restructuring. We illustrate that highdepth nextgen sequencing enables a high-precision microsatellite-based risk classifier analysis approach. This microsatellite-based platform approach confirms the potential to create clinically actionable diagnostics for lung cancer.

INTRODUCTION

Lung cancer has a high rate of incidence with 224,000 new cases projected this year alone: more than the next four cancers (colorectal, pancreatic, breast, and prostate) combined. Only 18% of those diagnosed with lung cancer will survive 5 years^{1, 2}; however, early detection can dramatically improve outcomes. About 80% to 85% of lung cancers are found to be non-small cell lung cancer ³. If found early the 5 year survival rate of non small cell lung cancer improves significantly: stage IA – 49%, stage IB – 54%, stage IIA – 30%, stage IIB – 31%, stage IIIA – 14%, stage IIIB – 5% and stage IV – 1%⁴. The differing stage dependent survival rate and varying provenance of new lung cancers underscores the value of developing a lung cancer genetic risk diagnostic – especially for screening of "at risk" populations (family members with lung cancer, second hand exposure to smoke or other hazards) which could be tested, with subsequent adjustments made to clinical observation or lifestyle. Interestingly, as the smoking rate has dropped in the US, it has been observed that ~20% of lung cancer deaths are from never smokers, attributable to other environmental exposures and genetic mutations^{5, 6}.

Studies of disease specific variation have largely neglected repetitive DNA in favor of Single Nucleotide Variants (SNVs). However, an abundance of neurological disorders have been linked to length specific variations in repetitive DNA microsatellites (MST)⁷. These microsatellites consist of short (1-6bp) units repeated in tandem. Recent studies have shown that microsatellites contribute to the genetic complexity of various cancers⁸⁻¹⁰. Based on these previous findings it is hypothesized that microsatellites may play a role in the genetics of lung cancer¹¹.

Our recent population-scale studies of MST loci and their repeat length variations have shown that MSTs can stratify risk, provide clinical decision support, and be potential therapeutic targets^{8-10, 12-14}. These observations were made possible by building robust computational pipelines to accurately genotype MST loci based repeat length variation^{8-10, 12}. Our previous work in computationally discovering clinically informative MST loci from publically available data sets (The Cancer Genome Atlas of affected individuals, the 1000 Genomes Project of healthy "normal" individuals) have yielded disease specific MST loci variations for breast cancer, ovarian cancer, glioblastoma, and lower-grade glioma^{8-10, 12}. We have also shown somatic MST variability (SMV) and the presence of minor alleles can act as indicative disease markers for colorectal and liver cancer¹⁵. Furthermore, microsatellite variations are somatically acquired in normal tissues as one ages at rates higher than SNVs and that they are a sensitive measure of toxic environmental exposures^{16, 17}.

The goal of this manuscript is to discover and validate a set of microsatellite markers for lung cancer risk via comparison of patient germline and normal control germline exome sequences. Validation utilizes a custom target enrichment kit for high depth next-gen targeted sequencing. The focused, ultra-high read depth multiplexed sequencing approach used here enables accurate economical genotyping, validation and final selection of informative loci to ultimately create a high sensitivity and specificity risk classifier assay.

METHODS

Computational identification of LUAD and LUSC specific MST loci

A total of 266 LUAD and 222 LUSC germline exome samples were downloaded from TCGA. For the non-tumor control population, 390 germline exome samples were downloaded from the 1kGP. A set of 1.8 million MST loci, that were extracted from the human genome (38 build) using the tandem repeat finder, were genotyped in these samples. A modal genotype was computed for each MST locus using the 1kGP samples. A 2 X 2 Fisher's exact test was computed for each locus comparing the modal and non-modal genotype distributions in these two samples groups¹⁰. A Benjamini-Hochberg cut-off of 0.01% was used as a false discovery rate cut-off. A binary classifier was generated using ROCR library in R for the two MST loci lists to determine their potential to differentiate their corresponding lung cancer subtype from the normal control samples^{42, 43}.

Assembling informative MST loci set to target enrich and validate

A set of 347 loci was assembled into the Illumina TruSeq Amplicon V1.5 kit target enrichment kit (Supplemental table 1). Of the 347, 119 were found to be specific for lung cancer, 144 were found in similar manner by analyzing other cancer datasets (Supplemental table 2) and 84 were included as controls (Supplemental tables 6, 7 and 8).

Genomic DNA library prep and sequencing

Thirty lung cancer samples and 89 B-Lymphocyte non-tumor samples were obtained from Origene and Coriell cell repositories. The cells were cultured following the suppliers' recommended conditions (Supplemental tables 3 and 4). Isolation of genomic DNA was done using the Qiagen DNA Blood and Tissue kit following the manufacturer's protocol.

Target sequencing, SMTEK

The assembled set of 347 MST loci was uploaded to Illumina's Design Studio tool, obtained in the form of a target enrichment kit and was used to target enrich and sequence the 30 lung cancer samples and 89 control samples.

Genotyping of target enriched samples

The 347 MST loci were genotyped in the target enriched samples using custom written scripts, after performing quality control steps using the Trimmomatic tool to ensure only high quality reads are used in genotyping⁴⁴. For each loci, a modal genotype and a predominant cancer genotype was computed. A modal genotype is the genotype that is found in more than 50% of the control samples and the predominant cancer genotype is the genotype that is found in more than 50% of the lung cancer samples. Any locus that has differing modal genotype and predominant cancer genotype was considered as a risk classifier (Supplemental table 5).

Statistical procedure to assess differentiating power of the validated risk markers

Of the 119 computationally found lung cancer specific MST loci, 13 were found to differentiate lung cancer and normal control validation samples. A binary classifier was generated using the ROCR library in R using the 13 MST loci to assess their statistical capacity to call lung cancer samples from normal control samples. The sensitivity, specificity and other ROC related calculations were computed using the ROCR library in R. Odds ratio was calculated using the formula: (TP/FP)/(FN/TN), where TP, FP, FN and TN are true positive, false positive, false negative and true negative, respectively⁴⁵. A set of 8 MST loci that were computationally found to be specific for other cancers were also found to differentiate the lung cancer samples from the normal control samples. This set was added to the 13 MST loci to form a

21 MST set. A similar statistical assessment was performed with this loci set. A leave one out cross validation was performed to quantify the consistency of the predictive power of the 21 loci classifier.

Mechanistic analysis

Genes for each marker were identified from the UCSC genome browser referencing HG38. Functional enrichment analysis of genes harboring microsatellite markers and gene ontologies were obtained through the David Bioinformatics 6.8 Database⁴⁶. Pathway analyses were performed using the Reactome database²⁶. Alterations and co-occurrence/mutual exclusivity of genes in gene set were analyzed in TCGA lung cancer studies using cbioportal⁴⁷. Studies included in cbioportal analyses were: Lung Adenocarcinoma⁴⁸, Lung Adenocarcinoma (TCGA, Provisional), Lung Squamous Cell Carcinoma⁴⁹, Lung Squamous Cell Carcinoma (TCGA, Provisional), and Pan-Lung Cancer⁵⁰. Drug-ability of gene set was analyzed using the DGIdb database²⁴.

RESULTS

Cancer risk classification pipeline

A computational pipeline was created for both candidate marker discovery and validation (Figure 1). The process to identify statistically informative individual MST loci and develop a classification signature (including Receiver Operating Characteristic (ROC) curves and sensitivity and specificity calculations), follows the approach we have used previously for other cancers studies 8-10, 12. We applied part (depicted on the left side of Figure 1) of the pipeline to compute classifiers for Lung Adenocarcinoma (LUAD) germline samples vs normal germline controls and Lung Squamous Cell carcinoma (LUSC) germline samples vs normal germline controls. Each of the individual loci found to be informative, i.e. which passed statistical and false discovery tests were harvested for inclusion on a custom nextgen target enrichment kit. Those loci were supplemented with additional informative loci gathered from an analysis of additional cancer types (breast, ovarian, melanoma and 3 different brain cancers) to identify potential pan-cancer markers. To the full set of informative loci were also added control loci that included random exon microsatellite loci, forensics/paternity testing loci, and MSI (microsatellite stability) loci to verify performance of the enrichment kit.

Once a set of potentially informative microsatellite loci were identified (left side of figure 1), lung cancer and control DNA samples were enriched for these markers using a custom Specific Microsatellite Target Enrichment Kit (SMTEK) and sequenced at high depth with 16 to 48 samples multiplexed on each sequencing run (right side of figure 1). The high depth sequencing of these regions enabled calling of high accuracy genotypes at each of the enriched loci. These genotypes were in turn used to validate those loci that could differentiate cancer from controls. Receiver Operating Characteristic curves were computed for the validated

loci from the lung cancer sets and for the lung cancer set plus informative loci from the other cancer types. Using these two verified sets of high accuracy loci, we analyzed them for possible mechanistic (ontology, pathway, function, drug-ability, etc.) relationships to illustrate their potential role in lung cancer.

Analysis of whole exome sequencing data for cancer and control germline samples

To compare MST genotypic variation in lung cancer germline samples and noncancer germline control samples, 266 LUAD and 222 LUSC germline cancer exome samples were downloaded from The Cancer Genome Atlas (TCGA) and 390 germline non-cancer control exome sequencing data were downloaded from the 1000 Genomes Project (1kGP). With our 95% accurate 14 MST allele calling method, a total of 1.8 million microsatellite loci were analyzed by comparing modal (most frequent genotype in control samples) and non-modal genotype distributions in the two lung cancer sub-types and the non-cancer control samples. Two sets (one each for LUAD and LUSC) of MST loci were identified having significantly different genotypic distributions compared to non-cancer controls. Of these two sets, 96 LUAD and 67 LUSC MST loci (Supplemental table 6) passed false discovery rate tests. A classification model was developed to assess how well each set of markers differentiates the disease samples from healthy controls¹⁰. The Receiver Operating Characteristic (ROC) demonstrates the predictive power of this classification scheme as well as the value of the underlying sets of loci: the area under the curve (AUC) is 0.94 (LUAD) and 0.92 (LUSC) (Supplemental figures 3 and 4). For each classification scheme an "at risk" score was established by plotting accuracy vs. cutoff, a sample with 39% or more of the 96 LUAD signature MST loci set with non-modal genotype will be classified as 'at-risk' for adenocarcinoma of the lung (Figure 2A) while a sample with 37% or more of the 67 LUSC signature MST loci

set with non-modal genotype will be classified as 'at-risk' for squamous cell carcinoma (Figure 2B). The specificity and sensitivity of the LUAD classification scheme is 0.87 and 0.87, respectively. The specificity and sensitivity of the LUSC classification scheme is 0.82 and 0.88, respectively. The specificity and sensitivity of the classification power of the LUAD signature set was found to be 0.87 and 0.87 the same for the LUSC signature set was found to be 0.82 and 0.88.

High-depth target sequencing of computationally harvested disease specific MST loci

To assess the differentiating power of the computationally harvested 119 (96 LUAD and 67 LUSC; of which 44 were in common) MST loci using high-depth enabled high accuracy genotyping to validate the computational findings, the 119 MST loci along with 144 MST loci computationally found to be specific for other cancers, and control loci were combined and enriched in 30 lung cancer samples (Supplemental table 3) and 89 non-cancer control samples (Supplemental table 4). Supplementary figures 1 and 2 show that more than 93% of the loci were called in all the lung cancer and non-cancer control samples. The average read depth per loci across all samples was 579x (Standard Deviation, 315x). The minimum read depth was 83x.

Control loci genotyping

A set of 84 control loci were added to the enrichment kit to demonstrate the hypermutable nature of forensic and paternity test MST loci and the resilience of random MST loci in exonic regions (highly conserved) of the genome to MSI in both the lung cancer and non-cancer control sample groups. Of the 84 control loci, 79 were reliably called in both sample groups. About 70% of the 64 control loci found in exon regions were found to have the same predominant genotype (found in greater than 50% of the control or cancer samples) in both sample groups while 86% of the

15 hyper mutable loci were found to have a wide spectrum of genotypes. None of the 79 control loci were found to have consistent genotypes that differed between the sample groups (cancer and normal), that is none of the control loci were informative for differentiating the two groups, as expected.

Validation of LUSC and LUAD MST loci sets

We successfully called the genotype for 105 out of 119 microsatellite markers that significantly differ in the lung cancer germline samples compared to non-cancer controls. Specifically, the predominant genotype for these 105 markers was calculated using high depth sequencing of 30 lung cancer samples (Supplemental table 3) and 89 non-cancer control samples (Supplemental table 4). A subset of 13 markers (from the 105) were found to have differing predominant genotypes between the high depth lung cancer and non-cancer control datasets.

Genotyping MST loci from other diseases in the lung cancer samples

Recent findings from pan-cancer studies suggest that different cancer types share oncogenic signatures^{18, 19}. We investigated this possibility by including 144 informative MST loci identified in studies of breast cancer, ovarian cancer, lower grade glioma, glioblastoma, melanoma, and medulloblastoma to the target enrichment kit. Of the 144 loci, 137 loci were reliably genotyped in both sample groups. Among these, 8 loci (Table 1) were found to have differing predominant genotypes in the high depth lung cancer and 1kGP non-cancer control datasets.

Performance of the high-depth informative loci as a classifier

A binary classification model was developed to assess the power of the 13 validated MST loci set (Table 1) to differentiate lung cancer samples from non-cancer control samples. The 13 MST loci signature differentiated lung cancer samples from non-

cancer control samples with a sensitivity of 0.90 and specificity of 0.94. The area under the ROC curve was 0.96 (Supplemental figure 5A). An optimal cutoff of 0.61 was identified by calculating the accuracy vs. cutoff (Supplemental figure 5B). This result has a simple interpretation: 8 or more predominant genotypes (out of 13) indicate an increased risk for non-small cell lung cancer. (Figure 3A).

A similar classification model was generated for all 21 validated MST loci set (Table 1). This model has higher classification power with sensitivity and specificity values of 0.93 and 0.97 respectively. The area under the ROC curve is 0.97 (Supplemental figure 6A). The accuracy vs. cutoff plot suggests a cutoff of 0.57. The 21 MST classifier (Supplemental figure 6B) shows that any sample with 57% or more of the 21 MST loci with predominant cancer genotype will be classified as 'at-risk' for non-small cell lung cancer (Figure 3B).

While the statistical power of the 21 MST loci to differentiate lung cancer from non-cancer control samples is significant, a leave one out cross validation was performed to estimate the performance of this model. The leave one out analysis (see methods) predicted 28 out of 30 lung cancer samples to be 'at-risk' and 88 out of 89 non-cancer control samples to be 'healthy'. The average sensitivity and specificity of this cross validation effort, corresponding to the 119 leave one out iterations (due to the 30 + 89 sample count), was found to be 0.93 and 0.97, respectively. This cross validation demonstrates the consistency of this prediction method.

Potential roles of the genes that harbor these informative loci

Of the 13 MST loci that are found to differentiate lung cancer samples from control samples, all were in the intronic regions of genes. To understand the mechanistic roles of these genes, the occurrence of mutations in these 13 genes were examined in 5 TCGA lung cancer studies. On average 37% of the lung cancer samples in these 5 studies contained mutations in at least one of the 13 genes (Supplemental table

10). An LUSC study with 177 lung cancer samples had ~50% of the samples with mutations in at least one out of the 13 genes (Supplemental table 10). Nine gene pairs were found to co-occur significantly (Supplemental table 11). Of these gene pairs, the REL gene significantly co-occurred with 4 genes (PPP1R21, CCDC88A, ATG3, and PRPF18) and ARID1B co-occurred with 2 genes (IMPG1, FUBP3). Interestingly, when these 13 genes were inspected for possible association with cancer using the COSMIC Cancer Gene Census²⁰, only REL and ARID1B were found to be previously implicated in cancer²¹⁻²³. When all 13 genes were examined for possible drug-ability, using DrugDB²⁴, REL and ARID1B were found to be clinically actionable. When clustering the 13 genes using the David ontology database we found alternative splicing (P value: 0.005) and splice variants (P value: 0.046) to be significant ontological characterizations (Supplemental table 12). It should be noted that all the 13 MST loci that are found to be lung cancer differentiating are found in the intron regions of genes (Table 1). It has been shown previously that alterations in the MST loci in the intronic regions of the genes can influence transcription, alternative splicing, or mRNA export to the cytoplasm²⁵. Upon further investigation of the 13 genes using Reactome²⁶, we found that two pathways were statistically enriched: the cellular response to stress pathway and the chromatin organization pathway.

DISCUSSION

Although substantial effort has been directed at identifying diagnostic actionable markers, there is a significant gap between the known genetic contributors to lung cancer and the number and power of known inherited and somatic variants. About 85% of all lung cancers are non-small cell lung cancer (NSCLC), and with a better understanding of the heterogeneity of NSCLC, more patient specific treatment options are on the rise²⁷. The success of tailored lung cancer treatment arises from improvements in genetic and epigenetic biomarker discovery²⁸; however, early detection still remains the most significant factor in cancer survival. Important to early discovery is the identification of genetic risk markers, inherited or spontaneous, that will aid in identifying high-risk patients for enhanced monitoring or preventative measures. Recent studies have found that 20% of newly diagnosed lung cancer patients are never-smokers, underscoring the need and potential for new genetic risk markers.^{2,5,6} The markers found in this study will potentially fill the gap by enabling risk stratification, allowing clinicians to monitor high-risk patients more closely leading to earlier detection.

By analyzing the modal and non-modal genotypic distribution of about 1.8 million MSTs in the two lung cancer sub-types in comparison with the non-cancer control samples, we found 67 LUSC and 96 LUAD MST loci (Supplemental table 7) that can differentiate their corresponding lung cancer sub-type from the non-cancer controls at significant sensitivities and specificities (Supplemental figures 3 and 4). Although we have previously demonstrated our genotyping accuracy from exome datasets to be 95%, the modest (~15x) read coverage in publically downloaded TCGA and 1000 Genome Project exome datasets limits the accuracy and ability to call genotypes at all loci¹³. Low coverage, reduced sequence

complexity and non-random variation, have hampered microsatellite based biomarker discovery^{13, 29}. While we have addressed these limitations in our previous efforts to identify cancer associated MST loci and tuned our genotyping algorithms accordingly, here we endeavored to mitigate the main source of genotyping error by dramatically increasing the depth of coverage at informative loci^{8-10, 12}. Hence we specifically enriched 347 (disease and control) MST loci (Supplemental table 1) in 119 multiplexed samples and attained an average per locus sample read depth of 579 (Supplementary figure 2) which is ~20 times the usual exome read depth^{8-10, 12}.

With high-depth enabled high accuracy genotyping, 13 MST loci were found to have one predominant genotype (a genotype found in more than 50% of group members) that differed in the lung cancer and the non-cancer control groups (Supplemental table 5). Eight MST loci previously found to be specific for other cancers were also able to differentiate lung cancer samples from the non-cancer control samples. The culling of uninformative loci in the validation study and incorporation of control loci significantly increased the overall reliability, sensitivity and specificity of the assay.

All MST loci were found in genes (Table 1), specifically within the introns of genes, which we have previously shown to influence alternative splicing²⁵. Of these genes, all 13 are expressed in the lung, giving confidence that genes could play a role in lung carcinogenesis. TCGA analysis suggests REL, ARID1B and associated genes can drive lung carcinogenesis through DNA damage and chromatin remodeling induced genomic instability (Figure 4).

ARID1B is a transcriptional modulator of specific genes through chromatin remodeling. ARID1B is a part of the switch/sucrose non-fermenting (SWI/SNF)

complex that is implicated in several cancers³⁰. More recently a study reported that loss of function in the SWI/SNF complex leads to genomic instability in lung cancer³¹. Lung cancer subtypes showed no significant differences between histology, implying that the loss of SWI/SNF function caused genomic instability regardless of lung cancer subtype, consistent with our observation that ARID1B is a marker for both LUAD and LUSC [Table 1].

REL is a proto-oncogene and member of the NFkB transcription factor family. Rel/NFκB transcription factors are critically involved in innate and adaptive immune responses through the up-regulation of chemokines, cytokines, cell adhesion molecules and proteases. It has been shown that chronic inflammation increases the likelihood of tumorigenesis through increased proliferation and DNA damage³². The role of tobacco smoke as a carcinogen has been highly correlated with lung cancer and one explanation is the production of reactive oxygen species that is known to cause DNA damage and to activate NFkB33. It can be deduced that alterations in REL could predispose a smoker to increased risk of cancer compared to a nonsmoker. Overexpression of REL has been associated to many lymphoid cancers such as Primary mediastinal B-cell lymphoma, Classical Hodgkin's Lymphoma, and solid tumors such as Breast cancer, Pancreatic cancer, and Head and Neck cancer but not lung cancer^{21, 34-37}. Interestingly, our lung cancer risk classifying locus harbored by the REL gene lies only 68 base pairs downstream of Exon 6 and 17 base pairs upstream of Exon 7, both of which are included in the REL Homology Domain (RHD). The RHD is an N-terminal protein domain which is shared by REL genes, which mediates DNA binding, inhibitor binding, nuclear localization signal and dimerization³³. It can be inferred that intronic mutations located in between two exons in close proximity of each other can affect protein structure in the RHD that can influence downstream effects of the NFkB pathway and consequently predispose individuals to cancer.

