**Supporting Information**

**SI Materials and Methods**

### **Sample Information**

Plasma was purified from 1348 healthy individuals and 883 patients with cancer using Qiagen kit catalog #937556 (QIAsymphony DSP Circulating DNA Kit) or Biochain kit catalog #K5011625MA. All individuals participating in the study provided written informed consent after approval by the institutional review board at the patients' participating institutions. Their demographic information is included in Dataset S6.

### **Primer Development**

We first calculated the frequency all possible 6-mers ( $4^6$  = 4096) in the genomic regions within the hg19 RepeatMasker track (Fig. S1). Next, we calculated the frequency of all possible 4-mers (4^4 = 256) within 75 bp upstream or downstream from the 6-mers. Joining the 6-mers with the 4-mers generated 2,097,152 candidate pairs. We narrowed these pairs based on the number of unique genomic loci expected from their PCR-mediated amplification, the average size between the 6-mer and its corresponding 4-mers, and the distribution of these sizes, aiming for a unimodal distribution. This filtering criteria generated 7 potential k-mer pairs that were each used to design primer pairs for PCR. (Supplementary Table 1). Each primer pair had with a 6-mer at the 3'-end of one primer and a 4-mer at the 3'-end of the other primer (Fig. S1). Nucleotides upstream of the 6-mers and 4-mers within the primers were then added, informed by the most common nucleotides at the predicted amplicons and their predicted melting temperatures; optimally, all amplicons generated with a specific primer pair should have identical melting temperatures. The seven primer pairs (Supplementary Table 1) that were generated in this way were then tested on genomic DNA in pilot tests. Two of the 7 primer pairs (REAL1 and REAL2) outperformed the remaining 5 primers in tests, as assessed by the number of unique loci that could be amplified and the size distribution of the amplicons. After further experimental testing on 100 peripheral blood samples, REAL-1 was chosen for all of the experiments described in the main text.

Bowtie2 was used to align reads of the amplicons to the human reference genome assembly GRC37 (1). Because we expected many amplicons to have non-perfect primer matching, we only searched for a section of the reverse primer (AGTC, CCCA, TACT, or ACTT ) during primer stripping. With REAL-1 primers, an average of 51.1% of the total reads could be uniquely aligned in this fashion. In Fig. S2 and in Dataset S1, we report the size of the unique genomic regions that were identified by this alignment. The average sizes of these genomic regions (bases between primers) was 43 bp. This is an estimate that does

not fully capture any amplicons that are very long or those in which there was more than one sequence that closely matched the reverse primer within a few hundred bases of the forward primer. A more precise way to calculate the size of each amplicon would be to perform paired end sequencing. From paired end sequencing of 40 different plasma and 40 different peripheral white blood cell samples, we found that 19% of the amplicons could be more accurately mapped if paired end sequencing were used. While paired end sequencing can thereby provide more accurate information of amplicon sizes, it is significantly more costly and time consuming that using single end sequencing. Moreover, the more accurate sizing of amplicons did not alter their mapping, which was the key to aneuploidy analysis. REAL1 was theoretically able to amplify up to 745,184 repetitive elements (Supplementary Data 1). However, an average of only 350,000 repetitive elements were observed among the 2231 plasma samples evaluated in this study. There are several potential reasons for the discrepancy between the potential number and the actual observed number of amplicons: 1) Polymorphisms within the amplified sequences may cause misalignment and result in "missing amplicons;" 2) Polymorphisms within the primers may result in amplification failures. 3) Each amplicon has a different PCR efficiency based on GC content, size and other variables. Low efficiency amplicons may be outcompeted during PCR and not be present. 4) Long amplicons may be absent in cell free DNA due to the small sizes of the DNA fragments in cell free DNA. 5) The amount of sequencing performed may not be high enough to observe every amplicon, especially those with low PCR efficiency. 6) Some repetitive elements may not be present in every individual.

Within REAL-1 primer-generated amplicons, we identified 52,762 polymorphisms. The average number of heterozygous sites per patient was 2,200 and these sites could be used to measure allelic imbalance, identify samples, and determine whether samples had been accidentally mixed together. Scripts for allelic imbalance are in a github repository and available upon request. Using the same SNPs, synthetic experiments were used to estimate that sample mixing could be detected when the amount of one DNA sample was >4% of the amount of the second DNA sample in a given mixture.