Further, REL, ARID1B and other genes in our set are members of pathways, the cellular response to stress pathway and the chromatin organization pathway, that could potentially play a role in carcinogenesis. Chromatin remodeling is a dynamic process which regulates DNA repair, recombination, and gene transcription, which if impaired can play a pivotal role in carcinogenesis^{38, 39}. Few studies have reported the association of the chromatin-remodeling pathway to lung cancer risk. For example, one recent study identified polymorphisms in the chromatin-remodeling pathway as a lung cancer risk classifier in a Chinese population⁴⁰. The cellular response to stress pathway is involved in damage control through protective or destructive cell response mechanisms that promote survival or initiate cell death⁴¹. Dysfunction in the cell response stress pathway can lead to inappropriate response to stress and accumulate mutations. For example, our previous studies revealed that a single exposure to carcinogens such as nicotine can cause mutations to accumulate in epithelial tissue, which can contribute to carcinogenesis¹⁶.

Taken together, our results propose a 13 loci lung cancer risk classifier that may reveal insight into the mechanism of lung carcinogenesis. Dysfunctions in the two significantly enriched pathways can possibly encourage lung carcinogenesis through chromatin remodeling, inflammation and tumor microenvironment restructuring. The genes ARID1B and REL are of special interest because of their druggability, oncogenic implications, odds risk ratio scores (Supplemental table 11) and co-occurrence with other implicated loci. These findings may be of interest because of the clinical potential value of this lung cancer risk classifier for novel therapeutic target discovery, lung cancer prediction, and cancer risk assessment.

FIGURES

Figure 3-1: Flow chart of informative loci identification and validation

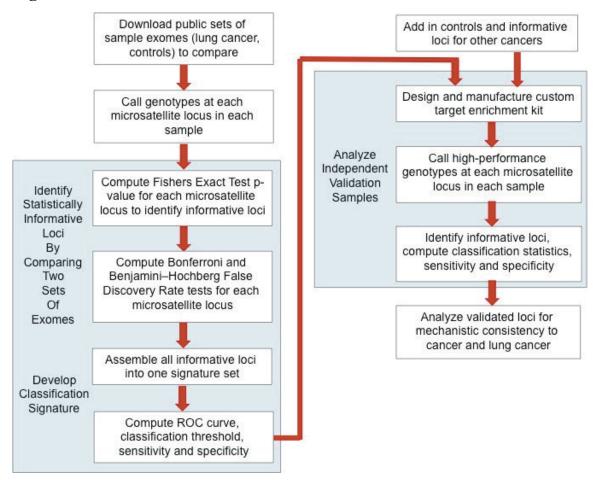


Figure 3-2: The computationally harvested LUAD and LUSC MST loci differentiate their corresponding cancer type from 1000 genomes non-cancer control samples with high sensitivity (LUAD: 0.87, LUSC: 0.88). (A) A sample with 39% (vertical black line; identified via ROC analysis) or more of the 96 LUAD specific MST loci with cancer genotype will be called 'at-risk' for adenocarcinoma of the lung. (B) A sample with 37% or more of the 67 LUSC specific MST loci with cancer genotype will be called 'at-risk' for squamous cell carcinoma. The orange and blue bars represent cancer germline and control germline samples, respectively.

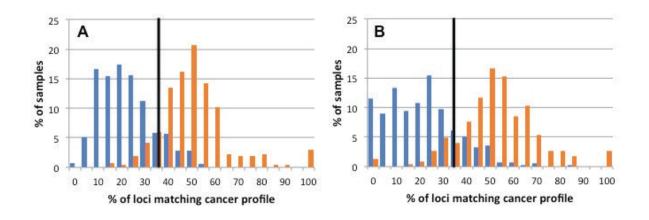


Figure 3-3: The 13 lung cancer specific MST loci and 8 MST loci specific for other diseases can differentiate between the lung cancer and non-cancer control sample groups. The blue and red bars represent the non-cancer control and lung cancer samples, respectively. (A) A sample with 61% or more of the 13 MST loci with cancer genotype will be termed 'at-risk' for lung cancer with sensitivity and specificity values of 0.90 and 0.94. (B) A sample with 57% or more of the 21 MST loci with cancer genotype will be termed 'at-risk' for lung cancer with sensitivity and specificity values of 0.93 and 0.97. The vertical black line corresponds to the optimum cut-off values found from the ROC analysis.

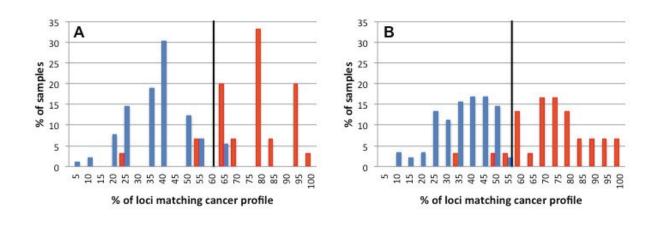


Figure 3-4: Schematic describing potential mechanism underlying lung carcinogenesis. Two genes out of 13 have significant oncogenic potential.

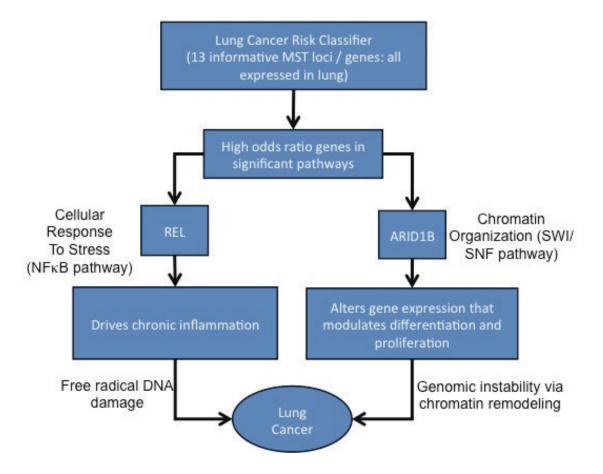


Table 3-1: MST loci that can precisely differentiate between the lung cancer samples and non-tumor samples.

Genomic	Re-	Gene		Entrez		Odds
position	peat	region	Gene	ID	Disease	ratio
chr2:60918364-	T	Intron	REL	5966	LUAD, LUSC	39.92
60918376						
chr6:157174818-	T	Intron	ARID1B	57492	LUAD, LUSC, MB,	13.57
157174831					SKCM	
chr6:76018867-	A	Intron	IMPG1	3617	LUSC, OV	12.28
76018880						
chr3:94035443-	T	Intron	ARL13B	200894	GBM, LUAD,	11.20
94035458					SKCM	
chr3:112534347-	A	Intron	ATG3	64422	GBM, LGG, LUAD,	10.29
112534360					LUSC	
chr8:129862369-	A	Intron	FAM49B	51571	LUAD, LUSC	7.01
129862381						
chr9:130622843-	A	Intron	FUBP3	8939	GBM, LGG, LUAD,	6.93
130622857					LUSC, MB, OV	
chr7:135414296-	A	Intron	CNOT4	4850	LUAD	5.07
135414309						
chr2:48461120-	T	Intron	KLRAQ1	129285	LGG, LUAD,	4.43
48461133					LUSC, MB, SKCM	
chr2:55332516-	A	Intron	CCDC88A	55704	LUAD, LUSC,	3.90
55332530					SKCM	
chr13:31148484-	A	Intron	HSPH1	3315	LUAD, SKCM	3.70
31148500						
chr15:20458509-	A	Intron	HERC2P3	283755	LUAD	3.00
20458521						

chr10:13591929- 13591943	T	Intron	PRPF18	8559	LUSC	2.25
chr2:202815832- 202815844	A	Intron	ICA1L	130026	BC, GBM, OV	7.61
chr13:114236623 -114236635	T	Intron	CDC16	8881	LGG, SKCM	6.19
chr12:106106383	A	Intron	NUAK1	9891	OV	5.74
chr3:98580864- 98580876	A	Intron	CPOX	1371	BC, OV	5.02
chr16:70839964- 70839978	T	Intron	HYDIN	54768	GBM	4.58
chr2:233460070- 233460083	A	Intron	DGKD	8527	OV	3.82
chr5:87383860- 87383873	T	Intron	RASA1	5921	OV	2.93
chr8:23852057- 23852082	TG	Intron	STC1	6781	BC	1.87

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SUPPLEMENTARY MATERIAL

Figure S3-1: Callable loci distribution in the lung cancer and non-tumor samples. In 93% of non-tumor samples and 100% of the lung cancer samples, 90 to 100% of the 326 MST loci were called. The figure shows that in the 89 + 30 target enriched samples a very high percentage of the loci included in the enrichment kit can be called with confidence.

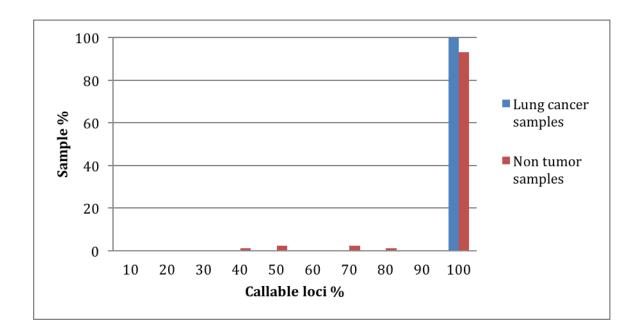


Figure S3-2: Read depth distribution in the lung cancer and non-tumor validation samples.

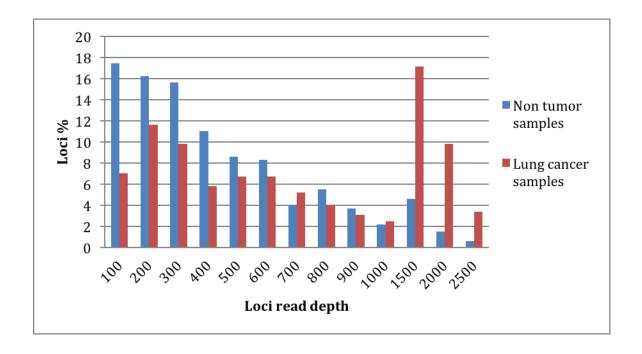


Figure S3-3: The 96 computationally found LUAD specific MST loci set differentiated LUAD germline samples from non-cancer 1kGP control samples with a sensitivity of 0.87 and a specificity of 0.87. The AUC value of this prediction was found to be 0.94.

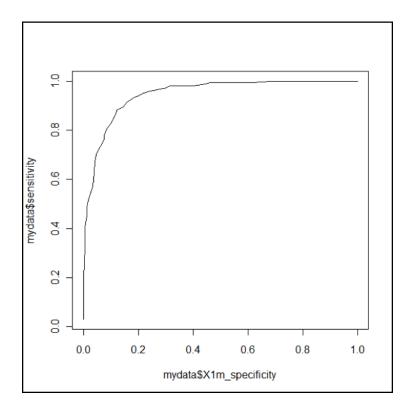


Figure S3-4: The 67 computationally found LUSC specific MST loci set differentiated LUSC germline samples from non-cancer 1kGP control samples with a sensitivity of 0.88 and a specificity of 0.82. The AUC value of this prediction was found to be 0.92.

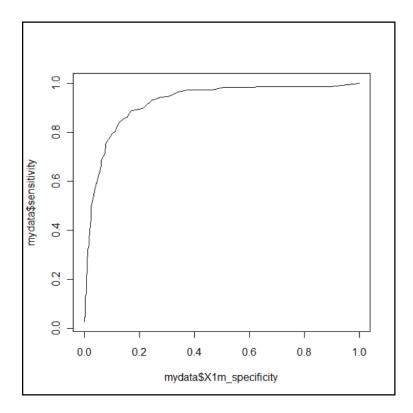


Figure S3-5: A set of 13 MST loci that were computationally associated with lung cancer was validated by the high-depth enabled high accuracy genotyping to differentiate lung cancer samples from non-cancer 1kGP control samples with a sensitivity and specificity of 0.90 and 0.94, respectively. (A) The AUC value for the classifier was found to be 0.96. (B) The accuracy versus cutoff plot gives the optimum point where the true positive value is high and the false positive value is low. According to the accuracy versus cutoff plot, a sample with 61% or more of the 13 MST loci set with predominant cancer genotype will be classified as 'at-risk' for NSCLC.

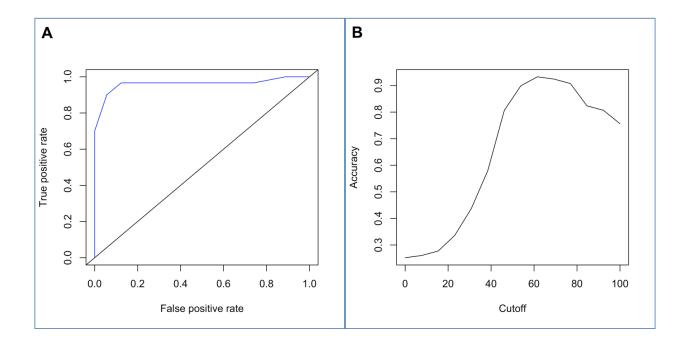


Figure S3-6: A set of 21 (13 computationally known to be associated with lung cancer and 8 that were found to be associated for other diseases) MST loci was validated by the high-depth enabled high accuracy genotyping to differentiate lung cancer samples from non-cancer 1kGP control samples with a sensitivity and specificity of 0.93 and 0.97, respectively. (A) The AUC value for the classifier was found to be 0.97. (B) The accuracy versus cutoff plot gives the optimum point where the true positive value is high and the false positive value is low. According to the accuracy versus cutoff plot, a sample with 57% or more of the 21 MST loci set with predominant cancer genotype will be classified as 'at-risk' for NSCLC.

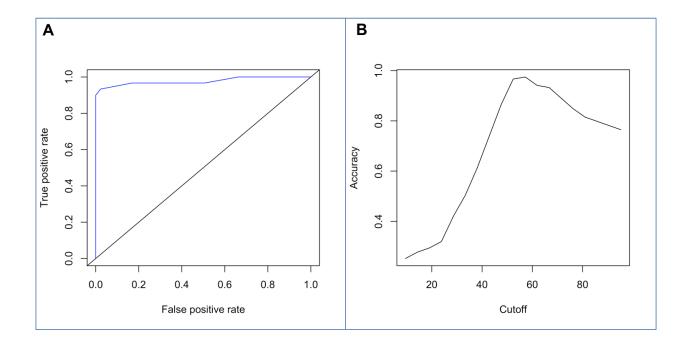


Table S3-1: The Specific Microsatellite Target Enrichment Kit (SMTEK) consisted of 347 MST loci of which 322 were genotyped in at least 10 tumor and non-cancer control samples. All 322 successfully genotyped loci had at least 10 reads in all the samples they were called.

		After sequencing	
Loci Type	Total before sequencing	Passed	Failed
Disease	263	242	21
Control	84	79	5
Total	347	322	28

Table S3-2: Genotyping all MST loci in several TCGA germline cancer sample types and comparing them to 1000 Genome Project sample genotypes yield disease specific sets of MSTs that can differentiate cancer and non-cancer control samples. Note, some loci were found to be informative for several cancer disease types

	# MST
Cancer disease type	loci
Lung squamous cell	
carcinoma	67
Lung adenocarcinoma	96
Skin cutaneous melanoma	68
Breast cancer	55
Ovarian cancer	57
Glioblastoma	48
Medulloblastoma	25
Lower grade glioma	38

Lung squamous cell carcinoma = LUSC; Lung adenocarcinoma = LUAD; Skin cutaneous melanoma = SKCM; Breast cancer = BC; Ovarian cancer = OV; Glioblastoma = GBM; Medulloblastoma = MB; Lower grade glioma = LGG.

Table S3-3: Details of the 30 lung cancer samples used to validate the LUSC and LUAD markers via SMTEK nextgen sequencing.

Sample #	Tissue	Sample source
1	Lung cancer	Origene 3398
2	Lung cancer	Origene 3538
2 3	Lung cancer	Origene 3619
4 5	Lung cancer	Origene 3803
5	Lung cancer	Origene 3842
6	Lung cancer	Origene 3844
7	Lung cancer	Origene 3863
8	Lung cancer	Origene 3931
9	Lung cancer	Origene 3950
10	Lung cancer	Origene 3989
11	Lung cancer	Origene 4031
12	Lung cancer	Origene 4033
13	Lung cancer	Origene 4056
14	Lung cancer	Origene 4119
15	Lung cancer	Origene 4176
16	Lung cancer	Origene CD07
17	Lung cancer	Origene CD22
18	Lung cancer	Origene CD26
19	Lung cancer	Origene CD28
20	Lung cancer	Origene CD36
21	Lung cancer	Origene CD44
22	Lung cancer	Origene CD56
23	Lung cancer	Origene CD57
24	Lung cancer	Origene CD59
25	Lung cancer	Origene CD61
26	Lung cancer	Origene CD62
27	Lung cancer	Origene CD66
28	Lung cancer	Origene CD71
29	Lung cancer	Origene CD77
30	Lung cancer	Origene CD97

Table S3-4: Details of the 1000 genomes germline samples used as control samples, i.e. were normal healthy individuals.

Sample #	Cell type	Sample source
1	B-Lymphocyte	Coriell HG00313
2	B-Lymphocyte	Coriell HG00180
3	B-Lymphocyte	Coriell HG00181
4	B-Lymphocyte	Coriell HG00138
5	B-Lymphocyte	Coriell HG00113
6	B-Lymphocyte	Coriell HG00100
7	B-Lymphocyte	Coriell HG00116
8	B-Lymphocyte	Coriell HG00107
9	B-Lymphocyte	Coriell HG00278
10	B-Lymphocyte	Coriell HG00269
11	B-Lymphocyte	Coriell HG00125
12	B-Lymphocyte	Coriell HG00182
13	B-Lymphocyte	Coriell HG00272
14	B-Lymphocyte	Coriell HG00273
15	B-Lymphocyte	Coriell HG00121
16	B-Lymphocyte	Coriell HG00186
17	B-Lymphocyte	Coriell HG00134
18	B-Lymphocyte	Coriell HG00131
19	B-Lymphocyte	Coriell HG00190
20	B-Lymphocyte	Coriell HG00102
21	B-Lymphocyte	Coriell HG00127
22	B-Lymphocyte	Coriell HG00135
23	B-Lymphocyte	Coriell HG00110
24	B-Lymphocyte	Coriell HG00274
25	B-Lymphocyte	Coriell HG00118
26	B-Lymphocyte	Coriell HG00115
27	B-Lymphocyte	Coriell HG00187
28	B-Lymphocyte	Coriell HG00104
29	B-Lymphocyte	Coriell HG00111
30	B-Lymphocyte	Coriell HG00122
31	B-Lymphocyte	Coriell HG00277
32	B-Lymphocyte	Coriell HG00139

33	B-Lymphocyte	Coriell HG00282
34	B-Lymphocyte	Coriell HG00183
35	B-Lymphocyte	Coriell HG00309
36	B-Lymphocyte	Coriell HG00119
37	B-Lymphocyte	Coriell HG00268
38	B-Lymphocyte	Coriell HG00310
39	B-Lymphocyte	Coriell HG00097
40	B-Lymphocyte	Coriell HG00312
41	B-Lymphocyte	Coriell HG00108
42	B-Lymphocyte	Coriell HG00308
43	B-Lymphocyte	Coriell HG00178
44	B-Lymphocyte	Coriell HG00132
45	B-Lymphocyte	Coriell HG00266
46	B-Lymphocyte	Coriell HG00129
47	B-Lymphocyte	Coriell HG00117
48	B-Lymphocyte	Coriell HG00099
49	B-Lymphocyte	Coriell HG00136
50	B-Lymphocyte	Coriell HG00133
51	B-Lymphocyte	Coriell HG00171
52	B-Lymphocyte	Coriell HG00188
53	B-Lymphocyte	Coriell HG00275
54	B-Lymphocyte	Coriell HG00176
55	B-Lymphocyte	Coriell HG00306
56	B-Lymphocyte	Coriell HG00103
57	B-Lymphocyte	Coriell HG00140
58	B-Lymphocyte	Coriell HG00098
59	B-Lymphocyte	Coriell HG00281
60	B-Lymphocyte	Coriell HG00177
61	B-Lymphocyte	Coriell HG00109
62	B-Lymphocyte	Coriell HG00271
63	B-Lymphocyte	Coriell HG00106
64	B-Lymphocyte	Coriell HG00105
65	B-Lymphocyte	Coriell HG00137
66	B-Lymphocyte	Coriell HG00128
67	B-Lymphocyte	Coriell HG00124
68	B-Lymphocyte	Coriell HG00096

69	B-Lymphocyte	Coriell HG00142
70	B-Lymphocyte	Coriell HG00284
71	B-Lymphocyte	Coriell HG00120
72	B-Lymphocyte	Coriell HG00285
73	B-Lymphocyte	Coriell HG00276
74	B-Lymphocyte	Coriell HG00123
75	B-Lymphocyte	Coriell HG00173
76	B-Lymphocyte	Coriell HG00280
77	B-Lymphocyte	Coriell HG00112
78	B-Lymphocyte	Coriell HG00174
79	B-Lymphocyte	Coriell HG00101
80	B-Lymphocyte	Coriell HG00311
81	B-Lymphocyte	Coriell HG00179
82	B-Lymphocyte	Coriell HG00114
83	B-Lymphocyte	Coriell HG00267
84	B-Lymphocyte	Coriell HG00130
85	B-Lymphocyte	Coriell HG00126
86	B-Lymphocyte	Coriell HG00189
87	B-Lymphocyte	Coriell HG00141
88	B-Lymphocyte	Coriell HG00270
89	B-Lymphocyte	Coriell HG00185

Table S3-5: A set of 13 lung cancer specific loci and 8 other loci that were found to be specific for other diseases were found to have differing genotypes in both the sample groups. All the 21 loci have predominant genotypes (larger than the sum of all the other genotypes, i.e. more than 50%) in both the groups. The genomic coordinates furnished correspond to the HG38 genome reference build.