### **Experimental Protocol**

PCR was performed in 25 uL reactions containing 7.25 uL of water, 0.125 uL of each primer, 12.5 uL of NEBNext Ultra II Q5 Master Mix (New England Biolabs cat # M0544S), and 5 uL of DNA. The cycling conditions were: one cycle of 98°C for 120 s, then 15 cycles of 98°C for 10 s, 57°C for 120 s, and 72°C for 120 s. Each plasma DNA sample was assessed in eight independent reactions, and the amount of DNA per reaction varied from ~0.1 ng to 0.25 ng. A second round of PCR was then performed to add dual indexes (barcodes) to each PCR product prior to sequencing. The forward and reverse primers used for the second round of PCR are listed in Supplementary Table 1. The second round of PCR was performed in 25 uL reactions containing 7.25 uL of water, 0.125 uL of each primer, 12.5 uL of NEBNext Ultra II Q5 Master Mix (New England Biolabs cat # M0544S), and 5 uL of DNA containing 5% of the PCR product from the first round. The cycling conditions were: one cycle of 98°C for 120 s, then 15 cycles of 98°C for 10 s, 65°C for 15 s, and 72°C for 120 s. Amplification products from the second round were purified

with AMPure XP beads (Beckman cat # a63880), as per the manufacturer's instructions, prior to sequencing. As noted above, each sample was amplified in eight independent PCRs in the first round. Each of the eight independent PCRs was then re-amplified using index primers in the second PCR round. The sequencing reads from the 8 replicates were summed for the bioinformatic analysis but could also be assessed individually for quality control purposes.

All oligonucleotides were purchased from IDT (Coralville, Iowa). Massively parallel sequencing was performed on an Illumina HiSeq 4000. During the first round of PCR, degenerate bases at the 5' end of one of the primers were used as molecular barcodes (unique identifiers, UIDs) to uniquely label each DNA template molecule (2). This ensured that each DNA template molecule was counted only once, as described in (2). In all instances in this paper, the term "reads" refers to uniquely identified reads (UIDs). Depending on the experiment, each read was sequenced on average 1.17 times. An average of 13.2 million reads per sample (IQR 7.9M to 15.2M) was assessed. If multiple reads had the same UID, we required at least 50% of the reads to map to the same genomic location. Reads with the same UID, but with discordant genomic locations were discarded from analysis.

# **ReqlSeqS Bioinformatic Analysis**

The Within-Sample Aneuploidy DetectiOn (WALDO) approach was developed to detect the presence of aneuploidy in amplicon sequencing reads (3). Unlike conventional WGS approaches that assess aneuploidy, WALDO does not compare normalized read counts in a test sample to the normalized read counts in a panel of normal samples. Direct comparisons are subject to batch effects and can introduce new artifacts (4). WALDO attempts to mitigate problematic batch effects using a within sample comparison. We tailored this approach for our RealSeqS assay and made several analytical improvements (Fig. S2). The major modifications included a new normalization step, a new way to evaluate copy number changes involving small regions of chromosome arms, and an improved way to detect genome-wide aneuploidy, as described below. These analytical improvements coupled with the increased genomic density of amplicons achieved with REAL1 primers enabled greater sensitivity as well as the detection of focal amplifications and deletions less than 1 Mb in size, which was not possible with FAST-SeqS.

### **Normalization**

We employed a new method of normalization which mitigated the impact of highly correlated chromosome region amplifications among samples and ultimately reduced the variability among samples. To perform this normalization, we employed the following steps:

Normalization Training: For all controls (n= C)

- 1) Bin read counts for each control sample into 5,344 autosomal intervals of 500 kb.
- 2) Divide the read counts by the total coverage to control for coverage differences.
- 3) Using the entire set of controls, project the 5,344 500kb intervals into PCA space using the builtin R function "prcomp". Principal component analysis is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Each principal component is a linear combination of the 5,344 500kb intervals.
- 4) Store the linear combinations of the 5,344 500kb intervals so that test samples can be projected into the same PCA space.
- 5) Store the first 5 PCA dimensions as a 5xC matrix.
- 6) Define a new variable termed "correction factor".

Unseen hidden variables can impact interval read counts. Because all control samples are euploid, we assume that read count variability for a particular interval will be caused by random noise and hidden variables.

In the prior steps, we calculated the principal components which serve as proxies for unseen hidden variables.

Ultimately, we would like to learn the relationship of hidden variables to read counts for a particular interval. By determining the relationship of principal components to the expected read counts for a particular interval, the read counts for a future unlabeled test sample can be appropriately adjusted given a its principal components.

**Note: you can only directly calculate the correlation factor term using the equation below for the euploid control samples.** A future unlabeled test sample may or may not euploid. If the sample is not euploid, read count variability within the interval maybe caused by amplifications/deletions not just random noise or hidden variables.

Correction Factor for 500kb Interval<sub>i</sub> =  $\frac{\mu_i}{Observed_i}$ 

where:

 $\mu_i$  is the numerical mean of read counts (after controlling for coverage differences)

# calculated for all controls in Interval;

Observed<sub>i</sub> is the observed read depth in Interval<sub>i</sub> (after controlling for coverage differences)

- 7) For each control sample, calculate the "correction factor."
- 8) Store every correction factor as a 1xC vector.
- 9) Define a regression model using the following equation (i=1).
	- a. Correction factors are calculated in Step 6.