Genomic position	Modal control GT	Modal control GT sample %	Predominan t cancer GT	Predominan t cancer GT sample %	Odds ratio
chr2:6091836	13_13	49/89 (55%)	13_12	29/30 (97%)	39.92
4-60918376					
chr6:1571748	14_14	51/89 (57%)	14_13	27/30 (90%)	13.57
18-157174831					
chr6:7601886	14_14	60/85 (71%)	14_13	24/30 (80%)	12.28
7-76018880					
chr3:9403544	16_16	46/88 (52%)	16_15	27/30 (90%)	11.20
3-94035458			. =		
chr3:1125343	15_15	46/83 (55%)	15_14	26/30 (87%)	10.29
47-112534360					- 0.4
chr8:1298623	13_13	57/86 (66%)	13_12	22/30 (73%)	7.01
69-129862381	15 15	55104 (6504)	15 14	22/20 (520/)	6.02
chr9:1306228	15_15	55/84 (65%)	15_14	22/30 (73%)	6.93
43-130622857	14 14	45/05 (5.40/)	1.4.12	22/20 (770/)	5.05
chr7:1354142	14_14	47/87 (54%)	14_13	23/30 (77%)	5.07
96-135414309	14 14	(0/00 (700/)	14 12	1.(/20.(520/)	4.42
chr2:4846112	14_14	69/89 (78%)	14_13	16/30 (53%)	4.43
0-48461133	15 15	E2/05 (C20/)	15 14	20/20 (670/)	2.00
chr2:5533251	15_15	53/85 (62%)	15_14	20/30 (67%)	3.90
6-55332530					

chr13:311484	17_16	43/83 (52%)	16_15	18/30 (60%)	3.70	
84-31148500 chr15:204585	13_12	48/89 (54%)	12_11	20/30 (67%)	3.00	
09-20458521 chr10:135919	15_15	56/89 (63%)	15_14	16/30 (53%)	2.25	
29-13591943 chr2:2028158	13_13	69/85 (81%)	13_12	18/30 (60%)	7.61	
32-202815844 chr13:114236	13_13	51/89 (57%)	13_12	24/30 (80%)	6.19	
623- 114236635						
chr12:106106 383-	14_14	40/61 (66%)	14_13	14/22 (64%)	5.74	
106106396 chr3:9858086	13 13	50/83 (60%)	13_12	22/30 (73%)	5.02	
4-98580876 chr16:708399	15 12	59/89 (66%)	12 12	19/30 (63%)	4.58	
64-70839978 chr2:2334600	- 14 14	44/88 (50%)	14 13	23/30 (77%)	3.82	
70-233460083 chr5:8738386	14 14	45/83 (54%)	14 13	20/30 (67%)	2.93	
0-87383873	_	,	_	,		
chr8:2385205 7-23852082	26_26	44/84 (52%)	26_24	16/30 (53%)	1.87	

Table S3-6: Out of 119 MST loci computationally found to be specific for LUAD and/or LUSC cancer types, 105 produced data in both sample groups. All loci produced at least 10 reads per loci in at least 10 samples in both sample groups. The genomic coordinates furnished attribute to the HG38 build.

		Gene		
Genomic position	Repeat	region	Gene	Disease
chr6:36484827-	A	intron	KCTD20	BC, GBM, LGG, LUAD,
36484842				LUSC, SKCM
chr13:44943348-	AC	intron	NUFIP1	BC, GBM, LUAD
44943377				
chrX:13757634-	T	intron	OFD1	BC, GBM, LUAD
13757649				
chr1:10297149-	T	intron	KIF1B	BC, LGG, LUAD, SKCM
10297165				
chr17:16070104-	T	intron	NCOR1	BC, LGG, LUSC, SKCM
16070120				
chr14:50881564-	T	intron	ABHD12B	BC, LUSC
50881580				
chr3:112534347-	A	intron	ATG3	GBM, LGG, LUAD, LUSC
112534360				
chr9:130622843-	A	intron	FUBP3	GBM, LGG, LUAD, LUSC,
130622857				MB, OV
chr17:42834438-	GA	intron	PSME3	GBM, LGG, LUAD, LUSC,
42834469				MB, SKCM
chr13:113310584-	T	intron	LAMP1	GBM, LGG, LUAD, LUSC,
113310595				MB, SKCM
chr4:5745180-5745201	TTC	intron	EVC	GBM, LGG, LUAD, LUSC,
				MB, SKCM

chrX:132097403- 132097440	AC	intron	FRMD7	GBM, LUAD
chr10:33182834- 33182862	CA	intron	NRP1	GBM, LUAD
chr6:31864580- 31864594	A	intron	SLC44A4	GBM, LUAD, LUSC
chr2:86894983- 86894997	T	intergenic	-	GBM, LUAD, LUSC, MB
chr1:16564320- 16564331	A	intron	NBPF1	GBM, LUAD, LUSC, MB
chr15:84512873-	A	3utr	FLJ40113	GBM, LUAD, MB
84512887 chr1:111762785-	A	intron	DDX20	GBM, LUAD, SKCM
111762800 chr3:94035443- 94035458	T	intron	ARL13B	GBM, LUAD, SKCM
chr3:196361939- 196361954	A	intron	UBXN7	LGG, LUAD
chr4:127699990- 127700002	T	intron	INTU	LGG, LUAD
chr3:50118451- 50118476	GA	exon	RBM5	LGG, LUAD, LUSC
chr2:110963566- 110963604	TG	intron	ACOXL	LGG, LUAD, LUSC, MB, SKCM
chr13:27559820- 27559834	A	intron	LNX2	LGG, LUAD, LUSC, MB, SKCM
chr7:65961068- 65961081	A	intron	GUSB	LGG, LUAD, LUSC, MB, SKCM

chr2:48461120- 48461133	T	intron	KLRAQ1	LGG, LUAD, LUSC, MB, SKCM
chr16:66912992-	GT	intron	CDH16	LGG, LUAD, LUSC,
66913023				SKCM
chr12:95094564-	A	intron	FGD6	LGG, LUAD, LUSC,
95094577				SKCM
chr4:112186674-	T	intron	C4orf32	LGG, LUAD, LUSC,
112186688				SKCM
chr13:77217965-	A	intron	MYCBP2	LGG, LUAD, LUSC,
77217977				SKCM
chr15:73126401-	T	intron	NEO1	LGG, LUAD, LUSC,
73126414				SKCM
chr5:137677662-	A	intron	KLHL3	LGG, LUAD, LUSC,
137677675				SKCM
chr15:43710473-	TG	intergenic	-	LGG, LUAD, LUSC,
43710501				SKCM
chr5:72889765-	T	intron	TNPO1	LGG, LUAD, LUSC,
72889779				SKCM
chr4:22442629-	A	intron	GPR125	LGG, LUAD, OV, SKCM
22442643				
chr9:115402097-	T	intron	DEC1'	LGG, LUAD, SKCM
115402108				
chr21:43068646-	A	intron	CBS	LGG, LUSC
43068659				
chr8:7359489-7359500	T	intergenic	-	LUAD
chr3:46709584-	AAG	exon	TMIE	LUAD
46709610		_		
chr16:19608281-	T	intron	C16orf62	LUAD
19608294				

chr12:80845943-	A	intron	LIN7A	LUAD
80845957 chr12:118383996- 118384007	T	intron	SUDS3	LUAD
chrX:133216975- 133216989	A	exon	TFDP3	LUAD
chr4:84635240- 84635255	T	intron	CDS1	LUAD
chr14:24102652- 24102664	A	intron	PCK2	LUAD
chr14:58208106- 58208119	A	intron	ACTR10	LUAD
chr14:62950568- 62950583	A	intron	KCNH5	LUAD
chr7:135414296- 135414309	A	intron	CNOT4	LUAD
chr6:13316549- 13316562	A	intron	TBC1D7	LUAD
chr6:95586994- 95587006	TA	intron	MANEA	LUAD
chr15:43635426- 43635437	A	intron	CATSPER2	LUAD
chr15:20458509- 20458521	A	intergenic	-	LUAD
chr1:186361564- 186361576	A	intron	TPR	LUAD
chr1:1988996-1989009 chr18:74129655- 74129666	A A	intron intron	KIAA1751 FBXO15	LUAD LUAD

T	intron	ATP6V0E1	LUAD
AG	intron	HAVCR2	LUAD
	intron		LUAD
T	intron	NAB1	LUAD
A	intron	MYH15	LUAD
T	intron	DNAJC13	LUAD
A	intron	LOC729384	LUAD
A	intron	WDR59	LUAD
T	intron	REL	LUAD, LUSC
T	intron	SNX9	LUAD, LUSC
T	upstream	SNX29	LUAD, LUSC
T	5utr	NEDD1	LUAD, LUSC
T	intron	TSHR	LUAD, LUSC
T	intergenic	-	LUAD, LUSC
A	intron	GUF1	LUAD, LUSC
	AG T T T A T A T T T T T T T T T	AG intron T intron A intron A intron A intron T intron	AG intron HAVCR2 T intron SNRNP48 T intron MYH15 A intron DNAJC13 A intron LOC729384 A intron WDR59 T intron REL T intron SNX9 T upstream SNX29 T 5utr NEDD1 T intron TSHR T intergenic -

chr10:104038216- 104038281	AC	intron	COL17A1	LUAD, LUSC
chr20:33367014- 33367027	A	intron	CDK5RAP1	LUAD, LUSC
chr8:129862369- 129862381	A	intron	FAM49B	LUAD, LUSC
chr8:109523216- 109523230	T	intron	PKHD1L1	LUAD, LUSC
chr11:108188043- 108188057	T	intron	NPAT	LUAD, LUSC
chr11:124754810- 124754824	A	intron	ESAM	LUAD, LUSC
chr3:161238095- 161238109	T	intron	NMD3	LUAD, LUSC, MB, SKCM
chr6:157174818-	T	intron	ARID1B	LUAD, LUSC, MB, SKCM
157174831 chr11:108271229- 108271243	T	intron	ATM	LUAD, LUSC, MB, SKCM
chr4:185267220-	A	intron	SNX25	LUAD, LUSC, OV
185267233 chrX:52753170- 52753183	T	intron	SSX2	LUAD, LUSC, SKCM
chr6:136389532- 136389546	A	intron	MAP7	LUAD, LUSC, SKCM
chr22:35323386- 35323400	A	intron	TOM1	LUAD, LUSC, SKCM
chr2:55332516- 55332530	A	intron	CCDC88A	LUAD, LUSC, SKCM

chr1:62578975- 62578989	A	intron	DOCK7	LUAD, LUSC, SKCM
chr4:73144839-	A	intron	ANKRD17	LUAD, MB
73144853 chrX:52895580-	GT	intron	XAGE3	LUAD, MB
52895606 (HG19) chr16:10689232-	A	intron	TEKT5	LUAD, OV
10689244 chr2:24327999-	A	intron	ITSN2	LUAD, SKCM
24328012 chr13:31148484-	A	intron	HSPH1	LUAD, SKCM
31148500 chr7:5199689-5199704	A	intron	WIPI2	LUAD, SKCM
chr1:172608725- 172608738	T	intron	Clorf9	LUAD, SKCM
chr1:100077147- 100077161	T	intron	HIAT1	LUAD, SKCM
chr4:165467674-	T	intron	CPE	LUAD, SKCM
165467685 chrX:48354751-	A	intron	SSX3	LUAD, SKCM
48354764 chr12:21638477-	A	intron	LDHB	LUSC
21638491 chr10:13591929-	T	intron	PRPF18	LUSC
13591943 chr3:186804505-	A	intron	RFC4	LUSC
186804518 chr19:6833152-	T	intron	VAV1	LUSC
6833167				

chr1:153645035- 153645049	T	intron	Clorf77	LUSC, MB, SKCM
chr6:76018867-	A	intron	IMPG1	LUSC, OV
76018880 chr4:145110085-	T	intron	ABCE1	LUSC, SKCM
145110100 chr1:94498584-	Т	intron	ABCD3	LUSC, SKCM
94498598	_			,
chr1:52481679- 52481693	A	intron	ZCCHC11	LUSC, SKCM
chr12:7368968- 7368991	GA	intron	CD163L1	LUSC, SKCM
7300991				

Genomic coordinates that have 'HG19' mentioned on the side were partially deleted in HG38 hence the coordinates from the previous build are given.

Table S3-7: Out of 144 MST loci computationally found to be specific for other cancer types, 137 produced data in both sample groups. All loci produced at least 10 reads per loci in at least 10 samples in both sample groups. The genomic coordinates furnished correspond to the HG38 genome reference build.

Genomic position	Repeat	Gene region	Gene	Disease
chr8:39749565-39749600	GT	intron	ADAM2	BC
chr8:23852057-23852082	TG	intron	STC1	BC
chr2:202765380-202765400	T	intron	FAM117B	BC
chr3:155116591-155116607	TA	intron	MME	BC
chr3:113360927-113360938	A	intron	WDR52	BC
chr16:20944777-20944802	AC	intron	DNAH3	BC
chr12:110396226-110396243	A	intron	ANAPC7	BC
chr16:56684104-56684123	T	exon	MT1X	BC
chr4:76144324-76144338	A	intron	NUP54	BC
chr14:102083733-102083750	A	intron	HSP90AA1	BC
chr17:59586236-59586253	A	intron	DHX40	BC
chr20:20038239-20038260	A	intron	CRNKL1	BC
chr7:148797703-148797719	T	intron	CUL1	BC
chrX:10141619-10141634	A	exon	WWC3	BC
chr1:113829711-113829722	A	intron	PTPN22	BC
chr10:45073089-45073105	T	intergenic	-	BC
chr15:81345017-81345037	GA	intron	TMC3	BC
chr4:54264835-54264851	A	intron	PDGFRA	BC
chr22:37912036-37912064	TG	intron	MICALL1	BC
chr18:46812342-46812357	A	exon	PIAS2	BC
chr5:87383679-87383696	A	intron	RASA1	BC
chr3:33836009-33836020	T	intron	PDCD6IP	BC
chr2:197469873-197469884	A	intron	COQ10B	BC

1			~ ~	- ~
chr2:75692147-75692171	AT	intron	C2orf3	BC
chr3:198153260-198153301	GCA	exon	FAM157A	BC
chr3:196257948-196257959	A	intron	PCYT1A	BC
chr11:118482323-118482338	T	intron	MLL	BC
chr15:83804574-83804590	T	intron	ADAMTSL3	BC
chr1:23082431-23082446	T	intron	AOF2	BC
chrX:71592599-71592613	T	intron	ACRC	BC, GBM
chr4:47744586-47744598	A	intron	CORIN	BC, GBM, MB
chr8:106692713-106692726	A	intron	OXR1	BC, GBM, OV
chr2:202815832-202815844	A	intron	ICA1L	BC, GBM, OV
chr7:38242530-38242549	GT	intron	TRG	BC, MB
chr9:5798652-5798666	A	intron	ERMP1	BC, OV
chr17:65750900-65750913	A	intron	CCDC46	BC, OV
chr20:5186510-5186522	T	intron	CDS2	BC, OV
chr7:123117666-123117678	A	intron	SLC13A1	BC, OV
chr11:110258201-110258215	A	intron	RDX	BC, OV
chr6:170572302-170572314	T	exon	TBP	BC, OV
chr8:31076301-31076312	T	intron	WRN	BC, OV
chr3:98580864-98580876	A	intron	CPOX	BC, OV
chr11:62798437-62798472	AAAAGA	intron	NXF1	BC, OV
chr15:89268652-89268664	T	intron	FANCI	BC, OV
chr5:134608354-134608369	T	intron	SAR1B	BC, OV
chr19:29615224-29615240	T	intron	POP4	BC, OV
chr15:62748318-62748333	A	intron	TLN2	BC, SKCM
chr6:70240579-70240595	AT	intron	COL9A1	GBM
chr3:171126228-171126241	A	intron	TNIK	GBM
chr16:70839964-70839978	T	intron	HYDIN	GBM
chr4:168275913-168275928	A	intron	DDX60	GBM
chr14:95099732-95099772	AC	intron	DICER1	GBM

chr17:56904211-56904226	A	intron	TRIM25	GBM
chr4:188142208-188142243	GT	intron	TRIML1	GBM
chr7:103185541-103185553	A	3utr	DPY19L2P2	GBM
chr7:73307734-73307743	CAA	exon	NSUN5	GBM
chr21:10516457-10516469	A	intergenic	-	GBM
chr7:83392484-83392501	A	intron	SEMA3E	GBM
chr10:87057822-87057837	A	intron	GLUD1	GBM
chr15:43618669-43618701	CAG	exon	STRC	GBM
chr14:35865700-35865714	T	intron	BRMS1L	GBM
chr10:121496816-121496831	T	intron	FGFR2	GBM
chr3:121483587-121483611	A	intron	POLQ	GBM
chr2:138550814-138550849	TC	intron	SPOPL	GBM
chr3:113000945-113000960	A	exon	GTPBP8	GBM
chr3:154284569-154284580	T	intron	DHX36	GBM
chr11:119274082-119274098	T	intron	CBL	GBM
chr1:225519570-225519585	A	intron	ENAH	GBM
chr1:117062509-117062522	T	intron	TTF2	GBM
chr12:33426063-33426109	CA	intron	SYT10	GBM
chr2:91698005-91698016	A	intergenic	-	GBM, OV
chr9:52626-52640	A	intergenic	-	GBM, OV,
				SKCM
chr14:50595519-50595543	TC	intron	ATL1	LGG
chr14:21468604-21468616	A	intron	RAB2B	LGG
chr17:15613747-15613758	A	intron	CDRT1	LGG
chr7:96146537-96146550	A	intron	SLC25A13	LGG
chrX:18164978-18164992	A	exon	BEND2	LGG
chr1:145456733-145456746	A	intron	POLR3GL	LGG
(HG19)				
chr3:132447305-132447317	T	intron	DNAJC13	LGG

chr10:100505295-100505339		intron	SEC31B	LGG, MB
chr19:21375214-21375230	CA TG	intergenic	-	LGG, OV
chr16:70142419-70142432	T	intron	PDPR	LGG, SKCM
chr12:50660091-50660105	T	intron	DIP2B	LGG, SKCM
chr13:114236623-114236635	T	intron	CDC16	LGG, SKCM
chr12:129081740-129081756	T	intron	TMEM132D	MB
chr5:36629700-36629712	A	intron	SLC1A3	MB
chr11:17089651-17089679	GT	exon	PIK3C2A	MB
chr10:119037061-119037072	C	intron	EIF3A	MB, SKCM
chr2:233460070-233460083	A	intron	DGKD	OV
chr6:49848161-49848174	T	intron	CRISP1	OV
chr3:50057664-50057685	T	intron	RBM6	OV
chr17:68045756-68045769	T	intron	KPNA2	OV
chr17:49821919-49821932	A	intron	MYST2	OV
chr19:20646413-20646427	AC	intron	ZNF626	OV
chr14:91462502-91462516	T	intron	SMEK1	OV
chr12:106106383-106106396	A	intron	NUAK1	OV
chr13:49376888-49376921	ATAG	intron	CAB39L	OV
chr4:71022616-71022630	T	intron	DCK	OV
chr7:31092622-31092634	T	intron	ADCYAP1R1	OV
chr7:82066527-82066542	A	intron	CACNA2D1	OV
chr7:36425998-36426012	T	intron	ANLN	OV
chrX:11169774-11169785	T	intron	ARHGAP6	OV
chr10:67939722-67939740	AT	intron	HERC4	OV
chr10:92506574-92506588	T	intron	IDE	OV
chr10:22226073-22226095	A	intergenic	-	OV
chr15:64680562-64680589	TG	intron	ZNF609	OV
chr1:236558153-236558165	A	intron	HEATR1	OV
chr1:149929094-149929109	A	intron	MTMR11	OV

110.01010255 01010275	Т	·	TNIZCO	OM
chr10:91819355-91819375	T	intron	TNKS2	OV
chr18:23540418-23540433	A	intron	NPC1	OV
chr8:120506629-120506642	T	intron	MTBP	OV
chr2:222474811-222474831	T	intron	SGPP2	OV
chr11:89800992-89801004	A	intron	TRIM49	OV
chr11:30417412-30417426	T	intron	MPPED2	OV
chr1:169586130-169586142	A	intron	F5	OV
chr5:87383860-87383873	T	intron	RASA1	OV
chr5:159084572-159084586	A	intron	EBF1	OV
chr5:123378441-123378458	A	intron	CEP120	OV
chr18:2960515-2960527	A	intron	LPIN2	OV
chr12:75508182-75508196	A	intron	KRR1	OV
chr4:140527442-140527455	T	intron	ELMOD2	OV, SKCM
chr6:88929270-88929284	A	intron	RNGTT	OV, SKCM
chr8:98042609-98042620	A	intron	RPL30	SKCM
chr6:125928610-125928624	T	intron	NCOA7	SKCM
chr16:3508263-3508275	T	intron	CLUAP1	SKCM
chr20:59922427-59922441	A	exon	SYCP2	SKCM
chr7:138749322-138749335	A	intron	ATP6V0A4	SKCM
chr6:100540391-100540403	A	intron	ASCC3	SKCM
chr15:32424717-32424732	A	3utr	FAM7A1	SKCM
chr11:115209592-115209633	TGG	exon	CADM1	SKCM
chr18:46844689-46844703	T	intron	PIAS2	SKCM
chr3:180961448-180961461	T	intron	FXR1	SKCM
chr1:243572909-243572923	T	intron	AKT3	SKCM
chr5:138177681-138177692	A	intron	BRD8	SKCM
chr19:21167718-21167729	A	intron	ZNF431	SKCM
chr19:4947051-4947063	T	intron	UHRF1	SKCM
chr12:95992869-95992882	CCCT	intron	HAL	SKCM

Table 3S-8: Out of 84 MST loci computationally found to be specific for other cancer types, 79 produced data in both sample groups. All loci produced at least 10 reads per loci in at least 10 samples in both sample groups. The genomic coordinates furnished attribute to the HG38 build.