- b. PCA coordinates are defined in Steps 2-4.
- c.  $\beta$  parameters are undefined.

Correction Factor for 500kb Interval,  $= \beta_{0i} + \beta_{1i} * PCA_1 + \beta_{2i} * PCA_2 + \beta_{3i} * PCA_3 + \beta_{4i} * PCA_4 + \beta_{5i} * PCA_5$ 

- 10) Estimate the β parameters using the built-in linear regression function "lm" in R. The correction factor is a 1xC vector from Step 8 and the PCA coordinates are a 5xC matrix from Step 5 (i=1).
- 11) Store the β parameters for Interval i (when i=1).
- 12) Repeat Steps 6-11 for the remaining 5,343 intervals (i=2…5344). At the conclusion of this process, we have a matrix of 6 columns (β parameters) by 5,344 (One for each 500kb interval).

Normalization of test samples:

- 1) Bin read counts for a new test sample into 5,344 500kb intervals.
- 2) Divide the observed read counts by the total coverage to control for coverage differences.
- 3) Using the predefined linear combinations defined above during PCA analysis (Step 4), calculate the test sample's principal components.
- 4) Using the regression β parameters from above, estimate the correction factor for the new test sample on Interval i=1 (ie how much should the sample differ from the average normal sample given its principal components).

Correction Factor for 500kb Intervali

 $= \beta_{0} + \beta_{1} * PCA_1 + \beta_{2} * PCA_2 + \beta_{3} * PCA_3 + \beta_{4} * PCA_4 + \beta_{5} * PCA_5$ 

- 5) Multiply the test sample's observed read count in Interval 1 by the estimated correction factor.
- 6) Repeat Steps 4 and 5 for the remaining 5343 intervals.

Scripts for normalization are in a github repository and available upon request.

# **Copy number variants affecting relatively small chromosome regions**

The original WALDO method required the specification of a particular genomic region of interest (usually an entire chromosome arm) and then calculate the statistical significance of the desired region. For REALSeqS, we incorporated the ability to detect copy number variants affecting relatively small regions of a chromosome arm. To do so, we calculated the log ratio of the observed test sample and WALDO predicted values from every 500 kb interval across each chromosomal arm. Using the log ratio, we applied a circular binary segmentation algorithm (5) to find copy number variants throughout each chromosome arm. Any copy number variant ≤ 5Mb in size was flagged. Before calculating the statistical significance across each chromosome arm, these flagged CNVs were removed. Because we were

interested in chromosomal abnormalities affecting a large part of a chromosome arm, these small CNVs were not critical for achieving the main goals of the current study. However, the small CNVs could be used to assess microdeletions or microamplifications, such as those occurring in DiGeorge Syndrome (chromosome 22q11.2 or in breast cancers (chromosome 17q12) (Fig. 3 in main text), and for other applications of RealSeqS in the future.

# **Genome Wide Aneuploidy**

A two-class support vector machine (SVM) (6) was trained to discriminate between euploid samples and aneuploid samples. The training set contained a negative class of 1348 presumably euploid plasma samples from normal individuals containing at least 2.5 M reads and 2651 aneuploid samples. The aneuploid class contained a mixture of 2016 *in silico* simulated samples and 635 actual aneuploid samples. SVM training was done with the e1071 package in R, using radial basis kernel and default parameters (7). Each sample had 39 Z-score features, representing chromosome arm gains and losses. During training, the positive class was randomly sampled so that the positive class was 10% the size of the negative class. The positive class was randomly sampled at a ratio of two real samples to one *in silico*  simulated sample. Ten iterations of this procedure were performed. The final genome wide aneuploidy score was the average of the raw svm score across the 10 iterations.

# **Sample Exclusion Criteria**

To ensure that all samples included in the results section of paper were of high quality, we developed several exclusion criteria. 1) Samples with less than 2.5M reads were excluded. 2) Samples with sufficient evidence of contamination from at least two genetically unrelated individuals were excluded. To be labeled as contaminated, the sample had to have at least 10 significant allelic imbalanced chromosome arms (z score  $>= 2.5$ ) and fewer than ten significant chromosome arms gains or losses (z  $>=$ 2.5 or z<= -2.5). Allelic imbalance is determined from SNPs, while gains or losses were assessed through WALDO (3). A large number of chromosome arms with allelic imbalance in the absence of a large number of gains or losses indicated that the tested sample contained DNA from at least two genetically unrelated individuals. 3) We excluded samples in which more than 8.15% of the amplicons were larger than 50 base pairs between the forward and reverse primers. Such samples were likely to be contaminated with leukocyte DNA, as inferred from the comparison to RealSeqS data in leukocyte DNA and the distribution of this metric in plasma DNA (Fig. S3). This criterion excluded 16 samples from cancer patients and 27 samples from normal individuals (Fig. S3). 4) An additional QC metric was designed because reads that map to chromosome arms 2q, 3q, 4q, 5q, 6q, 8q, and 13q were highly correlated, as indicated by the matrix in SI Appendix Table S7. The QC metric was defined in the following way:

$$
QCDynamic Range Metric = \sum_{i}^{2q,3q,4q,5q,6q,8q,13q} \frac{Reads \ on \ chr_i}{\sum_{j=1}^{39}Reads \ on \ chr_j}
$$