Genomic posiiton	Repeat	Gene region	Gene/ Repeat ID
chr8:19957980-19958041	AAAT	intron	LPL
chr8:25503396-25503417	GAAAG	exon	CDCA2
chr1:209432292-209432332	AGC	exon	LOC642587
chr2:48515217-48515259	TC	exon	KLRAQ1
chr2:1489620-1489686	AATG	intron	TPOX
chr6:110895439-110895479	GTTTT	exon	AMD1
chr7:149239672-149239691	CGG	exon	ZNF212
chr6:109632842-109632919	ATAG	exon	AKD1
chr3:49115555-49115580	TCTTCC	exon	USP19
chr3:18349641-18349687	CTG	exon	SATB1
chr16:69693627-69693682	CAG	exon	NFAT5
chr12:49033867-49033913	TGC	exon	MLL2
chr12:114355457-114355501	TC	exon	TBX5
chr9:127506124-127506152	CTCA	exon	FAM129B
chr9:132896597-132896621	GCT	exon	TSC1
chr9:71768574-71768616	CCTCCG	exon	TMEM2
chr16:67980293-67980324	GCA	exon	DPEP3
chr17:58756094-58756155	CCGAAC	exon	PPM1E
chr17:12992120-12992153	TGAT	exon	ELAC2

chr17:50835991-50836015	GCT	exon	WFIKKN2
chr17:17136248-17136283	CAG	exon	MPRIP
chr4:90127564-90127590	CT	exon	FAM190A
chr4:139889485-139889540	GCT	exon	MAML3
chr4:68349770-68349795	CCG	exon	YTHDC1
chr19:47742125-47742165	TTCC	exon	EHD2
chr14:94842043-94842108	[CTGT]n[CTA	AT]n	D14S1434
chr14:61321907-61321932	GGGA	exon	PRKCH
chr14:103385444-103385464	GCG	exon	MARK3
chr14:22883256-22883286	GCACAC	exon	REM2
chr12:76031129-76031189	GCT	exon	PHLDA1
chr12:4914286-4914330	ACAA	exon	KCNA1
chr12:5983962-5984074	AGAT	intron	VWA
chr17:42699813-42699840	GCTGT	exon	CNTNAP1
chr17:81996788-81996845	AGCAGG	exon	ASPSCR1
chr17:52158102-52158125	GCG	exon	CA10
chr4:54740022-54740046	AAAAC	exon	KIT
chr4:93829017-93829037	CCG	exon	ATOH1
chr20:49905305-49905338	AAAAC	exon	SPATA2
chrX:53077999-53078047	TC	exon	GPR173
chrX:134481487-134481569	AGAT	intron	HPRTB
chr1:965304-965347	TTTA	exon	KLHL17
chr1:15746939-15746954	TGC	exon	TMEM82
chr6:6321353-6321413	AAAG		
chr6:45422678-45422748	GCA	exon	RUNX2
chr10:129294237-129294302	GGAA		D10S1248
chr10:75028875-75028954	GAGGAA	exon	MYST4

chr15:40036336-40036424	CTG	exon	SRP14
chr1:247876957-247876991	CT	exon	TRIM58
chr1:2556549-2556574	TTCTCT	exon	TNFRSF14
chr1:26429657-26429681	CTTCC	exon	LIN28
chrY:18639710-18639764	GAAA		DYS385 a/b
chr11:3855884-3855906	TCTCT	exon	STIM1
chr3:45540732-45540809	AGAT		D3S1358
chr10:117548492-117548574	GA	exon	EMX2
chr10:49016119-49016146	TTTG	exon	C10orf72
chr3:126988622-126988658	TGC	exon	PLXNA1
chr18:63281662-63281742	GAAA		D18S51
chr22:37140281-37140335	ATT		D22S1045
chr18:69867388-69867414	TCTCT	exon	CD226
chr8:144530000-144530021	CAGGA	exon	KIAA1688
chr5:113017812-113017852	ATATCT	exon	DCP2
chr5:88684765-88684804	TC	exon	LOC645323
chr5:153490748-153490778	AAGG	exon	GRIA1
chr11:2171078-2171122	AATG	intron	TH01
chr16:67842859-67842951	GCA	exon	THAP11
chr1:226993391-226993405	TGC	exon	CDC42BPA
chr5:150076298-150076384	AGAT	intron	CSF1PO
chr5:146233608-146233675	CCAGGC	exon	RBM27
chr5:148982979-148983006	TGACAT	exon	SH3TC2
chr5:150651587-150651611	CTGGG	exon	SYNPO
chr19:11164698-11164760	CCAT	exon	KANK2
chr19:11466768-11466792	GGGCC	exon	ELAVL3
chr19:29926209-29926306	(AAGG)(AAA	AG)(AAGG)(TA	D19S433
	GG)[AAGG]r	1	
chr19:2514952-2515006	GA	exon	GNG7

chr18:37243909-37243929	CGG exon	BRUNOL4
chr11:6390698-6390746	GGCGCT exon	SMPD1
chr12:12297001-12297100	[AGAT]8-17[AGAC]6-	D12S391
	10[AGAT]0-1	
chr12:114406047-114406082	TC exon	TBX5
chr12:12643661-12643693	TCTAG exon	CREBL2

Table S3-9: The leave one out cross validation confirms that the predictive power of the model sustains when applied to a test set. The model consistently predicted 28 out of 30 lung cancer germlines samples to be 'at-risk' and 88 out of 89 thousand genome non-cancer control samples to be 'healthy'. The explanations of the sample types are as follows: LC – Lung cancer, 1kGPC – 1000 genome project control.

		% of loci		
		with	Leave one	Leave one
	Sample	cancer	out at-risk	out
Sample #	Type	GT	% cut off	prediction
1	LC	95.2	52.4	
2	LC	63.6	50.0	
3	LC	81.0	52.4	At risk
4	LC	54.5	50.0	At risk
5	LC	68.2	50.0	
6	LC	57.1	52.4	
7	LC	72.7	50.0	At risk
8	LC	81.8	50.0	At risk
9	LC	95.2	52.4	At risk
10	LC	77.3	50.0	At risk
11	LC	76.2	52.4	At risk
12	LC	47.6	52.4	Healthy
13	LC	57.1	52.4	At risk
14	LC	71.4	52.4	At risk
15	LC	90.5	52.4	At risk
16	LC	71.4	52.4	At risk
17	LC	72.7	50.0	At risk
18	LC	63.6	50.0	At risk
19	LC	66.7	52.4	At risk
20	LC	68.2	50.0	At risk
21	LC	72.7	50.0	At risk
22	LC	59.1	50.0	At risk
23	LC	57.1	52.4	At risk
24	LC	81.8	50.0	At risk
25	LC	31.8	50.0	Healthy
26	LC	66.7	52.4	At risk
27	LC	63.6	50.0	At risk

•	T 0	51. 4	50.4	1
28	LC	71.4	52.4	At risk
29	LC	50.0	50.0	At risk
30	LC	90.5	52.4	At risk
31	1KGPC	25.0	55.0	Healthy
32	1KGPC	45.0	55.0	Healthy
33	1KGPC	47.6	52.4	Healthy
34	1KGPC	40.0	55.0	Healthy
35	1KGPC	40.0	55.0	Healthy
36	1KGPC	52.4	52.4	Healthy
37	1KGPC	42.9	52.4	Healthy
38	1KGPC	30.0	55.0	Healthy
39	1KGPC	25.0	55.0	Healthy
40	1KGPC	50.0	59.1	Healthy
41	1KGPC	57.1	52.4	At risk
42	1KGPC	47.6	52.4	Healthy
43	1KGPC	40.0	55.0	Healthy
44	1KGPC	38.1	52.4	Healthy
45	1KGPC	38.1	52.4	Healthy
46	1KGPC	25.0	55.0	Healthy
47	1KGPC	47.6	52.4	Healthy
48	1KGPC	47.6	52.4	Healthy
49	1KGPC	31.8	59.1	Healthy
50	1KGPC	40.0	55.0	Healthy
51	1KGPC	33.3	52.4	Healthy
52	1KGPC	52.4	52.4	Healthy
53	1KGPC	52.4	52.4	Healthy
54	1KGPC	40.0	55.0	Healthy
55	1KGPC	38.1	52.4	Healthy
56	1KGPC	35.0	55.0	Healthy
57	1KGPC	52.4	52.4	Healthy
58	1KGPC	38.1	52.4	Healthy
59	1KGPC	45.5	59.1	Healthy
60	1KGPC	33.3	52.4	Healthy
61	1KGPC	45.5	59.1	Healthy
62	1KGPC	33.3	52.4	Healthy
63	1KGPC	38.1	52.4	Healthy
64	1KGPC	14.3	52.4	Healthy
65	1KGPC	31.8	59.1	Healthy
66	1KGPC	28.6	52.4	Healthy
67	1KGPC	50.0	59.1	Healthy
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68	1KGPC	42.9	52.4	Healthy
69	1KGPC	25.0	55.0	Healthy
70	1KGPC	36.4	59.1	Healthy
71	1KGPC	50.0	55.0	Healthy
72	1KGPC	40.0	55.0	Healthy
73	1KGPC	40.9	59.1	Healthy
74	1KGPC	38.1	52.4	Healthy
75	1KGPC	45.5	59.1	Healthy
76	1KGPC	18.2	59.1	Healthy
77	1KGPC	25.0	55.0	Healthy
78	1KGPC	33.3	52.4	Healthy
79	1KGPC	42.9	52.4	Healthy
80	1KGPC	9.5	52.4	Healthy
81	1KGPC	36.4	59.1	Healthy
82	1KGPC	23.8	52.4	Healthy
83	1KGPC	23.8	52.4	Healthy
84	1KGPC	35.0	55.0	Healthy
85	1KGPC	28.6	52.4	Healthy
86	1KGPC	47.6	52.4	Healthy
87	1KGPC	36.4	59.1	Healthy
88	1KGPC	36.4	59.1	Healthy
89	1KGPC	20.0	55.0	Healthy
90	1KGPC	23.8	52.4	Healthy
91	1KGPC	45.5	59.1	Healthy
92	1KGPC	40.0	55.0	Healthy
93	1KGPC	42.9	52.4	Healthy
94	1KGPC	50.0	59.1	Healthy
95	1KGPC	50.0	59.1	Healthy
96	1KGPC	42.9	52.4	Healthy
97	1KGPC	31.8	59.1	Healthy
98	1KGPC	25.0	55.0	Healthy
99	1KGPC	40.0	55.0	Healthy
100	1KGPC	50.0	59.1	Healthy
101	1KGPC	38.1	52.4	Healthy
102	1KGPC	35.0	55.0	Healthy
103	1KGPC	15.0	55.0	Healthy
104	1KGPC	40.0	55.0	Healthy
105	1KGPC	31.8	59.1	Healthy
106	1KGPC	10.0	55.0	Healthy
107	1KGPC	25.0	55.0	Healthy
				-

108	1KGPC	54.5	50.1	Ugolthy
				Healthy
109	1KGPC	23.8	52.4	Healthy
110	1KGPC	40.9	59.1	Healthy
111	1KGPC	20.0	55.0	Healthy
112	1KGPC	42.9	52.4	Healthy
113	1KGPC	27.3	59.1	Healthy
114	1KGPC	33.3	52.4	Healthy
115	1KGPC	27.3	59.1	Healthy
116	1KGPC	47.6	52.4	Healthy
117	1KGPC	36.4	59.1	Healthy
118	1KGPC	42.9	52.4	Healthy
119	1KGPC	45.5	59.1	Healthy

Table 3S-10: Investigation of TCGA lung cancer data reveal that alterations in genes in lung cancer risk classifiers occur on average in 37% of studied individuals.

TCGA Lung Cancer Study	Percentage of cases altered		
Lung Adenocarcinoma (TCGA, Nature 2014)	Gene set altered in 31.7% of 230 cases.		
Lung Adenocarcinoma (TCGA, Provisional)	Gene set altered in 33.5% of 230 cases.		
Lung Squamous Cell Carcinoma (TCGA, Nature 2012)	Gene set altered in 39.9% of 178 cases.		
Lung Squamous Cell Carcinoma (TCGA, Provisional)	Gene set altered in 49.7% of 177 cases.		
Pan-Lung Cancer (TCGA, Nat Genet 2016)	Gene set altered in 34.5% of 1144 cases.		

Table S3-11: Analysis of TCGA Pan Cancer lung cancer studies reveal indicate that 9 gene pairs tend to significantly co-occur within lung cancer risk classifiers.

Co-occurrence of gene set in TCGA Lung Cancer Studies					
Gene A	Gene B	p-Value	Log Odds	Association	
ATG3	ARL13B	<0.001	2.815	Tendency towards co-occurrence	Significant
PPP1R21	REL	<0.001	2.421	Tendency towards co-occurrence	Significant
PPP1R21	CCDC88A	<0.001	2.262	Tendency towards co-occurrence	Significant
REL	CCDC88A	<0.001	>3	Tendency towards co-occurrence	Significant
ATG3	REL	0.002	1.612	Tendency towards co-occurrence	Significant
FUBP3	CNOT4	0.005	2.402	Tendency towards co-occurrence	Significant
REL	PRPF18	0.017	1.892	Tendency towards co-occurrence	Significant
ARID1B	IMPG1	0.017	1.02	Tendency towards co-occurrence	Significant
FUBP3	ARID1B	0.049	1.459	Tendency towards co-occurrence	Significant

Table S3-12: Analysis of ontologies indicates alternative splicing, acetylation, and splice variants to be significant terms among the 12 genes in lung cancer risk classifier.

DAVID ONTOLOGY ANALYSIS					
Category Term Count % PValue Genes		Genes			
UP_KEYWORDS	Alternative splicing	12	92.308	0.005	HSPH1, FUBP3, CCDC88A, FAM49B, REL, IMPG1, PPP1R21, ARID1B, PRPF18, ATG3, CNOT4, ARL13B
UP_KEYWORDS	Acetylation	6	46.154	0.040	HSPH1, FUBP3, REL, ARID1B, PRPF18, ATG3
UP_SEQ_FEATURE	splice variant	9	69.231	0.047	HSPH1, FUBP3, CCDC88A, PPP1R21, ARID1B, PRPF18, ATG3, CNOT4, ARL13B
UP_KEYWORDS	Coiled coil	5	38.462	0.063	HSPH1, CCDC88A, PPP1R21, CNOT4, ARL13B
GOTERM_CC_DIRECT	GO:0005929~cilium	2	15.385	0.069	FAM49B, ARL13B
UP_KEYWORDS	Ubl conjugation	4	30.769	0.072	FUBP3, ATG3, CNOT4, ARL13B

Chapter 4: Dysfunctional DNA repair pathway via defective FANCD2 gene engenders multifarious exomic and transcriptomic effects

ABSTRACT

Fanconi Anemia (FA) affects only 1 in 130,000 births, but has severe and diverse clinical consequences. It has been theorized that defects in the FA DNA repair complex lead to a spectrum of variants that are responsible for those diverse clinical phenotypes. Here we show using nextgen sequencing that a clinically-derived FA cell line relative to its retrovirally corrected line continued to accumulate variants. especially INDELs. Over 200 SNV and 25 INDEL robust impact variants (introduction of start/stop codons, nonsense and missense mutations) distinguished the FA and corrected cell lines, including many high-impact variants. Further, sequences from biological replicates indicated that new mutations accumulated during a single 30-hour culture. These genetic modifications had a devastating effect on the transcriptome, with statistically significant changes in the expression of 270 These genetic and transcriptomic variants significantly impacted many pathways and functional ontologies, spanning those associated with many diverse disease phenotypes/symptoms. The downstream continuously accumulating variant diversity is consistent with the disease diversity seen in FA patients. These results underscore the consequences of defects in DNA repair mechanisms, and indicate that accumulating diverse mutations from individual parent cells make it difficult to anticipate the longitudinal clinical behavior of emerging disease states in an individual with FA.

INTRODUCTION:

Fanconi anemia (FA) is a congenital disorder that is phenotypically expressed in the daughter generation usually due to an autosomal recessive genetic condition in the parent generation. FA is characterized by bone marrow failure, infection susceptibility and a predisposition to cancer, specifically acute myeloid leukemia (AML)¹. FA cells have been found to be enriched with chromosomal aberrations that occur due to unrepaired DNA crosslinking that are left uncorrected by the dysfunctional DNA repair mechanism; the FA pathway ²⁻⁴. The presence of increased chromosomal aberrations is used as a preliminary diagnostic test that can confirm FA⁵. DNA crosslinking agents have been used as cytotoxic drugs to disrupt cell division in cancer but the cell's response to this method has not been entirely understood⁶. Recruiting DNA repair proteins to the interstrand crosslinks (ICLs) has been known to be the primary function of the FA pathway, and recent studies show the involvement of the FA pathway in maintaining general genome stability⁷. About 16 genes have been identified to be coding for the FA pathway core protein complex. These genes have been classified into complementation groups: A, B, C, D1, D2, E, F. G. I. J. L. M and N $^{8-15}$.

A major portion of previous research that has been conducted has tried to understand the causes of these DNA lesions and have extensively discussed the complementation groups of genes that have mutations that lead to a dysfunctional FA pathway^{1,8-12,16-18}. The complementation studies show that the dysfunction of anyone of the 16 genes can cause FA. In this work, we undertake an effort to understand the genome-wide and transcriptome-wide downstream effects of dysfunctional FANCD2 gene in PD20 cells. We hypothesize that one of the downstream consequences of FA caused ICL is disrupted transcription, which can

lead to altered transcriptional products. It has been shown that transcriptional products can be altered during cancer¹⁹. A significant level of transcriptome instability has been shown to always be present in cells and several stabilizing mechanisms have been known to be in place to respond to them²⁰. However, in the absence of a functional FA pathway, we propose that an increased level of unrepaired ICLs can overwhelm the transcriptome stability maintaining mechanisms and lead to altered transcriptional products, in which case consequent impairments of cellular function is imminent. While the ICL repair function of FA pathway is well known, there are studies that suggest that the FA pathway may be involved in the general upkeep of genomic stability⁷. Microsatellite instability has been linked to dysfunctional mismatch repair but recent studies show the contribution of the crosslink repair (FA) pathway to microsatellite instability²¹⁻²³. Hence we also aim to understand possible effects of a dysfunctional FA pathway on the microsatellite instability.

METHODS:

Cell lines and DNA/RNA sample preparation: PD20 cell lines containing a defective FANCD2 gene and retrovirally corrected FANCD2 were obtained from the cell repository at Oregon Health and Science University (http://www.ohsu.edu/research/fanconi-anemia/celllines.cfm/forum/index.cfm). The cells were seeded onto six well plates at 1.5×10^4 cells/well. After ~24 hours of incubation, the medium (5 ml of DMEM-10% FBS) was changed. After 4 hours of incubation, the cells were tripsin-ized and collected for DNA (Qiagen Allprep kit) and RNA (Qiagen RNA prep kit) extraction. DNA and RNA from two PD20 samples and two PD20 RV corrected for FANCD2 gene were sent for exomic sequencing and RNASeq analysis.

DNA variant detection: Paired-end sequencing reads of the 4 Fanconi Anemia DNA samples were obtained in the form of fastq files. The samples had a mean of 30 million reads with a standard deviation of 3 million reads. The samples were then checked for quality using the Trimmomatic tool. The Trimmomatic tool utilizes a window based system to check for the sequencing quality of bases. The tool requires user input for three parameters: sliding window length, quality score threshold and minimum length of sequencing read. The following values were used: 10, 20 and 70. Only sequences that contained both the mate pairs reads were used for further processing. After quality trimming, the samples on overage had 27 million reads with a standard deviation of 3 million. The 'mem' function of the BWA package was used to map the sequencing reads to GRCh38 reference genome. On average 99% of reads in all the samples were mapped to the reference genome. The SAMTOOLS package was used to convert the SAM file into a sorted and indexed BAM file. The AddOrReplaceReadGroups function in the Picard package was used

to add read groups to the BAM files. All the four BAM files were pooled together to create INDEL realignment targets using the RealignerTargetCreator function in GATK package. The GATK IndelRealigner function was then used on individual samples to create INDEL realigned BAM files. The GATK HaplotypeCaller was used to create VCF files with INDEL and SNP calls and the SelectVariants function was used to separate SNPs and INDELs.

Python and shell scripts were written to calculate the number of commonly present SNPs and INDELs in the FA and FA_RV samples (Table 2). The BEDTOOLS coverage function was used to calculate the percentage of the exome that is covered by the reads and the SAMTOOLS depth function (samtools depth sample.bam | awk '{sum+=\$3} END { print "Average = ",sum/NR}') was used to calculate the coverage of the read covered exome (Table 3).

The VCF files were fed to the SNPEff program to annotate the SNP and INDEL calls. The SNPEff annotation output was used to classify the detected variants according to the type and genomic region (Supplemental table 2). The SNPEff program outputs the possible effects of a given variant and classifies the effect into 4 categories: high, low, moderate and modifier.

Custom written python scripts were used perform the pairwise comparison of DNA variants (tables) that were predicted as high impact by SNPEff. A variant is considered to be specific to a sample, during the pairwise comparison, if the variant position is covered in the both samples and does not have the same variant call.

The calculations describing the pairwise comparisons in Table 5 and 6 are described in detail in the Supplemental table 3 and 4.

RNA-Seq data processing and analysis: The single end sequencing reads of the RNA samples were obtained in the form of fastq files. On average each sample contained 36 million reads with a standard deviation of 1 million. They were quality trimmed using Trimmomatic tool with the same parameters used for the DNA samples. After quality trimming, the samples retained on average 35 million reads (standard deviation 1 million). The quality trimmed RNA sequence reads were then mapped to the GRCh38 reference genome by the Tophat2 program with a prebuilt transcriptome index. On average 90% (Standard deviation: 3%) of the reads were uniquely mapped. The mapped BAM file was passed through the Cufflinks and Cuffmerge programs and were finally passed through the Cuffdiff program as 4 separate sample groups. The Cuffdiff program generates a pairwise comparison of the FPKM values for each gene in all the 4 samples, providing 6 pairwise comparisons. Genes found to have statistically significant (P value < 0.05) differential expression in comparisons across the FA and FA RV sample groups and no significant differential expression within the FA and FA RV sample groups are provided in the supplemental table 4 as differentially expressed between the two sample groups.

Microsatellite genotyping: Microsatellite (MST) genotyping of the Fanconi Anemia samples was performed using the Repeatseq program²⁴. The program requires three user inputs: mapped sequencing reads in the form of a BAM file, a list of MST genomic coordinates and the reference genome. Repeatseq outputs a variant call file listing all possible alleles detected for each microsatellite. Custom written perl scripts were written to generate a list of MSTs with their primary, secondary and minor allele information. An MST is considered to have a minor allele only if the minor allele is covered by at least 3 reads.

Generating the query list of microsatellites: A list of microsatellites in version 19 of the human reference genome was generated with a custom perl script 'searchTandemRepeats.pl' using default parameters. This script has been used in microsatellite studies and is available online previous at http://genotan.sourceforge.net/# Toc324410847. The initial list generated with this script included 1,671,121 microsatellites. To mitigate the likelihood of improper read mapping between microsatellites we removed all subsets of microsatellites possessing the same motif between identical 3' and 5' flanking regions. For example, the microsatellites 'GCTGC(A)³⁴CTTAG' and 'GCTGC(A)¹⁵CTTAG' were preemptively removed from our initial list of microsatellites. The fact that there were many of these potentially ambiguous regions is not surprising considering microsatellites are often embedded in larger repetitive motifs such as LINES and SINES. Our filtered list included 611,515 microsatellites.

Mechanistic analysis: The DAVID online bioinformatics tool was used to perform the ontological gene enrichment analysis²⁵. The DAVID tool was used on the 270 genes that were found to be differentially expressed between the FA and FA_RV sample groups. The REACTOME pathway online tool was used to find the pathways in which the two sets of genomic variant associated genes are involved²⁶. The pathway hits that were found to have significant (P value < 0.05) involvement are considered for analysis and are furnished in supplemental tables 8 and 9.

RESULTS AND DISCUSSION

Verification of FANCD2 retroviral correction:

To assess the extent of genomic damage that can be caused by the dysfunction of only one of the DNA repair genes, in this case FANCD2, it is first necessary to establish the differential expression of FANCD2 in the two sample groups i.e. 2 biological replicates of the original clinical FA sample and 2 FA samples that were corrected for FANCD2 expression using a retroviral vector. Table 1 shows the statistically significant differential expression of FANCD2 gene in these two sample groups by comparing the FPKM values from RNA sequencing. All the four comparisons (FA1 vs FA_RV1, FA2 vs FA_RV1, FA1 vs FA_RV2, FA2 vs FA_RV2) of FPKM (Fragments Per Kilobase of transcript per Million mapped reads) values across the two sample groups show significant difference while both the comparison within groups (FA1 vs FA2, FA_RV1 vs FA_RV2) do not show any such difference. This confirms that expression of FANCD2 is quenched in the FA samples, and restored in the corrected samples.

The RNA sequencing derived differential expression data in Table 1 demonstrates that the retrovirus mediated correction of the FANCD2 gene in the FA_RV sample group is restoring proper expression of the gene and that the FA_RV sample group can be utilized as a control to study the propagation of genomic damage in the FA sample group. The gene expression fold change of all 17 Fanconi Anemia related genes show that only FANCD2 had a significant gene expression change between FA and FA_RV sample groups and the other 16 genes did not show any such change in gene expression (Supplemental Table 1). Hence, the genomic damage and associated transcriptional profile change in non-FA genes found to be specific to the

FA sample group can be attributed to the dysfunctional DNA repair mechanism caused by the incorrect expression of the FANCD2 gene.

Genomic variant analysis:

The four DNA samples, 2 biological replicates for FA cell line and 2 biological replicates for the FA_RV cell line were sequenced and mapped to the human genome version 38 reference to identify genomic variants, such as SNPs and INDELs, and assess their potential impact. About 55% of the INDELs were found in all four samples while 65% of the SNPs were commonly found in all the four samples (Table 2), thus confirming a common origin, i.e. that these had existed in the clinical sample prior to creating the cell lines. About 70% of INDELs and 75% of SNPs were found to be shared by samples within groups (Table 2). The remaining fraction of unshared variants indicate that the biological replicates continue to develop different variants that go uncorrected, illustrating a mechanism for enhanced heterogeneity.

A significant increase in the fraction of INDELs in all the four samples was observed, in comparison to the 1000 Genome Project samples (1kGP) (Table 3). Chromosomal aberrations such as DNA lesions are signature variants of Fanconi Anemia⁵. The increased fraction of INDEL variants observed in all 4 Fanconi Anemia samples is consistent with the specific correction mechanism defect in FA. It should be noted that such a difference in SNP-INDEL ratio is found while the fraction of the exome being sequenced and the depth of coverage are approximately equal in the 4 Fanconi Anemia samples and the 1kGP samples. The constancy of the SNP: INDEL ratio in three different 1kGP samples (9.2:0.8) serves as a reference which shows all the FA samples have a higher fraction of INDELs (8.8:1.2) than what is seen in a normal population.

Analyzing the high impact genomic variants in all the 4 Fanconi anemia samples, a set of 82 genes was found to be associated with variants that were found only in the FA samples and a set of 618 genes was found to be associated with variants that were found commonly in all the 4 samples (FA and FA RV sample groups).

Microsatellite genotyping was done to understand the effect of crosslink repair mechanism on MST instability. It has been suggested that MST instability is not only caused by the mismatch repair mechanism but could also be caused by nucleotide excision repair and crosslink repair mechanisms²¹⁻²³. The fraction (5% - 256 MSTs) of heterozygous MST in the Fanconi anemia samples is found to be higher than the fraction (3.5% - 138 MSTs) in the 1kGP samples which is consistent with the increase in the percentage of MST with minor alleles. The fraction of callable MSTs with minor alleles is 5% (200 MSTs) in the 1kGP samples while the fraction of callable MSTs with minor alleles is 8.5% (437 MSTs) in the Fanconi anemia samples.

To explore in detail the heterogeneity in these 4 samples, pairwise comparisons of SNP and INDEL occurrences were made. SNP and INDEL-containing loci were compared only if the corresponding genomic location in the other sample was sequenced and called. On average, 24% of SNPs was found to sample specific, demonstrating, again, the high heterogeneity between these samples (Table 5 and Supplemental Table 3). Around 14% of INDELs were found to be sample specific (Table 6 and supplemental table 4). It should be noted that such high level of variance in genome is consistent with the fact that Fanconi Anemia patients are highly predisposed to cancer²⁷. ICLs can directly affect DNA replication by phenomenally increasing DNA errors which can lead to cell death or uncontrolled cell growth²⁷.

RNA sequencing to measure expression changes:

Having realized the extent of genomic damage caused by a dysfunctional DNA repair gene, it is pertinent to examine the downstream effect of this DNA damage on the transcriptome, i.e. on gene expression. Along with FANCD2, a set of 270 genes (Supplemental Table 5) were found to be differentially expressed in the biological replicates between the FA and the FA_RV samples groups. Significant changes in expression ranged from 1.1 to 11.5. The top most 8 genes with altered expression are shown in Table 7.

The pairwise comparisons of the number of differentially expressed genes in all 4 samples showed that on average all 4 pairwise comparisons across sample groups had 375 differentially expressed genes (FA1 - FA_RV1 = 376; FA1 - FA_RV2 = 384; FA2 - FA_RV1 = 373; FA2 - FA_RV2 = 369) while the two comparisons within sample groups (FA1-FA2 = 1, FA_RV1-FA_RV2 = 1) had only 1 differentially expressed gene each. This confirms that although there was some divergence in the genomes of the biological replicates, that the effect was very minor on the transcriptome. Also, as a control, and to put these numbers into context, three 1kGP RNA-Seq samples were downloaded and pairwise analyzed for differentially expressed genes. The number of differentially expressed genes in these 3 samples ranged from 105 to 236. It should be noted that the expression measurements in the 1kGP samples were for different individuals under differing conditions, while the FA samples were from the same individual under controlled culture conditions.

In addition to the raw expression level changes, there are indications that these genes are alternatively spliced. Pairwise comparisons of exon count in genes within and across the FA and FA_RV sample groups show that on average 29% of expressed genes have varying exon counts across sample groups while 24% of expressed genes

have varying exon counts within sample groups. An increase of 5% of genes (795 genes) with varying exon counts between FA and FA_RV sample groups shows the effects of the dysfunctional FANCD2 gene on alternative splicing. These findings might suggest that a dysfunctional DNA repair mechanism leads to DNA damage which in turn affects gene expression through truncated RNA transcripts rather than directly affecting the number of genes that are expressed.

Mechanistic analysis of genes with differential expression and genomic variants:

In order to understand the mechanistic role of genes that were affected by a DNA repair gene (FANCD2) dysfunction, three sets of genes where analyzed for their gene ontology term enrichment and their overrepresentation in pathways: 1) set of genes (270) were found to be differentially expressed (RNA-Seq) between the FA and FA_RV sample groups; 2) set of genes (82) that were associated with DNA variants that were specific to the FA sample group and were not found in the FA_RV sample group and; 3) set of genes (618) that were found to associated with genomic variants (SNPs and INDELs) that were occur in both sample groups.

The gene ontology enrichment analysis of differentially expressed genes and pathway analysis of the 82 genes that were found to be specific for the FA sample group are consistent. Both sets showed the common involvement of genes in immune functions such as antigen presentation and signaling pathways (Supplemental Table 7 and 8). These genes were also found to be involved in immune related signaling pathways (Supplemental Table 8).

Pathway analysis of the FA specific gene set, in comparison to the gene variants that are commonly found in all samples, show involvement in a wider variety of functionalities such as apoptosis and transcriptional regulation, along with known immune related FA functions such as antigen presentation and immune related signaling. The common gene variant set, on the other hand, is only involved in immune related pathways. This could suggest that earlier mutations target the immune system while further addition of mutations that are caused by the unrepaired FA pathway may lead to a wider variety of genomic effects that can initiate apoptosis.

Pathway analysis of the differentially expressed genes show that signaling genes are specifically involved in immunological processes such as T cell receptor signaling. One of the highly overrepresented pathways as indicated by the differentially expressed genes was found to be the endosomal pathway. The Cathespin L gene (CTSL) that is mainly involved in the lysosomal degradation of proteins was not only differentially expressed between the FA and FA RV sample group but it was up-regulated in the FA samples and down-regulated in the FA RV samples. It has already been suggested that dysfunction of FANCD2 affects the transcripome by the production of broken transcripts which can be translated into malformed proteins that can require overactive lysosomal activity. Other overrepresented pathways are the PD-1 (programmed cell death) signaling pathway and ER-phagosome pathway. For example, one gene involved in the phagosome pathway is MYD88 which again was found to be more highly expressed in the FA sample group and not in the FA RV sample group. We observed the up-regulation of 12 collagen genes (COL4A2, COL5A2, COL1A2, COL6A2, COL6A1, COL8A1, COL11A1, COL4A1, COL3A1, COL16A1, COL5A3, COL6A3) in the FA sample group. Cell viability and the regulation of the extra cellular matrix has been convincingly linked

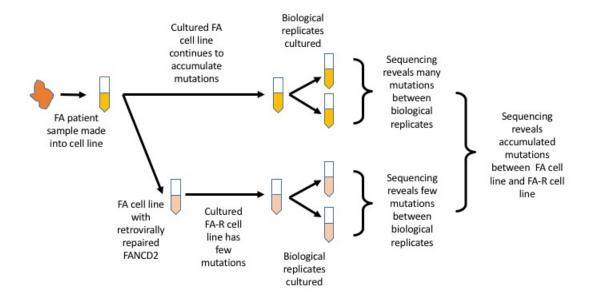
to cancer progression and the up-regulation of a collection of collagen coding proteins is consistent with up-regulation of cell death signaling and phagosomal activity²⁸. It should be noted that an up-regulation of cell death and collagen genes can lead to cancer and, recalling, Fanconi Anemia patient are predisposed to acute myeloid leukemia²⁸.

CONCLUSION:

These findings are unexpected and surprising. We find it surprising that so many variants, so many high-impact variants, accumulate so quickly as a consequence of uncorrected genomic mistakes. We find it unexpected that so many genes can be altered and/or disrupted, yet tolerated, at least such that the cells survive. Further, we find it surprising that although there were many coding variants, these and other non-coding variants resulted in fewer genes with altered expression. One must consider cause and effect. How much does the genomic variants modify the expression level, and how much has the expression level of various genes shifted to compensate and ensure cell survival. One must also wonder how many cellular/genomic trajectories are possible, and how cells compensate accordingly. In this experiment, we quantified the variants from but one of the many (currently estimated at 16) genes that are members of this DNA repair complex. It begs the question as to how each of these genes contribute to the repair process, and how defects in each manifest themselves as to the number and spectrum of variants that persist.

FIGURES:

Figure 4-1: Two types of Fanconi anemia – PD20 cell lines were included in this experiment. The cell lines represented in yellow are FA cell lines with a dysfunctional FANCD2 gene while the cell lines represented in pink are FA cell lines that were corrected with a functional FANCD2 gene using retroviral transduction. Variants with respect to the human genome reference found in common among all samples are indicative of variants accumulated prior to extraction from the patient. Variants found in common in each of the pairs of biological replicates are indicative of mutations that diverged when the original cell line was repaired. Differences between the biological replicates indicates the divergence of each of the cell line cultures as different uncorrected errors are made in each sample.



TABLES

Table 4-1: Pairwise comparison of FANCD2 gene expression in 2 FA samples and 2 FANCD2 RV corrected FA samples. Gene expression calculated by FPKM confirms that compared to FA samples, the expression of FANCD2 in the FA_RV samples is significant. This verifies the retroviral correction of the FANCD2 gene in the FA_RV samples.

		Sample 1	Sample2	log2(fold_		_
Sample 1	Sample 2	FPKM	FPKM	change)	P value	Significance
FA1	FA2	4.6	3.4	-0.4	0.4	No
FA1	FA_RV1	4.6	108.6	4.5	0.0	Yes
FA2	FA_RV1	3.4	108.6	5.0	0.0	Yes
FA1	FA_RV2	4.6	124.2	4.7	0.0	Yes
FA2	FA_RV2	3.4	124.2	5.1	0.0	Yes
FA_RV1	FA_RV2	108.6	124.2	0.1	0.5	No

FPKM is the Fragments Per Kilobase of exon per Million fragments mapped.

Table 4-2: Variant calls for the 2 FA and 2 FANCD2 RV corrected FA sample, with respect to the human reference genome. While a significantly large number of SNPs and INDELs were found to be repeated in all the 4 samples, the difference in the number of variants within biological replicates show evidence of heterogeneity in these replicate cell line cultures.

Variant		Campla	Variant count				
Type	Sample	Sample Type	#	Repeated in replicates	Repeated in all samples		
	GRL1398	FA	28053	19556			
IMDEL	GRL1399	FA	27218	19330	15022		
INDEL	GRL1400	FA_RV	27386	10026	15023		
	GRL1401	FA_RV	25966	18836			
	GRL1398	FA	201940	152042			
CNID	GRL1399	FA	198816	153043	120170		
SNP	GRL1400	FA RV	194954	144266	- 128179		
	GRL1401	FA_RV	191593	144200			

Table 4-3: Distribution of SNPs and INDELs in the FA, FA_RV and 1kGP samples. While the ratio of SNP vs INDELs in the FA and FA_RV samples are constant, an increase in the INDEL events is seen in the FA and FA_RV samples, compared to the 1kGP samples, which we include as another type of control.

	C 1	T ()			SNP-	F 0/	
	Sample	Total			INDEL	Exome %	
Sample	Type	variants	SNP	INDEL	ratio	covered	Coverage
GRL1398	FA1	234244	205,613	28631	8.8:1.2	92	13
GRL1399	FA2	229972	202,186	27786	8.8:1.2	92	10
GRL1400	FA_RV_1	226132	198,180	27952	8.8:1.2	92	11
GRL1401	FA_RV_2	221086	194,671	26415	8.8:1.2	91	11
HG02003	1KG	281236	258,715	22521	9.2:0.8	86	12
HG02008	1KG	271595	250,147	21448	9.2:0.8	87	10
HG02009	1KG	252543	232,261	20282	9.2:0.8	86	11
HG02010	1KG	278559	255,466	23093	9.2:0.8	86	11

Table 4-4: Microsatellite genotyping of the 4 Fanconi Anemia samples and healthy controls from the 1kGP. On average, 8.4% of the callable MST loci have minor allele while only 5% of the callable MST in 1kGP samples have minor alleles which indicates a higher rate of mutations in MSTs in the Fanconi Anemia samples.