The distribution of this metric had long tails (Fig. S4). Samples which were outliers as defined by this metric (<0.2320 or > 0.2450). This QC metric removed 30 cancer samples and 24 normal samples. Nine samples failed both DNA size and QC.

# **Generation of** *in silico* **simulated samples harboring aneuploidy.**

We first selected data from 84 presumably euploid plasma samples, each containing at least 10 million reads. *In Silico* simulated aneuploid samples were created by adding (or subtracting) reads from several chromosome arms to the reads from these normal DNA samples. We added or subtracted the reads from 1, 10, 15, or 20 chromosome arms to each sample. The additions and subtractions were designed to represent neoplastic cell fractions ranging from 0.5% to 1.5% and resulted in *in silico* simulated samples containing exactly ten million reads. The reads from each chromosome arm were added or subtracted according to the pseudocode in Fig S6 and S7. For example, when we modeled five chromosome arms that were lost, each was lost to the identical degree and we did not incorporate tumor heterogeneity into the model. Furthermore, we did not create *in silico* simulated samples containing more than three of any chromosome arm; e.g. 4 copies of chromosome 3p. This simplified approach did not comprehensively cover all biologically plausible aneuploidy events. However, limiting the possible combinations of altered arms made sample generation computationally tractable, and the resulting support vector machine appeared to work well in practice. The synthetically generated samples in which reads from only a single chromosome arm were added or subtracted enabled us to estimate the performance of WALDO when only a single chromosome arm of interest was gained or lost.

# **Comparison to Various Massively Parallel Sequencing Technologies**

We selected 10 publicly available plasma samples from normal individuals on which whole genome sequencing had been performed (8). Each of the ten samples had been sequenced at a depth of  $\sim$ 144 M reads. The authors performed bioinformatic filters to remove highly polymorphic locations (9) and common insertions/deletions (10). Reads on the sex chromosomes, contigs, and acrocentric chromosome arms were dropped. The fraction of reads for each of the 39 non-acrocentric chromosome arms were calculated from the remaining reads. The fraction of reads for each of the 39 non-acrocentric autosomal chromosome arms is reproduced in Supplementary Table 2.

We then selected ten samples of normal individuals studied by FAST-SeqS with an average of 10 M reads and ten samples from normal individuals studied by ReqlSeqS with an average of 28 M reads. The fraction of reads on each chromosome arm is recorded in Supplementary Tables 3 and 4, respectively.

*In silico* simulated aneuploid samples were generated at 5% cell fraction to represent the amount of fetal DNA typically present in noninvasive prenatal testing (NIPT) to compare whole genome sequencing, FAST-SeqS, and ReqlSeqS. We evaluated trisomies and monosomies for each of the 39 chromosome arms as well as the 1.5 MB DiGeorge deletion (22:19009792-20509792). Next, we generated focal amplifications of ERBB2 (17:37819167-37911679 20 copies) at 1% cell fraction to represent the amount of tumor DNA typically present in liquid biopsies from late stage patients. FAST-SeqS does not have the spatial genomic density to cover the region of interest of ERBB2 and could not be evaluated for this purpose.

Aneuploidies were generated at various sequencing depths of 2M, 10M, 40M reads. The statistical significance was calculated using a simple z score defined below. Sensitivities were calculated based on Z > 2.575 and Z < -2.575 (alpha=0.01).

 $Z_{chr@Depth} = \frac{Observed_{@Depth}-\mu_{normal}}{\sigma_{normal\ panel\ @Depth}}$ 

# **Reduced Requirements for DNA Input**

A major advantage of amplicon sequencing is the reduced requirement for input DNA. To test whether ReqlSeqS could reliably detect aneuploidy with less than one genome equivalent, we evaluated trisomy 21 samples and normal euploid DNA at various amounts of input DNA (3 to 225pg). The relationship of reads to DNA was based on negative controls (water wells with no DNA) and the known concentration of the euploid control (Sample DNA concentration in picograms=7e-5\*Read Depth-0.5196). Trisomy 21 was scored as detected in samples with z>5. No other arms were aneuploid in the trisomy 21 samples at this z-score and no arms were aneuploid in the euploid controls at this z-score (Supplementary Data 2).