Sample	Callable MST	Homozygous	Heterozygous	Minor alleles
FA1	5395	95.4	4.6	7.6
FA2	5011	94.9	5.1	7.7
FA_RV1	5818	94.9	5.1	9.2
FA_RV2	4519	95.0	5.0	9.3
HG02003	4485	96.6	3.4	5.5
HG02008	3834	97.1	2.9	4.5
HG02009	3211	96.6	3.4	4.0
HG02010	4158	95.6	4.4	6.1

Table 4-5: Pairwise comparison of high impact SNPs in FA and FA_RV samples show the extent of SNP variability within biological replicates. To ensure accurate comparison, only SNPs that were sequenced in both samples in a sample pair were considered.

	FA1	FA2	FA_RV1	FA_RV2
FA1	*	142	167	252
FA2		*	169	255
FA_RV1			*	234
FA_RV2				*

Table 4-6: Pairwise comparison of high impact INDELs in FA and FA_RV samples show the extent of INDEL variability within biological replicates. To ensure accurate comparison, only genomic positions that were sequenced in both samples were used.

	FA1	FA2	FA_RV1	FA_RV2
FA1	*	27	25	36
FA2		*	23	30
FA_RV1			*	29
FA_RV2				*

Table 4-7: Of 270 differentially expressed genes, the most significant are illustrated here. Eight had a high gene expression fold change and was significantly divergent from the exponential distribution of the full set of genes, when comparing FA and FA_RV sample groups. A "+" indicates higher gene expression in FA_RV sample group and a "-" sign indicates higher gene expression in FA sample group. See supplement table 5 for the full list.

		Gene		GE fold	High expression
#	Gene ID	Symbol	Genomic position	change	in FA_RV
1	XLOC_003069	-	chr1:239266341- 239270392	11.5	+
2	XLOC_014162	COLEC12	chr18:318126- 500729	10.5	-
3	XLOC_015674	ZNF626	chr19:20619938- 20661596	10.0	-
4	XLOC_033910	FGF13	chrX:138631570- 139222889	9.8	+
5	XLOC_011076	MT1E	chr16:56625653- 56627112	9.5	-
6	XLOC_002609	GLUL	chr1:182381703- 182392206	8.8	-
7	XLOC_018786	COL6A3	chr2:237324011- 237422190	8.8	-
8	XLOC_002401	C1orf85	chr1:156292686- 156295689	8.8	-

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SUPPLEMNTAL INFORMATION

FIGURES

Figure S1-1: Of 270 genes that were found to have significant difference in gene expression between the FA and FA_RV sample groups, 8 were found to have a high gene expression fold change that diverged significantly from the exponential fit. These genes, with the most significant gene expression difference, were chosen to illustrate these significant changes. The full list of genes is found below.

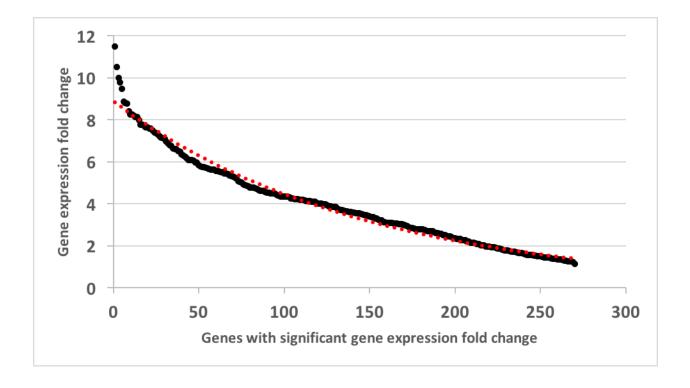


Table S4-1: The log2(fold change) in gene expression for all the genes (16) that are known to be related to Fanconi Anemia for all 6 pairwise comparisons of 2 FA cell lines and FANCD2 RV corrected FA cell lines. Only FANCD2 gene shows any discernible fold change in gene expression. This confirms that the FANCD2 gene was disrupted in the FA cell lines and restored in the FA_RV cell lines.

Gene	Gene expression fold change						
	FA1/FA2	FA1/FA_RV1	FA2/FA_RV1	FA1/FA_RV2	FA2/FA_RV2	FA_RV1/FA_RV2	
BRCA1	0.11	0.10	-0.02	0.03	-0.08	-0.06	
BRCA2	0.12	-0.18	-0.30	-0.06	-0.18	0.12	
FANCD2	-0.45	4.54	5.00	4.73	5.19	0.19	
PALB2	0.16	0.29	0.13	0.32	0.16	0.02	
FANCG	-0.08	0.15	0.23	0.11	0.19	-0.04	
FANCF	0.24	0.77	0.53	0.68	0.44	-0.09	
FANCE	-0.03	0.59	0.62	0.64	0.66	0.04	
FANCC	0.14	-0.12	-0.26	-0.21	-0.35	-0.09	
FANCB	0.23	-0.38	-0.61	-0.34	-0.57	0.04	
FANCA	-0.17	0.71	0.88	0.59	0.76	-0.12	
BRIP1	0.10	-0.81	-0.91	-1.03	-1.14	-0.22	
FANCM	0.13	0.16	0.04	0.20	0.07	0.04	
FANCL	-0.07	-0.05	0.01	-0.22	-0.16	-0.17	
RAD51C	0.14	-0.56	-0.70	-0.59	-0.72	-0.02	
FANCI	0.12	0.22	0.10	0.24	0.11	0.02	
SLX4	0.16	-0.02	-0.18	0.11	-0.05	0.13	

Table S4-2: Distribution of the DNA variants with respect to the human genome reference (build - Grch38) in all the four Fanconi Anemia samples. There were a significant number of variants found, many that are high impact. The classification of variants was done using the SNPEff program that annotates GATK VCF output. This also illustrates that many variants had already been acquired when the primary cells were taken from the patient to establish the defective and corrected cell lines.

				FA_R	FA_R
#	DNA variant event	FA1	FA2	V1	V2
1	intron_variant	664039	650794	644703	631624
2	downstream_gene_variant	289232	283457	278135	276387
3	upstream_gene_variant	200121	194620	190464	188488
4	3_prime_UTR_variant	59656	59324	57570	57931
5	non_coding_transcript_exon_variant	59060	58437	56577	56950
6	synonymous_variant	33460	33362	32162	32662
7	missense_variant	30275	30518	29686	31696
8	intergenic_region	30699	30131	29501	27426
9	splice_region_variant	14149	14279	13791	14389
10	5_prime_UTR_variant	13877	13618	13058	13405
11	sequence_feature	5716	5569	5509	5455
12	structural_interaction_variant	2965	3044	2998	2987
13	5_prime_UTR_premature_start_codon_gain_variant	1855	1815	1746	1831
14	TF_binding_site_variant	1175	1074	1120	1130
15	frameshift_variant	643	650	647	727
16	stop_gained	354	410	368	767
17	splice_acceptor_variant	391	424	343	428
18	splice_donor_variant	361	308	343	367
19	disruptive_inframe_deletion	317	307	311	312

20	disruptive_inframe_insertion	227	229	219	210
21	conservative_inframe_insertion	170	149	167	176
22	protein_protein_contact	154	154	154	153
23	conservative_inframe_deletion	72	101	89	66
24	start_lost	70	76	61	68
25	stop_lost	52	52	56	55
26	stop_retained_variant	46	47	39	41
27	non_coding_transcript_variant	37	27	30	23
28	intragenic_variant	24	20	19	19
29	TFBS_ablation	10	15	11	5
30	initiator_codon_variant	4	4	4	4
31	bidirectional_gene_fusion	2	2	3	3
32	gene_fusion	1	1	1	1

Table S4-3: Variability in high impact SNPs. This table presents the calculation of pairwise SNP comparisons in and across the FA and RA_RV sample groups. The number of unique high impact SNPs that are found specific in each sample shows the heterogeneity of the Fanconi anemia samples.

	# high impa	ct SNPs	et SNPs SNPs specific to sample				
Sample pair	S 1	S2	S 1	S2	Mean high impact	Mean specific SNPs	% of specifi c
FA1 - FA2	810	808	139	145	809	142	18
FA1 - FA RV1	810	786	178	155	798	167	21
FA1 - FA RV2	810	960	173	331	885	252	28
FA2 - FA RV1	808	786	182	155	797	169	21
FA2 - FA_RV2	808	960	179	331	884	255	29
FA_RV1 -							
FA_RV2	786	960	147	321	873	234	27

S1 – First sample of the samples in the sample pair column. S2 – Second sample of the samples in the sample pair column.

Table S4-4: Variability in high impact INDELs. This table presents the calculation of pairwise INDEL comparisons in and across the FA and RA_RV sample groups. The number of unique high impact INDELs that are found specific in each sample confirms the heterogeneity of the Fanconi anemia samples.

	# high in INDE	-	INDELs specific to sample				
Sample pair	S1	S2	S1	S2	Mean high impact	Mean specific INDEL s	% of specifi c INDE Ls
FA1 - FA2	205	209	25	28	207	26	13
FA1 - FA RV1	205	204	25	25	204	25	12
FA1 - FA RV2	205	209	34	38	207	36	17
FA2 - FA RV1	209	204	24	21	206	22	11
FA2 - FA RV2	209	209	30	29	209	29	14
FA_RV1 -							
FA_RV2	204	209	27	31	206	29	14

S1 – First sample of the samples in the sample pair column. S2 – Second sample of the samples in the sample pair column.

Table S4-5: A total of 270 genes were found to be statistically significantly differentially expressed between the FA and FA_RV sample groups. The genes are sorted according to the gene expression fold change. This table furnishes the entire list of 270 genes that were differentially expressed. The very large number of genes, with very large expression changes illustrate the significant impact that the many variants have on the cell lines.

				High
			GE fold	expression
Gene Id	Gene symbol	Genomic position	change	in FA_RV
XLOC_003069	-	chr1:239266341-239270392	11.48	+
XLOC_014162	COLEC12	chr18:318126-500729	10.50	-
XLOC_015674	ZNF626	chr19:20619938-20661596	10.00	-
		chrX:138631570-		
XLOC_033910	FGF13	139222889	9.79	+
XLOC_011076	MT1E	chr16:56625653-56627112	9.46	-
XLOC_002609	GLUL	chr1:182381703-182392206	8.85	-
XLOC_018786	COL6A3	chr2:237324011-237422190	8.80	-
XLOC_002401	Clorf85	chr1:156292686-156295689	8.78	-
XLOC_022046	CDCP1	chr3:45082273-45146422	8.39	-
XLOC_019959	MX1	chr21:41420557-41459214	8.25	-
XLOC_006994	CLEC2B	chr12:9852368-9869859	8.25	-
XLOC_017545	GALNT5	chr2:157257547-157314078	8.18	-
XLOC_008950	LOC440157	chr14:19298728-19303582	8.14	+
XLOC_022006	SUSD5	chr3:33149927-33219215	8.14	-
XLOC_021235	MYD88	chr3:38138477-38143022	7.97	-
XLOC_011492	XYLT1	chr16:17102323-17470881	7.77	-
_		chr14:103121351-		
XLOC_008904	LOC102723726,TNFAIP2	103137439	7.76	-

		chr14:105481517-		
XLOC_008934	CRIP1	105488789	7.70	-
XLOC 031419	-	chr8:122168573-122171056	7.65	+
XLOC 029150	PEG10	chr7:94656324-94669695	7.65	-
XLOC_007989	ZIC2	chr13:99981771-99986765	7.57	+
XLOC_008412	FLJ39632	chr14:19076243-19096796	7.57	+
XLOC_015095	RCN3	chr19:49527617-49543634	7.48	-
XLOC_015837	ATP1A3	chr19:41966475-41994276	7.40	+
XLOC_032446	SLC35D2	chr9:96313436-96383710	7.35	_
XLOC_030357	C8orf48	chr8:13566842-13568288	7.31	_
XLOC_017040	EMILIN1	chr2:27078566-27086403	7.22	-
XLOC_030680	-	chr8:122139981-122168546	7.16	+
XLOC_017096	QPCT	chr2:37344609-37373322	7.13	-
XLOC_024738	ZNF354C	chr5:179060406-179083771	7.09	_
XLOC_003948	PCBD1	chr10:70882279-70888784	6.97	-
XLOC_008753	IFI27	chr14:94110732-94116699	6.87	-
XLOC_002724	Clorf116	chr1:207018520-207032761	6.78	-
XLOC_031978	PHYHD1	chr9:128920894-128942041	6.76	-
XLOC_010362	CYP1A1	chr15:74719541-74725610	6.63	+
		chr12:119178789-		
XLOC_006805	HSPB8	119194746	6.59	-
XLOC_011239	PLCG2	chr16:81779293-81958294	6.59	-
XLOC_026014	CUL9	chr6:43182174-43224587	6.50	-
XLOC_027033	LAMA4	chr6:112107930-112306683	6.47	-
XLOC_000273	THEMIS2	chr1:27872542-27886685	6.37	-
XLOC_015133	CD33	chr19:51225078-51240019	6.29	+
XLOC_002809	ITPKB	chr1:226631689-226739327	6.25	-
XLOC_032358	-	chr9:78848554-78863649	6.17	+
XLOC_012078	ZFP3	chr17:5078458-5096374	6.09	-

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XLOC_023003	LIMCH1	chr4:41359606-41700044	6.08	
XLOC_012093	XAF1	chr17:6755836-6775647	6.07	
XLOC_022879	STK32B	chr4:5051545-5501001	6.06	-
XLOC_000296	SERINC2	chr1:31409564-31434680	5.97	-
XLOC_028763	FAM20C	chr7:192958-260774	5.96	-
XLOC_007833	FREM2	chr13:38687035-38887131	5.85	+
XLOC_020937	-	chr22:15854177-15855201	5.77	+
XLOC_009291	FBLN5	chr14:91869409-91947702	5.75	-
XLOC_014387	-	chr18:14858969-14863974	5.75	+
XLOC_009235	MLH3	chr14:75013763-75051532	5.71	-
XLOC_006696	-	chr12:98289603-98305388	5.69	+
		chrX:155276206-		
XLOC_034013	CLIC2	155334681	5.66	-
XLOC_005225	H19,MIR675	chr11:1995175-1997835	5.62	+
XLOC_007091	TMTC1	chr12:29500812-29784759	5.62	+
XLOC_013665	-	chr17:41110001-41112904	5.62	+
XLOC_021327	KLHDC8B	chr3:49171565-49176486	5.56	-
XLOC_004657	SERPING1	chr11:57597553-57614853	5.55	-
XLOC_022019	SCN5A	chr3:38548061-38649675	5.54	+
XLOC_007107	KIF21A	chr12:39293227-39443390	5.51	+
XLOC_030536	TRIM55	chr8:66127042-66175485	5.50	-
XLOC_005657	CD248	chr11:66314486-66317044	5.44	-
XLOC_010530	-	chr15:30488358-30490284	5.43	-
XLOC_017645	COL3A1	chr2:188974372-189012746	5.42	-
XLOC_012724	C1QTNF1	chr17:79019208-79049788	5.34	-
XLOC_011438	PPL	chr16:4882506-4937135	5.33	-
XLOC 006569	DTX3	chr12:57604326-57609804	5.28	-
XLOC 012992	USP32P2	chr17:18511261-18531380	5.25	_
XLOC_019537	TSPY26P	chr20:32186497-32190526	5.21	-

XLOC 023332	GUCY1B3	chr4:155758973-155807631	5.07	+
XLOC_005429	PAMR1	chr11:35431826-35530300	5.05	-
XLOC_012186	TRPV2	chr17:16415541-16437003	5.00	-
XLOC_019717	LAMA5	chr20:62309059-62367312	4.93	-
XLOC_023129	ANXA3	chr4:78551587-78610451	4.89	-
XLOC_021138	FANCD2	chr3:10026383-10108291	4.87	+
XLOC_015509	COL5A3	chr19:9959560-10010471	4.84	-
XLOC_029774	NSUN5	chr7:73302515-73308867	4.77	-
XLOC_000113	TNFRSF1B	chr1:12166942-12209220	4.76	-
XLOC_011062	MMP2	chr16:55479168-55506674	4.76	-
XLOC_025963	MAPK13	chr6:36130483-36144524	4.74	-
XLOC_025635	DSP	chr6:7540450-7586713	4.70	-
XLOC_017001	KCNS3	chr2:17877846-17932985	4.65	+
XLOC_004032	PPP1R3C	chr10:91628439-91633101	4.63	-
XLOC_030912	NEFL	chr8:24950954-24956869	4.62	-
XLOC_024221	CCDC152	chr5:42756805-42811922	4.61	-
		chr10:114431109-		
XLOC_004154	ABLIM1	114779903	4.56	-
XLOC_022647	BDH1	chr3:197509782-197573323	4.53	-
XLOC_015498	ZNF560	chr19:9466354-9498603	4.52	-
XLOC_000682	GSTM1	chr1:109687795-109693745	4.49	-
XLOC_002107	GSTM3	chr1:109733931-109741038	4.49	-
		chr12:108589845-		
XLOC_007460	TMEM119	108598118	4.48	-
XLOC_019438	FERMT1	chr20:6074844-6123544	4.47	-
XLOC_005789	ME3	chr11:86441022-86672636	4.41	-
XLOC_032395	SEMA4D	chr9:89360790-89498014	4.36	-
XLOC_017690	CDK15	chr2:201790453-201895550	4.35	-
XLOC_023402	SLC25A4	chr4:185143262-185150384	4.35	-

XLOC_014991	APOE	chr19:44905781-44909393	4.34	-
XLOC_001078	PRRX1	chr1:170662727-170739400	4.34	-
XLOC_033198	FAM133A	chrX:93674012-93712274	4.33	+
XLOC_020061	TMPRSS15	chr21:18268866-18477284	4.30	+
XLOC_003939	AIFM2	chr10:70052600-70132934	4.26	-
XLOC_009515	SNRPN,SNURF	chr15:24823646-24978582	4.25	-
XLOC_001304	MARK1	chr1:220528182-220664457	4.23	+
XLOC_007768	TNFRSF19	chr13:23570369-23676105	4.22	-
XLOC_019508	NINL	chr20:25452696-25585531	4.21	-
_		chr13:111320667-		
XLOC_008016	TEX29	111344247	4.20	-
XLOC_029826	SEMA3A	chr7:83957817-84492768	4.20	-
XLOC_018505	DPP4	chr2:161992240-162074542	4.18	-
XLOC_008768	BDKRB2	chr14:96204797-96244329	4.15	-
XLOC_017714	ADAM23	chr2:206443543-206621130	4.14	+
XLOC_020507	APOBEC3G	chr22:39077004-39087743	4.14	-
XLOC_025666	GMPR	chr6:16238579-16295549	4.13	-
XLOC_013997	ANKRD30B	chr18:14748239-14854702	4.11	+
XLOC_001631	MFAP2	chr1:16974501-16981586	4.09	-
XLOC_014195	PIEZO2	chr18:10670189-11149534	4.09	-
XLOC_019417	ADAM33	chr20:3667972-3682131	4.03	-
XLOC_009672	GCHFR	chr15:40764086-40767713	4.00	-
XLOC_002292	CTSK	chr1:150796207-150808441	4.00	-
XLOC_011431	CDIP1	chr16:4510674-4538815	4.00	-
XLOC_019053	SPTLC3	chr20:13008953-13169001	3.99	-
XLOC_020436	TCN2	chr22:30607082-30627060	3.97	-
XLOC_021152	PPARG	chr3:12287849-12434356	3.95	-
XLOC_009076	FOXA1	chr14:37589551-37595120	3.89	+
XLOC_019744	STMN3	chr20:63639704-63654977	3.88	-

XLOC 001759	COL16A1	chr1:31652246-31704242	3.86	-
XLOC 002087	COL11A1	chr1:102876466-103108496	3.86	-
XLOC 032002	AIF1L	chr9:131096475-131123152	3.84	+
XLOC 011603	STX1B	chr16:30989255-31010508	3.79	-
XLOC 018582	FRZB	chr2:182833274-182866770	3.74	-
XLOC 024507	TGFBI	chr5:136028894-136063818	3.70	-
XLOC_024998	F2RL2	chr5:76403254-76708132	3.70	-
XLOC_007942	SLAIN1	chr13:77697736-77764242	3.66	+
XLOC_029710	GRB10	chr7:50590062-50793462	3.65	-
XLOC_032192	ELAVL2	chr9:23690098-23826344	3.64	+
XLOC_016959	RSAD2	chr2:6877664-6898232	3.61	-
XLOC_017085	LTBP1	chr2:32947153-33399509	3.60	-
XLOC_032494	ABCA1	chr9:104781001-104928246	3.57	-
XLOC_000275	XKR8	chr1:27959992-27968093	3.57	-
XLOC_020790	FOXRED2	chr22:36487185-36507101	3.56	+
XLOC_021231	CTDSPL	chr3:37862152-37984469	3.54	-
XLOC_013620	SECTM1	chr17:82321023-82334045	3.54	-
XLOC_007808	MEDAG	chr13:30882561-30932608	3.52	-
XLOC_020014	COL6A1	chr21:45981748-46005049	3.50	-
XLOC_019958	MX2	chr21:41362022-41408943	3.47	-
		chr12:121020291-		
XLOC_007542	OASL	121039242	3.46	-
		chr12:132840351-		
XLOC_007614	CHFR	132887618	3.42	-
XLOC_002410	BCAN	chr1:156640499-156661441	3.39	-
XLOC_012316	CCL2	chr17:34255276-34257203	3.37	-
XLOC_028862	GPNMB	chr7:23246685-23275110	3.35	-
XLOC_031933	OLFML2A	chr9:124777137-124814891	3.30	-
XLOC_022011	TRANK1	chr3:36826816-36945057	3.29	-