# **Detection of leukocyte DNA in cell free DNA**

Leukocyte DNA (gDNA) has an average size of >1000 bp while cell-free plasma DNA has an average size of < 200 bp. DNA size impacts PCR efficiency and long amplicons may not be present in cfDNA. ReqlSeqS enables the detection of leukocyte DNA contamination by virtue of the amplicons generated with REAL-1 primers.

We selected 50 plasma samples aand 50 gDNA samples. We found 1241 amplicons (Supplementary Data 3) that were not present in the plasma samples (< 5 reads across all samples) but were present in the gDNA samples (>1000 reads across all samples).

We mixed DNA from leuokocytes into cell free DNA from a euploid plasma sample at various dilutions ranging from 4% to 54%. The fraction of reads mapping to the 1241 amplicons in the contaminated samples were more than 3 times higher than the euploid sample (Supplementary Table 5).

# **Comparison of Aneuploidy Detection and Somatic Mutation Detection**

For this study, we evaluated aneuploidy in plasma from 1348 healthy individuals and 883 cancer patients. We selected a cutoff (0.441) that produced 99% specificity in 1348 healthy individuals and calculated sensitivity on the 883 cancer patients. A detailed table of the aneuploidy results is included in Supplementary Data 4.

Cohen et al evaluated 812 plasma samples from healthy patients for somatic mutation detection. We selected an omega cutoff (1.77) that produced 99% specificity and calculated sensitivity on the same 883 cancer patients that were used in our study.

# **Detection of cancer using a multi-analyte test**

Cohen *et al*. (11) demonstrated that combining somatic mutations and protein markers can better predict cancer status of plasma samples than either type of marker alone. We determined whether aneuploidy could be integrated as an additional biomarker into the published logistic regression framework.

In Cohen *et al*., 812 plasma samples were from healthy individuals and 1005 were from cancer patients. Our study analyzed 1348 plasma samples from healthy individuals and 883 from cancer patients. Of the 1348 healthy samples, only 248 overlapped with the original study. All 883 cancer samples were included in the original study. The sample demographic information is provided in Supplementary Data 5.

Using the original 812 healthy samples and the 883 cancer samples, we trained a logistic regression model and assessed performance using ten rounds of tenfold cross validation. A full list of samples and their biomarker values was provided in Supplementary Data 6. Because 564 of the original healthy samples were not analyzed for aneuploidy, we randomly sampled the list of scores from the 1348 normal samples and assigned each missing sample an aneuploidy value. Ten rounds of analysis were performed and each new round, we randomly sampled the collection of 1348 normal scores again to assign the 564 samples a new score.

To account for variations in the lower limits of detection across different experiments, we found the 90<sup>th</sup> percentile feature value in the healthy training samples. We then found any feature value below that

threshold and set all values to the 90<sup>th</sup> percentile threshold. This transformation was done for all training and testing samples. This procedure was done for aneuploidy scores, somatic mutation scores, and protein concentrations. The 90<sup>th</sup> percentile thresholds were listed in Supplementary Table 6. The results from each round and each cross validation fold are included in Supplementary Data 7. The final feature coefficients from the logistic regression model are listed in Supplementary Table 6.

# **Aneuploidy Tumor Concordance**

As noted in the main test, we compared chromosomal gains or losses in the plasma to those observed in primary tumors from the same patients. If RealSeqS data indicating aneuploidy were "real", one would expect that those chromosome arms exhibiting gains in plasma would also exhibit gains in the corresponding primary tumors. Similarly, one would expect that those chromosome arms exhibiting losses in the plasma would also exhibit losses in the corresponding primary tumors. We were able to perform this analysis in 243 instances (214 patients) in which chromosome arm losses or gains were significant (z-scores >4 or <-4) in plasma DNA. Of these 243, 188 (77%) were found to be concordant in their respective tumors at a z-score >2 or <-2 when assessed by FAST-SeqS and previously reported (Supplementary Appendix and Dataset S9). Note that concordance was directional; if a gain of a chromosome arm was found in the plasma, a gain (rather than a loss) had to be identified in the primary tumor and vice versa. Concordance was calculated as the number of concordant arms in the plasma divided by the total number of significant gains and losses in plasma. Chromosome arms 19p and 19q were RealSeqS due to the high false positive rate on these arms.

We did not expect perfect concordance between the plasma and tumors for the following reasons. Plasma samples with focal amplifications or deletions can produce highly significant arm level scores. These focal changes may have been captured with REALSeqS performed on the plasma DNA as a result of the increased spatial genomic coverage but missed in FAST-SeqS performed on the primary tumor DNA. Additionally, using a within sample normalization has been shown to improve performance at low amounts of tumor DNA but the statistical assumptions underlying the normalization principle breakdown with increased amounts of tumor DNA. Evaluating widely aneuploid tumor samples using a within sample normalization approach can produce false negatives, particularly on the smaller chromosome arms.

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**Table S1:** The 7 primer pairs chosen for experimental analysis. The 6mer and 4mer used during design are in red font

cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNGGTGAAACCCCGTCTCTACA	REAL1a z4	cacacaggaaacagctatgaccatgCCTCCTAAGTAGCTGGGACTACAG		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNGGTGAAACCCCGTCTCTAC	REAL1b z4	cacacaggaaacagctatgaccatgCCTCCTAAGTAGCTGGGACTACAG		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNGGTGAAACCCCGTCTCTACT	REAL1c z4	cacacaggaaacagctatgaccatgCCTCCTAAGTAGCTGGGACTACAG		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNCATGCCTGTAGTCCCAGCTACT	REAL2 z4	cacacaggaaacagctatgaccatgTGCAGTGGCACGATCATAGCTCACTGCAGCCTTGA		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNATAGTGAAACCCCATCTCTACAAAA	REAL3 z4	cacacaggaaacagctatgaccatgCTCCCGAGTAGCTGGGACT		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNGGTGAAACCCCATCTCTACAA	REAL4 z4	cacacaggaaacagctatgaccatgCTCCCGAGTAGCTGGGACTAC		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNATAGTGAAACCCCATCTCTACAAA	REAL5 z4	cacacaggaaacagctatgaccatgCCCGAGTAGCTGGGACTACA		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNGAGGTGGGAGGATTGCTT	REAL6 z4	cacacaggaaacagctatgaccatgAGGCTGGAGTGCAGTGG		
cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNNNACCAGCCTGGGCAACATA	REAL7 z4	cacacaggaaacagctatgaccatgCCACCATGCCTGGCTAA		

N1\_WGS |N2\_WGS |N3\_WGS |N4\_WGS |N5\_WGS |N6\_WGS |N7\_WGS |N8\_WGS |N9\_WGS |N10\_WGS 1p 0.04817 0.04831 0.04804 0.04841 0.04790 0.04815 0.04817 0.04815 0.04798 0.04812 1q 0.03932 0.03926 0.03927 0.03948 0.03915 0.03929 0.03928 0.03928 0.03916 0.03928 2p 0.03003 0.03003 0.03008 0.03019 0.03001 0.03009 0.03007 0.03000 0.02999 0.03005 2q 0.06194 0.06182 0.06191 0.06190 0.06183 0.06192 0.06190 0.06176 0.06187 0.06175 3p 0.03740 0.03740 0.03730 0.03746 0.03741 0.03744 0.03745 0.03734 0.03745 0.03744 3q 0.04250 0.04237 0.04244 0.04248 0.04234 0.04247 0.04247 0.04239 0.04234 0.04235 4p 0.01790 0.01799 0.01793 0.01775 0.01806 0.01792 0.01792 0.01789 0.01806 0.01801 4q 0.05568 0.05542 0.05550 0.05533 0.05544 0.05541 0.05561 0.05553 0.05548 0.05534 5p 0.01765 0.01772 0.01774 0.01753 0.01785 0.01766 0.01764 0.01774 0.01789 0.01779 5q 0.05516 0.05509 0.05511 0.05510 0.05510 0.05514 0.05520 0.05495 0.05495 0.05508 6p 0.02457 0.02460 0.02458 0.02487 0.02444 0.02466 0.02465 0.02461 0.02445 0.02455 6q 0.04271 0.04254 0.04271 0.04254 0.04264 0.04269 0.04268 0.04267 0.04265 0.04261 7p 0.02024 0.02029 0.02039 0.02037 0.02034 0.02036 0.02032 0.02023 0.02039 0.02033 7q 0.03332 0.03323 0.03327 0.03303 0.03339 0.03322 0.03330 0.03342 0.03334 0.03319 8p 0.01207 0.01203 0.01207 0.01194 0.01212 0.01206 0.01208 0.01212 0.01210 0.01206 8q | 0.03978 | 0.03972 | 0.03980 | 0.03964 | 0.03978 | 0.03976 | 0.03971 | 0.03981 | 0.03974 9p 0.01041 0.01040 0.01034 0.01029 0.01044 0.01036 0.01040 0.01037 0.01041 0.01039 9q 0.02792 0.02798 0.02799 0.02816 0.02793 0.02801 0.02798 0.02790 0.02796 0.02799 10p 0.01516 0.01509 0.01520 0.01524 0.01510 0.01515 0.01518 0.01523 0.01510 0.01510 10q 0.03301 0.03296 0.03307 0.03311 0.03292 0.03302 0.03301 0.03285 0.03290 0.03297 11p 0.01817 0.01815 0.01810 0.01821 0.01814 0.01816 0.01816 0.01804 0.01813 0.01817 11q 0.03020 0.03032 0.03030 0.03026 0.03027 0.03033 0.03028 0.03018 0.03026 0.03032 12p 0.01181 0.01183 0.01180 0.01193 0.01174 0.01186 0.01185 0.01181 0.01179 0.01181 12q 0.04007 0.04001 0.03997 0.03990 0.04005 0.03988 0.04001 0.04008 0.03993 0.04003 13q 0.03760 0.03752 0.03757 0.03760 0.03764 0.03762 0.03748 0.03763 0.03774 0.03764 14q 0.03368 0.03365 0.03363 0.03364 0.03363 0.03360 0.03361 0.03362 0.03358 0.03357 15q 0.02791 0.02797 0.02793 0.02817 0.02785 0.02797 0.02794 0.02790 0.02790 0.02804