XLOC_031238	MTSS1	chr8:124550769-124728507 chr12:112906933-	3.25	+
XLOC 006782	OAS1	112919907	3.22	_
XLOC 002412	CRABP2	chr1:156699605-156713174	3.22	_
XLOC 014114	SERPINB2	chr18:63887704-63903890	3.13	_
XLOC 024819	CMBL	chr5:10277594-10308056	3.13	_
XLOC 020015	COL6A2	chr21:46098118-46132849	3.10	_
XLOC 003369	PLAU	chr10:73909968-73922777	3.10	_
_		chr13:113883636-		
XLOC 008041	LINC00452	113926238	3.10	-
XLOC 018250	CAPG	chr2:85394747-85414074	3.08	-
XLOC 032636	CRAT	chr9:129094793-129110791	3.07	-
XLOC_026169	POU3F2	chr6:98834703-98838790	3.06	+
XLOC_022447	HLTF	chr3:149029382-149102823	3.05	_
XLOC_018202	PAIP2B	chr2:71182663-71227103	3.04	+
XLOC_021488	COL8A1	chr3:99638364-99799220	3.02	-
XLOC_022698	-	chr3:75483604-75489296	3.02	+
XLOC_002345	S100A4	chr1:153543495-153545806	2.99	-
		chr12:112978346-		
XLOC_006784	OAS2	113011723	2.96	-
		chrX:102513681-		
XLOC_033765	TMSB15A	102516771	2.94	+
XLOC_018606	SDPR	chr2:191834304-191847280	2.88	+
XLOC_004976	FAT3	chr11:92224640-92896533	2.85	+
XLOC_026946	ELOVL4	chr6:79914811-79947598	2.85	-
XLOC_027008	CD24	chr6:106969830-106975454	2.83	+
XLOC_015120	EMC10	chr19:50466787-50505802	2.80	-
XLOC_010197	FBN1	chr15:48408305-48645788	2.80	-
XLOC_000565	IFI44	chr1:78649791-78664078	2.80	-

XLOC_031709	PGM5	chr9:68355188-68531061	2.80	-
XLOC 015457	C3	chr19:6677834-6720651	2.77	-
XLOC 004350	EPS8L2	chr11:706116-727727	2.74	-
XLOC 003177	KIAA1217	chr10:23694745-24557525	2.71	-
XLOC 018507	FAP	chr2:162114440-162243535	2.70	-
XLOC 000564	IFI44L	chr1:78620381-78646255	2.70	-
XLOC_004340	IFITM1	chr11:313990-315272	2.68	-
XLOC_008248	KCTD12	chr13:76880168-76886405	2.68	+
XLOC_026181	AIM1	chr6:106360807-106570460	2.64	-
XLOC_002167	TBX15	chr1:118882758-118989556	2.61	-
XLOC_004418	TRIM22	chr11:5689586-5710863	2.59	-
XLOC_018593	COL5A2	chr2:189031914-189179879	2.58	-
XLOC_000213	EPHB2	chr1:22710769-22915330	2.56	-
XLOC_020308	USP18	chr22:18149953-18177397	2.52	-
XLOC_029590	IGF2BP3	chr7:23310208-23470491	2.51	-
XLOC_001732	IFI6	chr1:27666060-27672213	2.49	-
XLOC_020801	RAC2	chr22:37225260-37244299	2.46	-
XLOC_013434	CYB561	chr17:63432303-63446363	2.45	-
XLOC_032599	ANGPTL2	chr9:126914773-127223166	2.43	-
XLOC_031215	ENPP2	chr8:119557076-119673404	2.37	-
XLOC_006963	C1R	chr12:7080208-7092570	2.36	-
		chr13:110148962-		
XLOC_008336	COL4A1	110307149	2.34	-
XLOC_017455	INHBB	chr2:120346142-120351807	2.34	+
XLOC_031995	ASS1	chr9:130444706-130501274	2.33	-
XLOC_023921	DDX60	chr4:168216290-168318807	2.28	-
XLOC_004926	DGAT2	chr11:75768732-75801536	2.27	+
XLOC_004725	FADS2	chr11:61799624-61867354	2.27	-

		chr11:102783675-	
XLOC 005840	MMP1	102843611	2.20 -
XLOC 012791	NXN	chr17:799312-979775	2.19 -
XLOC 023355	CPE	chr4:165378944-165498330	2.15 -
XLOC 017529	KIF5C	chr2:148875222-149026759	2.14 +
XLOC 019324	CDH4	chr20:61252425-61940617	2.14 +
_		chr14:104924849-	
XLOC_009361	AHNAK2	104978357	2.12 -
XLOC_006972	SLC2A3	chr12:7919227-7936296	2.07 -
XLOC_000012	ISG15	chr1:1013466-1014540	2.07 -
XLOC_026239	GJA1	chr6:121435598-121449727	2.03 -
XLOC_022561	CAMK2N2	chr3:184249656-184293031	2.02 +
XLOC_023165	HERC6	chr4:88378685-88443097	2.02 -
XLOC_014654	CD97	chr19:14380590-14408725	1.96 -
XLOC_026329	SASH1	chr6:148212113-148552049	1.96 -
XLOC_030733	LY6K	chr8:142700110-142726973	1.95 +
		chr12:112938443-	
XLOC_006783	OAS3	112973251	1.94 -
XLOC_031767	CTSL	chr9:87726058-87731469	1.93 -
XLOC_027083	MOXD1	chr6:132296054-132401525	1.93 -
XLOC_026400	MLLT4	chr6:167826916-167972023	1.91 -
XLOC_002032	GBP1	chr1:89052303-89065360	1.88 -
		chr11:119308523-	
XLOC_005937	MCAM	119318377	1.86 +
XLOC_026130	TPBG	chr6:82363205-82367422	1.85 -
XLOC_018508	IFIH1	chr2:162267078-162318708	1.81 -
XLOC_002314	S100A10	chr1:151982909-151994238	1.79 -
XLOC_023670	ANTXR2	chr4:79901217-80073472	1.78 -
XLOC_029195	PCOLCE	chr7:100586332-100608175	1.77 -