**Table S2:** Fractional Representation of the the REAL1 prim Normal Samples with Whole Genome Sequencing that were used for the NGS technology comparison. Reproduced from Leary et al.



Bowtie2 Supplementary Table 3 Reports Various Alignment Rates for 100bp unpaired reads ranging from 70% for Bowtie (original); 73% for SOAP2; 90-93% for BWA depending on quality score; and 73-97% for Bowtie2 depending on quality score

	FAST1 N	FAST2 N	FAST3 N	FAST4 N	FAST5 N	FAST6 N	FAST7 N	FAST8 N	FAST9 N	FAST10 N
1p	0.03534	0.03566	0.03553	0.03537	0.03559	0.03530	0.03545	0.03537	0.03567	0.03529
1q	0.03766	0.03745	0.03754	0.03747	0.03736	0.03729	0.03727	0.03731	0.03741	0.03754
2p	0.03148	0.03149	0.03151	0.03125	0.03142	0.03157	0.03161	0.03158	0.03170	0.03150
2q	0.05955	0.05968	0.05996	0.05961	0.05964	0.05956	0.05974	0.05976	0.05973	0.05966
3p	0.03579	0.03607	0.03602	0.03600	0.03618	0.03642	0.03633	0.03602	0.03617	0.03590
3q	0.04850	0.04801	0.04814	0.04826	0.04816	0.04829	0.04810	0.04853	0.04859	0.04842
4p	0.02095	0.02067	0.02099	0.02052	0.02062	0.02111	0.02065	0.02050	0.02088	0.02075
4q	0.06919	0.06893	0.06889	0.06902	0.06897	0.06904	0.06922	0.06870	0.06963	0.06937
5p	0.02200	0.02223	0.02237	0.02181	0.02197	0.02217	0.02217	0.02201	0.02218	0.02204
5q	0.05918	0.05882	0.05885	0.05928	0.05902	0.05924	0.05895	0.05912	0.05891	0.05917
6p	0.01689	0.01688	0.01685	0.01700	0.01691	0.01701	0.01678	0.01693	0.01670	0.01691
6q	0.05094	0.05112	0.05117	0.05121	0.05116	0.05119	0.05130	0.05089	0.05063	0.05127
7p	0.01884	0.01887	0.01872	0.01894	0.01890	0.01857	0.01873	0.01874	0.01873	0.01882
7q	0.03908	0.03906	0.03901	0.03900	0.03900	0.03910	0.03925	0.03917	0.03902	0.03889
8p	0.01534	0.01536	0.01540	0.01527	0.01527	0.01523	0.01504	0.01533	0.01535	0.01521
8q	0.04447	0.04482	0.04451	0.04458	0.04469	0.04445	0.04449	0.04448	0.04450	0.04444
9p	0.01942	0.01928	0.01938	0.01919	0.01948	0.01912	0.01933	0.01927	0.01926	0.01931
9q	0.02142	0.02148	0.02131	0.02151	0.02168	0.02160	0.02162	0.02152	0.02112	0.02144
10 <sub>p</sub>	0.01455	0.01436	0.01465	0.01471	0.01439	0.01465	0.01435	0.01450	0.01434	0.01464
10q	0.03049	0.03042	0.03019	0.03040	0.03048	0.03018	0.03027	0.03059	0.03050	0.03024
11p	0.02194	0.02182	0.02188	0.02218	0.02206	0.02199	0.02189	0.02212	0.02195	0.02190
11q	0.03037	0.03042	0.03036	0.03077	0.03039	0.03029	0.03048	0.03044	0.03058	0.03046
12p	0.01367	0.01357	0.01359	0.01358	0.01351	0.01363	0.01352	0.01341	0.01341	0.01363
12q	0.03940	0.03909	0.03925	0.03894	0.03921	0.03917	0.03905	0.03899	0.03942	0.03946
13q	0.04004	0.04039	0.04024	0.04024	0.04009	0.04024	0.04011	0.04024	0.04030	0.04004
14q	0.03073	0.03094	0.03079	0.03077	0.03090	0.03056	0.03078	0.03037	0.03075	0.03089
15q	0.02354	0.02363	0.02371	0.02335	0.02331	0.02349	0.02353	0.02346	0.02347	0.02316
16p	0.00904	0.00902	0.00873	0.00906	0.00916	0.00914	0.00916	0.00922	0.00902	0.00908

**Table S3**: Fractional Representation of the 10 Normal Samples with FAST-SeqS that were used for the NGS technology comparison



**Table S4:** Fractional Representation of the 10 Normal Samples with REAL-SeqS that were used for the NGS technology comparison.