XLOC_026113	CD109	chr6:73694235-73828317	1.76	-
	~~~	chr13:110307283-		
XLOC_008010	COL4A2	110513027	1.72	
XLOC_003446	IFIT1	chr10:89392545-89406487	1.72	
XLOC_005802	CHORDC1	chr11:90200428-90223364	1.71	+
XLOC_000513	PGM1	chr1:63593275-63660245	1.69	-
XLOC_030901	TNFRSF10D	chr8:23135587-23164030	1.66	+
XLOC_002230	TXNIP	chr1:145992434-145996631	1.66	-
		chr13:113815609-		
XLOC_008358	GAS6	113864073	1.65	-
XLOC_005644	RNASEH2C	chr11:65711995-65720938	1.62	+
XLOC_013563	LGALS3BP	chr17:78971252-78979979	1.60	-
XLOC_029851	SAMD9	chr7:93099512-93118023	1.57	-
XLOC_008580	LGALS3	chr14:55129216-55145430	1.57	-
XLOC_005191	IFITM3	chr11:319672-320914	1.56	-
XLOC_012598	MRC2	chr17:62627400-62693601	1.55	-
XLOC_005821	MRE11A	chr11:94417299-94493874	1.52	+
XLOC_001666	HSPG2	chr1:21812264-21937257	1.52	-
XLOC_006321	EMP1	chr12:13196667-13216774	1.51	-
XLOC_003133	OPTN	chr10:13100074-13138291	1.50	-
XLOC_030737	LY6E	chr8:143018484-143022410	1.50	-
XLOC_007246	ITGA5	chr12:54395260-54419266	1.48	-
XLOC_025847	HLA-A	chr6:29887759-29945884	1.45	-
XLOC_003443	IFIT2	chr10:89301948-89309276	1.44	-
XLOC_032210	DDX58	chr9:32455301-32526324	1.44	-
XLOC_004997	CEP57	chr11:95790460-95832693	1.44	+
XLOC_026696	HLA-B	chr6:31353871-31357212	1.42	-
XLOC 030925	CLU	chr8:27596916-27615031	1.39	-
XLOC_019496	CST3	chr20:23627896-23638048	1.38	-

XLOC_025239	DPYSL3	chr5:147390807-147510056	1.37 -
XLOC_002343	S100A6	chr1:153534596-153536241	1.36 -
XLOC_029148	COL1A2	chr7:94394560-94431232	1.35 -
XLOC 013255	VAT1	chr17:43014566-43022442	1.35 -
XLOC 021728	MME	chr3:155079646-155183729	1.32 -
XLOC 005507	UBE2L6	chr11:57551654-57568330	1.30 -
_		chr11:104942866-	
XLOC 005851	CASP4	104968598	1.28 +
_		chr11:102110419-	
XLOC 005005	YAP1	102233423	1.27 +
XLOC 009729	EID1	chr15:48823678-48963507	1.26 -
XLOC 019547	E2F1	chr20:33675485-33686404	1.25 +
XLOC 002315	S100A11	chr1:152032505-152037035	1.22 -
XLOC_004759	STIP1	chr11:64185271-64204548	1.13 +

**Table S4-6: Pairwise comparison of the number of exons in the most expressed transcript of genes in 4 Fanconi Anemia samples.** The % of expressed genes with varying exon counts when comparing within sample groups is 23.5 but % of expressed genes with varying exon counts when comparing samples across sample groups is about 28.5%. This table explains the effect of a dysfunctional FANCD2 gene on the transcriptome.

Sample pair	Transcripts with equal exons	Expressed genes	Transcripts with varying exon count
FA1 - FA2	12221	15903	23
FA_RV1 -			
FA_RV2	12016	15903	24
FA1 - FA_RV1	11311	15903	29
FA1 - FA_RV2	11351	15903	29
FA2 - FA_RV1	11401	15903	28
FA2 - FA_RV2	11432	15903	28

Table S4-7: Ontological gene enrichment analysis of the 270 genes that were found to be differentially expressed the FA and FA_RV sample groups. The exceptional p-values seen for these GO ontology terms, especially for terms involved in infectious disease, development and cancer illustrate the potential connections with the observed symptoms and diseases seen in FA patients. The DAVID online bioinformatics tool was used to this GO enrichment analysis.

Term			List		
type	Term	Count	Total	<b>PValue</b>	Genes
BP	GO:0060337~type I interferon	17	241	4.71E-	IFITM1, IFITM3, OAS3,
	signaling pathway			16	HLA-A, RSAD2, OAS1,
					HLA-B, OAS2, IFIT2,
					OASL, IFIT1, IFI27,
					ISG15, XAF1, MX1,
					MX2, IFI6
BP	GO:0030574~collagen catabolic	16	241	1.17E-	COL4A2, COL4A1,
	process			14	MRC2, COL3A1,
					COL5A3, COL5A2,
					MMP2, MMP1, CTSL,
					CTSK, COL6A3,
					COL6A2, COL1A2,
					COL6A1, COL8A1,
					COL11A1
BP	GO:0009615~response to virus	19	241	1.73E-	IFIH1, CYP1A1, IFITM1,
				14	IFITM3, CLU, OAS3,
					RSAD2, OAS1, IFI44,
					OAS2, TRIM22, DDX58,
					IFIT2, OASL, IFIT1,

					MYD88, DDX60, MX1, MX2
BP	GO:0030198~extracellular matrix	23	241	7.75E-	COL4A2, COL4A1,
	organization			14	COL3A1, FBN1, HSPG2,
					BCAN, OLFML2A,
					COL5A3, COL16A1,
					COL5A2, EMILIN1,
					LAMA4, ITGA5,
					LAMA5, FBLN5,
					COL6A3, TGFBI,
					COL1A2, COL6A2,
					COL6A1, MFAP2,
DD	CO 0007155 II II :	20	241	5.06E	COL8A1, COL11A1
BP	GO:0007155~cell adhesion	28	241	5.26E-	MTSS1, CCL2, FERMT1,
				10	BCAN, CDH4,
					LGALS3BP, FAP, TGFBI,
					COL6A1, CD24, CDNMP
					COL6A1, CD24, GPNMB, COL8A1, ADAM23,
					COL16A1, MCAM,
					TPBG, GAS6, EMILIN1,
					LAMA4, PGM5, FREM2,
					ITGA5, CD33, SUSD5,
					SEMA4D, THEMIS2
BP	GO:0051607~defense response to	17	241	1.90E-	IFITM1, IFITM3, OAS3,
	virus			09	RSAD2, APOBEC3G,
					IFI44L, OAS1, OAS2,
					TRIM22, IFIT2, OASL,

					IFIT1, ISG15, DDX60, MX1, MX2, GBP1
BP	GO:0045071~negative regulation	10	241	3.99E-	IFIT1, OASL, ISG15,
	of viral genome replication			09	IFITM1, IFITM3, OAS3,
	-				RSAD2, APOBEC3G,
					OAS1, MX1
BP	GO:0071230~cellular response to	8	241	7.58E-	COL4A1, ASS1,
	amino acid stimulus			06	COL3A1, COL1A2,
					COL6A1, COL16A1,
					MMP2, COL5A2
BP	GO:0035987~endodermal cell	6	241	3.58E-	COL4A2, ITGA5,
	differentiation			05	COL6A1, COL8A1,
					COL11A1, MMP2
BP	GO:0060333~interferon-gamma-	8	241	6.83E-	OASL, OAS3, HLA-A,
	mediated signaling pathway			05	OAS1, OAS2, HLA-B,
					TRIM22, GBP1
BP	GO:0001525~angiogenesis	13	241	9.88E-	COL4A2, CCL2, LAMA5,
				05	ITGA5, FAP, TGFBI,
					HSPG2, MCAM,
					COL8A1, TNFAIP2,
					MMP2, PLAU, EPHB2
BP	GO:0022617~extracellular matrix	8	241	1.06E-	CTSL, CTSK, CAPG,
	disassembly			04	FBN1, HSPG2, BCAN,
					MMP2, MMP1
BP	GO:0006955~immune response	18	241	1.19E-	SECTM1, CRIP1, CCL2,
				04	ENPP2, C3, IFITM3,
					OAS3, HLA-A, OAS1,
					C1R, OAS2, HLA-B,
					TRIM22, TNFRSF1B,

					TNFRSF10D, CD24, SEMA4D, IFI6
BP	GO:0009612~response to	7	241	3.01E-	TXNIP, INHBB, CCL2,
DF	mechanical stimulus	/	<b>241</b>		COL3A1, PPARG,
	inechanical stiniulus			04	BDKRB2, PIEZO2
DD	CO.0070200 matrix	4	241	0.0012	, and the second
BP	GO:0070208~protein	4	241	0.0012	C1QTNF1, COL1A2,
DD	heterotrimerization	2	241	0.0012	COL6A2, COL6A1
BP	GO:0010716~negative regulation	3	241	0.0012	FAP, CST3, DPP4
DD	of extracellular matrix disassembly	2	0.41	0.0020	ICC15 LIDEAL ( CHED
BP	GO:0019941~modification-	3	241	0.0020	ISG15, UBE2L6, CHFR
D.D.	dependent protein catabolic process	_	0.41	0.0000	GOT 2.11 GOT 1.2
BP	GO:0030199~collagen fibril	5	241	0.0023	COL3A1, COL1A2,
	organization				COL5A3, COL11A1,
		_	• • •		COL5A2
BP	GO:0006952~defense response	6	241	0.0027	INHBB, CST3, COLEC12,
					HLA-B, MX1, MX2
BP	GO:0008637~apoptotic	4	241	0.0027	IFIT2, AIFM2, SLC25A4,
	mitochondrial changes				CD24
BP	GO:0045087~innate immune	15	241	0.0039	DDX58, IFIH1, CASP4,
	response				MYD88, LGALS3,
					DDX60, CLU, PPARG,
					APOBEC3G, SERPING1,
					COLEC12, C1R, HLA-B,
					MX1, MX2
BP	GO:0006508~proteolysis	16	241	0.0041	C3, ADAM23, MME,
					C1R, MMP2, PCOLCE,
					MMP1, CTSL, CTSK,
					CASP4, BACE2, FAP,

					ADAM33, DPP4, PLAU, TMPRSS15
BP	GO:0035456~response to interferon-beta	3	241	0.0069	IFITM1, IFITM3, XAF1
BP	GO:0050776~regulation of immune response	8	241	0.0080	IFITM1, C3, CD33, CLEC2B, COL3A1, HLA- A, COL1A2, HLA-B
BP	GO:0035455~response to interferon-alpha	3	241	0.0085	IFITM1, IFITM3, MX2
BP	GO:0035457~cellular response to interferon-alpha	3	241	0.0085	IFIT2, OAS1, GAS6
BP	GO:0032480~negative regulation of type I interferon production	4	241	0.0088	DDX58, IFIH1, ISG15, UBE2L6
BP	GO:0007229~integrin-mediated signaling pathway	6	241	0.0138	ADAM23, LAMA5, ITGA5, COL3A1, ADAM33, COL16A1
BP	GO:0051091~positive regulation of sequence-specific DNA binding transcription factor activity	6	241	0.0174	DDX58, FOXA1, PPARG, TRIM22, ANXA3, ZIC2
BP	GO:0033627~cell adhesion mediated by integrin	3	241	0.0189	ITGA5, FBN1, COL16A1
BP	GO:0006024~glycosaminoglycan biosynthetic process	4	241	0.0220	XYLT1, GALNT5, SLC35D2, HSPG2
BP	GO:0090280~positive regulation of calcium ion import	3	241	0.0240	CCL2, LGALS3, TRPV2
BP	GO:0030334~regulation of cell migration	5	241	0.0255	DDX58, LAMA4, LAMA5, ENPP2, DPYSL3

BP	GO:0030168~platelet activation	6	241	0.0256	F2RL2, RAC2, PLCG2, COL3A1, COL1A2, GAS6
BP	GO:0043691~reverse cholesterol transport	3	241	0.0268	APOE, CLU, ABCA1
BP	GO:0044267~cellular protein metabolic process	6	241	0.0273	TGFBI, CST3, HSPG2, UBE2L6, MMP2, MMP1
BP	GO:1902998~positive regulation of neurofibrillary tangle assembly	2	241	0.0284	APOE, CLU
BP	GO:0034344~regulation of type III interferon production	2	241	0.0284	DDX58, IFIH1
BP	GO:0048285~organelle fission	2	241	0.0284	MX1, MX2
BP	GO:0060700~regulation of ribonuclease activity	2	241	0.0284	OAS3, OAS1
BP	GO:1900221~regulation of beta- amyloid clearance	2	241	0.0284	APOE, CLU
BP	GO:1902622~regulation of neutrophil migration	2	241	0.0284	MYD88, RAC2
BP	GO:0032355~response to estradiol	6	241	0.0328	TXNIP, ASS1, C3, FOXA1, CST3, BDH1
BP	GO:0008544~epidermis development	5	241	0.0348	CRABP2, IFT172, DSP, POU3F2, EMP1
BP	GO:0042730~fibrinolysis	3	241	0.0358	SERPINB2, SERPING1, PLAU
BP	GO:0060279~positive regulation of ovulation	2	241	0.0423	INHBB, PLAU
BP	GO:0071400~cellular response to oleic acid	2	241	0.0423	ASS1, DGAT2
BP	GO:0002486~antigen processing and presentation of endogenous	2	241	0.0423	HLA-A, HLA-B

	peptide antigen via MHC class I via ER pathway, TAP-independent				
BP	GO:0035583~sequestering of TGFbeta in extracellular matrix	2	241	0.0423	LTBP1, FBN1
BP	GO:0060741~prostate gland stromal morphogenesis	2	241	0.0423	CRIP1, FOXA1
BP	GO:0070458~cellular detoxification of nitrogen compound	2	241	0.0423	GSTM1, GSTM3
BP	GO:0039528~cytoplasmic pattern recognition receptor signaling pathway in response to virus	2	241	0.0423	DDX58, IFIH1
BP	GO:0051260~protein homooligomerization	7	241	0.0439	KCNS3, GLUL, CEP57, C1QTNF1, DPYSL3, COLEC12, KCTD12
BP	GO:0045880~positive regulation of smoothened signaling pathway	3	241	0.0457	FOXA1, IFT172, PRRX1
BP	GO:0016032~viral process	10	241	0.0476	DDX58, IFIH1, ISG15, SLC25A4, HLA-A, RSAD2, APOBEC3G, HLA-B, TRIM22, MMP1
BP	GO:0001501~skeletal system development	6	241	0.0482	COL3A1, FBN1, COL1A2, BCAN, FRZB, COL5A2
MF	GO:0005201~extracellular matrix structural constituent	10	232	4.10E- 07	COL4A2, LAMA4, COL4A1, COL3A1, FBN1, COL1A2, BCAN, COL5A3, COL11A1, COL5A2

MF	GO:0001730~2'-5'-oligoadenylate synthetase activity	4	232	1.11E- 05	OASL, OAS3, OAS1, OAS2
MF	GO:0005178~integrin binding	10	232	1.81E- 05	ADAM23, LAMA5, ITGA5, FAP, FBLN5, TGFBI, COL3A1, FBN1, GPNMB, COL16A1
MF	GO:0005518~collagen binding	7	232	2.00E- 04	CTSL, CTSK, C1QTNF1, TGFBI, MRC2, COL5A3, PCOLCE
MF	GO:0003725~double-stranded RNA binding	7	232		DDX58, IFIH1, OASL, DDX60, OAS3, OAS1, OAS2
MF	GO:0048407~platelet-derived growth factor binding	4	232	4.25E- 04	COL4A1, COL3A1, COL1A2, COL6A1
MF	GO:0016740~transferase activity	8	232	_	GSTM1, OASL, SPTLC3, XYLT1, GALNT5, OAS3, OAS1, OAS2
MF	GO:0042802~identical protein binding	20	232	0.0012	S100A4, MTSS1, ASS1, PCBD1, PPARG, CST3, OPTN, EPHB2, DDX58, TRIM55, GLUL, GSTM3, MYD88, APOE, HSPB8, COL1A2, POU3F2, NEFL, DPP4, GBP1
MF	GO:0005509~calcium ion binding	22	232	0.0014	S100A4, S100A6, ME3, LTBP1, ENPP2, CD248, PAMR1, FAM20C, FBN1, HSPG2, S100A11, S100A10, C1R, CDH4,

MF	GO:0005102~receptor binding	14	232	0.0016	MMP1, ANXA3, GAS6, FAT3, FBLN5, AIF1L, NINL, RCN3 MTSS1, CCL2, C3, HLA- A, GJA1, HLA-B, ABCA1, CRAT, GAS6, EPHB2, LAMA4, SEMA4D, ANGPTL2, DPP4
MF	GO:0004252~serine-type endopeptidase activity	11	232	0.0019	CTSL, CTSK, C3, FAP, PAMR1, C1R, MMP2, DPP4, PLAU, MMP1, TMPRSS15
MF	GO:0030023~extracellular matrix constituent conferring elasticity	3	232	0.0029	COL4A1, FBN1, EMILIN1
MF	GO:0008270~zinc ion binding	30	232	0.0030	ABLIM1, S100A6, IFIH1, ENPP2, PPARG, MME, APOBEC3G, OAS1, OAS2, MMP2, MMP1, PEG10, CUL9, MT1E, ADAM33, XAF1, CRIP1, ADAM23, CA12, DTX3, HLTF, TRIM22, VAT1, QPCT, DDX58, TRIM55, CPE, LIMCH1, CHORDC1, CHFR
MF	GO:0030674~protein binding, bridging	6	232	0.0047	COL1A2, DSP, OPTN, TRIM22, COL11A1, NEFL

MF	GO:0050840~extracellular matrix binding	4	232	0.0057	CD248, TGFBI, OLFML2A, COL11A1
MF	GO:0030246~carbohydrate binding	9	232	0.0075	LGALS3, CD33, CLEC2B, CD248, GALNT5, MRC2, BCAN, CD24, AIM1
MF	GO:0043394~proteoglycan binding	3	232	0.0101	CTSL, CTSK, COL5A3
MF	GO:0015075~ion transmembrane transporter activity	3	232	0.0120	S100A6, TRPV2, GJA1
MF	GO:0005515~protein binding	105	232	0.0139	S100A4, S100A6, LTBP1, CRABP2, FAM20C, FGF13, APOBEC3G, ITPKB, MYD88, ISG15, APOE, ELOVL4, C80RF48, FAP, CUL9, TGFBI, MX1, TMPRSS15, KIF5C, HLA-A, CST3, SERPING1, OPTN, MOXD1, GRB10, HSPB8, CD33, COL1A2, DSP, CHORDC1, EMP1, GBP1, EID1, IFIH1, IFITM1, CLU, MME, OAS1, IGF2BP3, BDKRB2, ABCA1, PPP1R3C, PEG10, PPL, AHNAK2, LGALS3, ADAM23, FOXRED2, MRC2, UBE2L6,

S100A10, COL16A1, GAS6, EMILIN1, TRIM55, DDX58, C1ORF116, ITGA5, PLCG2, ANTXR2, IFI6, PLAU, E2F1, PPARG, GJA1, CDCP1, MLH3, FAM133A, USP18, DDX60, YAP1, DPP4, SLC25A4, CLIC2, HLTF, INHBB, CTSL, CTSK, FANCD2, SEMA4D, CHFR, C3, COL3A1, RSAD2, PCOLCE, PAIP2B, TNFRSF1B, CEP57, C1QTNF1, CD24, COL8A1, GPNMB, SCN5A, NEFL, GCHFR, TXNIP, FBN1, DTX3, HSPG2, ELAVL2, TRIM22, IFIT2, IFIT1, FBLN5, CAPG

MF	GO:0004222~metalloendopeptidase activity	6	232	0.0238	ADAM23, FAP, MME, ADAM33, MMP2, MMP1
ME	<b>-</b>	4	222	0.0200	,
MF	GO:0005044~scavenger receptor	4	232	0.0288	LGALS3BP, ENPP2,
	activity				COLEC12, TMPRSS15
MF	GO:0046977~TAP binding	2	232	0.0419	HLA-A, HLA-B
MF	GO:0005031~tumor necrosis	3	232	0.0449	TNFRSF1B, TNFRSF10D,
	factor-activated receptor activity				TNFRSF19

MF	GO:0008022~protein C-terminus	7	232	0.0462	SASH1, FBLN5, HSPG2,
	binding				STIP1, YAP1, OPTN,
					NEFL

Count: The number of genes in the input list that was found to be associated with the given GO term. List total: The total number of genes in the input list that are associated with GO terms in the DAVID database.

Table S4-8: Pathway analysis of 82 genes that were found to be associated with genomic variants that were specific to the FA sample group. Pathway analysis also confirms the association of the differentially expressed genes with the observed signs, symptoms and diseases typically seen in FA patients. The pathway analysis was performed using the REACTOME pathway online tool.

	#Entities	#Entities	Entities
Pathway name	found	total	pValue
Translocation of ZAP-70 to Immunological synapse	4	42	0.0002
Phosphorylation of CD3 and TCR zeta chains	4	45	0.0003
PD-1 signaling	4	45	0.0003
Generation of second messenger molecules	4	58	0.0007
Downstream TCR signaling	5	124	0.0016
MHC class II antigen presentation	5	142	0.0028
TCR signaling	5	146	0.0032
Costimulation by the CD28 family	4	96	0.0042
Synthesis of PIPs at the late endosome membrane	2	21	0.0091
TFAP2 (AP-2) family regulates transcription of growth			
factors and their receptors	2	21	0.0091
Metabolism of Angiotensinogen to Angiotensins	2	26	0.0136
Synthesis of PIPs at the early endosome membrane	2	29	0.0167
Activation of Matrix Metalloproteinases	2	35	0.0237
Defective SLC22A18 causes lung cancer (LNCR) and			
embryonal rhabdomyosarcoma 1 (RMSE1)	1	4	0.0266
Vpr-mediated induction of apoptosis by mitochondrial outer			
membrane permeabilization	1	4	0.0266
Adaptive Immune System	13	1076	0.0284
Interferon gamma signaling	4	176	0.0317
Transport of the SLBP independent Mature mRNA	1	5	0.0332

Defective CYP19A1 causes Aromatase excess syndrome			
(AEXS)	1	5	0.0332
Formation of apoptosome	1	5	0.0332
SMAC-mediated apoptotic response	1	5	0.0332
SMAC-mediated dissociation of IAP:caspase complexes	1	5	0.0332
SMAC binds to IAPs	1	5	0.0332
Lysosome Vesicle Biogenesis	2	43	0.0345
Transport of the SLBP Dependant Mature mRNA	1	6	0.0397
PLCG1 events in ERBB2 signaling	1	6	0.0397
Signaling by Overexpressed Wild-Type EGFR in Cancer	1	6	0.0397
Inhibition of Signaling by Overexpressed EGFR	1	6	0.0397
Activation of caspases through apoptosome-mediated			
cleavage	1	7	0.0462
Cytochrome c-mediated apoptotic response	1	7	0.0462
Transcriptional regulation by the AP-2 (TFAP2) family of			
transcription factors	2	52	0.0486

Entities found: Number of genes in the input list that were found to be associated with a pathway. Entities total:

Total number of genes that are associated with a given pathway in the reactome database.

Table S4-9: Pathway analysis of 618 genes that were found to be associated with variants that were commonly found in all 4 Fanconi Anemia samples. The genomic variants are found in pathways that were highly correlated with the significant pathways identified through expression changes. The pathway analysis was performed using the REACTOME pathway online tool.

	#Entities	#Entities	Entities
Pathway name	found	total	pValue
Interferon gamma signaling	19	176	0.0016
Antigen Presentation: Folding, assembly and peptide loading of			
class I MHC	11	102	0.0142
Defective GALNT3 causes familial hyperphosphatemic tumoral			
calcinosis (HFTC)	4	20	0.0182
Defective GALNT12 causes colorectal cancer 1 (CRCS1)	4	20	0.0182
Defective C1GALT1C1 causes Tn polyagglutination syndrome			
(TNPS)	4	20	0.0182
Translocation of ZAP-70 to Immunological synapse	6	42	0.0193
Endosomal/Vacuolar pathway	9	82	0.0227
Interferon alpha/beta signaling	13	140	0.0244
PD-1 signaling	6	45	0.0259
TRKA activation by NGF	2	5	0.0260
Olfactory Signaling Pathway	31	432	0.0272
Interferon Signaling	22	291	0.0354
APC truncation mutants are not K63 polyubiquitinated	1	1	0.0483

Entities found: Number of genes in the input list that were found to be associated with a pathway. Entities total: Total number of genes that are associated with a given pathway in the reactome database.

**Chapter 5: Concluding remarks and future directions** 

### RESEARCH OVERVIEW AND CONCLUSION

The thesis presented here consists of three comprehensive studies that shed light on different research paradigms of repetitive DNA, microsatellites (MST) in particular, which have been relatively understudied, despite being linked to several disorders such as Huntington disease and Fragile X syndrome¹⁻³. This thesis represents a much-needed improvement in building computational tools, a novel utilization of target specific sequencing techniques to facilitate MST genomics research, and a possible validation of the involvement of MST instability (MSI) in cancer progression based on MSI signatures for congenital inheritance of cancer⁴. A part of this work also investigates the role of molecular level cellular processes that may give rise to MST instability, other than the well-studied mismatch repair process⁵⁻⁸.

The results of this work can be useful in three areas of research: 1. The utilization of global MST enrichment to further genomic research, 2. The power of target specific MST enrichment and its utility in the development of high-accuracy companion diagnostics in cancer (and other diseases) and 3. Recommendations for further MST instability research using DNA repair deficient cellular systems.

### **Global MST enrichment:**

Since the advent of genomic research, the focus of biologists on the coding regions of the genome and the development of tools for studying these protein coding genomic sequences have resulted in a large gap in our understanding of repeat regions that form about 47% of the human genome⁴. This has not only directly contributed to the existence of the incomplete knowledge of the euchromatic DNA, but has also contributed to the failure to address the possibility of uncovering important functional elements that could be hidden among the repetitive regions of

the human genome. Since the completion of the human genome project, at which point 94% of the euchromatic DNA was known, recent efforts have advanced the euchromatic DNA framework to 99%^{9,10}. Using our newly developed molecular techniques and computational methods we successfully sequenced novel MST sequences in the human genome, demonstrating the potential for detecting novel MST sequences that can help in the possible identification of the 1% of unknown euchromatic DNA. Specifically, our assembly technique can detect longer MSTs, which is not possible through currently available genomic enrichment and computational methods⁴. This work also identifies novel functional elements that could potentially shed light on biological issues such as the existence of multiple isoforms of rRNA.

The results, while showing potential for aiding in the completion of the euchromatic human DNA, also holds the promise of advancing the completion of other genomes that have even higher content of repetitive DNA sequences. Figure S2-4 shows the distribution of the length of the novel contiguous sequences that were assembled using our global MST enrichment technique. While sequencing of MSTs by whole genome or exome enrichments usually allow the detection of 100 to 200 bp MST sequences, the global MST enrichment, coupled with appropriate assembling tools, enables the detection of longer MST sequence regions (250 to 500 bp) (Figure S2-4).

## This technique shows promise in 3 ways:

1. With the advent of better sequencing technologies, in the future, that can provide longer sequencing reads without compromising the read depth, longer novel contiguous sequences (contigs) can be assembled. This will aid in the sequencing of more functional elements, directly adding to the knowledge of human genetics and

disease. For example, 37 novel contigs assembled (Table 2-3) using the global MST enrichment technique were found in 1kGP RNA-Seq samples. The contig with the highest number of hits in the 10 RNA-Seq samples was found in large clone DNA sequences that were sequenced as a part of the original (pre-nextgen) human genome project but was, conspicuously, not found in the reference genome. This contig is 370 bp and a portion of which was found to match with high sequence identity (99%) to multiple rRNA subunits. Recent studies in parasite models suggest the diverse evolution of rRNA subunits to accommodate specific functions that are, specific to subnuclear compartments¹¹. The study by Deveau *et al* shows the diversification of two rRNA subunits in a protozoan parasite. By the targeted sequencing of MST, novel functional elements identification is possible and their discoveries, like the rRNA sequence, have the potential to contribute to answering numerous biomolecular questions.

- 2. This technique may contribute even more when used for genomes of plants and amphibians. The repetitive DNA content of amphibians, plants and insects have been shown to be higher than that of the human genome¹². The probability of finding functional elements and genes in the refractory regions of these repeat heavy genomes is high.
- 3. One of the most interesting findings of this study was the abundance of two pentamer MST repeats. While the telomere regions are known to have a high percentage of the hexamer repeat GGGTTA, the finding of these pentamer repeats, AATGG and GTGGA, and their comparative abundance sheds new light onto the repeat rich telomere and centromere regions of the chromosomes. Telomere shortening has been linked to aging, cancer and other diseases¹³⁻¹⁶. Access to the functional elements of these repeat heavy regions can possibly help understand the

reason behind the connection between telomere shortening and associated disorders¹⁶.

### **Target specific MST enrichment:**

Coupled with the inefficiency (especially low depth coverage, that limits accuracy) of normal exome enrichment methods for sequencing MSTs, the high sequence (40X) coverage requirement of MST genotyping programs present a highly challenging problem^{4,17,18}. The MST genotyping methodology involves specific statistical steps that allow the accommodation of low MST sequence coverage from exome enrichments to be efficiently utilized¹⁹⁻²². While the Garner lab has shown convincingly the statistical significance of the MST instability in breast, ovarian and brain cancers, the validation of these findings remained to be completed¹⁹⁻²² By using Illumina's target specific enrichment, this validation was made possible in a lung cancer scenario that involved lung cancer and normal sample sets apart from the publically downloaded LUSC and LUAD germline samples from the TCGA and 1kGP (Tables S3-3 and S3-4). This work resulted in a signature set of 21 MST loci (all located in gene regions), 57% or more of which were found in a cancer genotype with a sensitivity ratio of 0.93 (Figure 3-3).

## **Applications and future directions:**

This work, while providing the first validation for a possible link between specific microsatellite mutations and cancer, is also a technique that can be adapted to be used as a companion diagnostic in oncological health care facilities. Next to the wide spread usage of the Bethesda markers for forensic identifications, this technique presents an opportunity for introducing a MST based marker kit for disease diagnostics.

While MSI based markers for colon cancer is well known, the involvement of MSI in cancer was not confirmed until recently ²³⁻²⁵. This target specific MST enrichment will show the possibility of developing a next generation sequencing (ultra-high resolution) based diagnostic kit for all MSI positive disorders. More importantly, as demonstrated in Chapter 3, it is known that ultra-high-depth sequencing and normal exome sequencing can indicate different genotypes. This method, hence, not only presents an accurate way of MST genotyping but also introduces the opportunity to develop a genome wide MST specific enrichment sequencing process. Also, this enrichment method will allow us to revise observations from previous genome wide MST genotyping studies that may be incorrect, and will also provide a strong platform to understand in high resolution the heterozygosity-homozygosity ratio of cancer tissues and MST^{17,18}.

Perhaps one of the most appealing direct applications of this work, specific to lung cancer, is the early diagnosis of lung cancer in never smokers. About 20% of lung cancer cases with non-small cell lung cancer are reported to be non-smokers²⁶. The theory that these cases could have inherited lung cancer signature from their parents is highly probable. As this work is based on genotyping MST from the germline cells of patients, this diagnostic kit could be applied to detect any future onsets of lung cancer in never smokers with a lung cancer familial trait^{27,28}.

### Fanconi anemia

# Fanconi anemia, as a DNA repair deficiency disorder:

Fanconi anemia is an autosomal recessive disorder that occurs mainly in Jewish populations²⁹. When one of the 16 genes, that code for the DNA inter-strand crosslink repair complex of the Fanconi anemia (FA) pathway, harbor a protein

modifying mutation, FA is likely to occur^{30,31}. Much information about the FA genes that are involved in crosslink repair have been reported, thanks to the availability of a variety patient samples, which has divided the FA genes into complementation groups³²⁻³⁷. Although the FA core complex has been studied extensively, the details of this pathway are not entirely understood. It is well established that the FA pathway recruits DNA repair proteins to crosslink sites, however, there are also studies that suggest that the FA pathway might also be involved in the maintenance of general genomic stability³⁸. Also, recent studies reveal the involvement of the FA pathway in MST instability³⁹⁻⁴¹.

The hypothesis of this project is twofold: 1. By sequencing PD20-FA cell lines with defective FANCD2 gene and PD20-FA cell lines with retrovirus corrected FANCD2 gene and understanding their genomic variants and difference in gene expression patterns, we will be able to understand the effects of a dysfunctional FANCD2 gene on the genome and the transcriptome and by that come to a first-hand understanding of the other roles of a functioning FA pathway. 2. By performing MST genotyping on FA samples we can estimate any possible effects of a dysfunctional FA pathway on MST instability.

### Over all conclusion:

Genomic variant analysis on the ratio of SNPs vs. INDELs show an increased percentage of INDELs in the FA samples, compared to 1kGP samples. This suggests an increased amount of DNA lesions which can be the result of uncorrected DNA crosslinks (Table 4-3). The difference in SNP and INDEL variations within biological replicates (tables 4-5 and 4-6) suggest a high heterogeneity and a significant effect of a dysfunctional FA pathway on the transcriptome. Unlike non-existent gene expression difference between biological replicates, the exon count

(transcript length) of the most expressed transcript of genes show that a large number of genes (23.5%) within biological replicates have varying exon counts (Table S4-6) which is consistent with the observed genomic damage. This, again, demonstrates the pronounced effect of a dysfunctional FA pathway on the transcriptome. Also, the significant increase in the percentage of MSTs with minor alleles in the FA samples (Table 4-4), compared to the 1kGP samples, suggest that the FA pathway, when not functional, could also be another source of MST instability, along with the DNA mismatch repair mechanisms.

### **Future directions:**

Owing to the significant increase in the MST instability (MST with minor alleles) in the FA samples, the hypothesized possibility of the FA pathway contributing to MST instability becomes more evident. While this confirms the FA cell line system to be a prospective platform for studying the FA pathway and MSI, a few factors should be included in future experimental designs. A time-lapse longitudinal study that involves DNA extraction from FA and FA_RV samples at different time points or at different passage numbers during cell culturing is needed to understand the progression rate of DNA damage in FA cells and the progression rate of DNA damage in FA RV cells.

Quantifying DNA breaks that occur in the form of chromosomal translocations in FA genomes are important to better understand inter-strand crosslink occurrences. While SNPs and INDELs form an essential variant determination paradigm, the quantification of DNA translocations is a critical way of determining the effect of a corrected or dysfunctional DNA repair gene on the genome. Recent advances in translocation sequencing present an opportunity to quantify double strand break caused chromosomal translocations 42-44. DNA samples from cells that are treated

with crosslink inducing agents such as mitomycin C were previously thought to be unsuitable for sequencing, but with the advent of translocation sequencing, the genome-wide effect of mitomycin and the counter effect of a functional FA pathway can be studied with high precision.

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