**Table S6:** Logistic Regression Coefficients and Thresholds for the Aneu+Mutations+Proteins.



**Table S7:** Correlation Matrix for 39 autosomal chromosome arms used in the manuscript. We found several chromosome arms are highly correlated. We calculated the correlation (Pearson Correlation Coefficient) for the fraction of reads that map to a particular chromosome arm compared to another chromosome arm.





**Table S8:** List of the Well Barcode Indices Used in the second round of PCR for RealSeqS.















Schematic of final sequencing library (5' to 3')

Universal primer sequence:

Binding site for the second round PCR amplification and universal sequencing primers

Illumina Grafting Sequence:

Facilitates hybridization to the sequencing instrument**First Round of PCR:**

Forward Primer for amplifying ~350,000 regions; the 6-mers used for design are highlighted:

cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNN GGTGAAACCCCGTC*TCTACA*

Reverse Primer for amplifying ~350,000 regions; the 4-mers used for design are highlighted:

cacacaggaaacagctatgaccatgCCTCCTAAGTAGCTGGGACT*ACAG*

Example amplicon containing a 37 bp sequence amplified by the forward and reverse primers (black font)

cgacgtaaaacgacggccagtNNNNNNNNNNNNNNNN GGTGAAACCCCGTC**TCTACA** AAAAATACAAAAATTAGCTGGCCGTGGTGGCGCATGC **CTGT**AGTCCCAGCTACTTAGGAGG catggtcatagctgtttcctgtgtg

### **Second Round of PCR:**

Forward, with 8 bp sample bar code in red font:

AATGATACGGCGACCACCGAGATCTACACCGTGCAGGcgacgtaaaacgacggccagt

Reverse, with 8 bp sample bar code in red font:

CAAGCAGAAGACGGCATACGAGATACAAGTATcacacaggaaacagctatgaccatg

A full list of indices used in the manuscript is included in SI Appendix Table S8.



**Fig. S1:** Schematic of final sequencing library (5' to 3')



**Fig. S2**. Distribution of amplicon sizes obtained by ReqlSeqS



**Fig. S3.** Distribution of the number of amplicons observed in cell free DNA from 2231 plasma samples.



**Fig. S4.** Distribution of the DNA Size Metric used by RealSeqS to identify outlier samples. Samples with a metric greater than 8.15%, indicated by the horizontal line, were excluded.



**Fig. S5.** The distribution of the QC Dynamic Range metric used by RealSeqS to identify outlier samples. Samples with values < 0.2320 or >0.2450, indicated by the horizontal black lines, were excluded.

#### *In Silico* **simulated samples with monosomy or trisomy of one chromosomal arm**

N <- number of normal samples used

f <- desired neoplastic cell fraction

r <- chromosome arm (1p..22q)

r\_type <- alteration type (gain or loss)

rho <- desired unique read depth of synthetic sample

j<-desired number of repeats

For  $j=1:5$ 

For i=1:N

s <- sample[i]

s\_fraction<-vector that contains the fraction of reads that map to each of the 39 chr arm

for sample s

For f in 1:F

For r in 1p:22q

For r\_type in gain loss

h <- new *in silico* sample

t <- copy of s

t\_fraction<- vector that contains the fraction of reads that map

to each of the 39 chr arm for sample t

if r\_type== gain

t\_fraction[r]<-t\_fraction[r]\*3/2 ###trisomy on arm r

else (r\_type == loss)

t\_fraction[r]<-t\_fraction[r]\*1/2###monosomy on arm r

Endif

h\_normal<-weighted random select (1-f)\*rho where the

weights are r\_fraction

h\_aneuploid<-weighted random select f\*rho where the weights

# are t\_fraction

### h<-h\_normal+h\_aneuploid

End

End

End

End

End

**Fig. S6.** Pseudocode to generate the *in silico* trisomy and monosomy samples used for the comparison of whole genome sequencing, FAST-SeqS, and ReqlSeqS.

#### *In Silico* **simulated samples with alterations of many chromosome arms**

- N <- number of normal plasma samples used
- d <- desired degree of aneuploidy (number arms altered)
- f <- desired neoplastic cell fraction
- r <- chromosome arm (1p..22q)
- r\_type<-arm alteration type (gain or loss)
- p(r) <- probability that an arm is gained or lost in cancer (Estimated from (11))
- rho <- desired unique read depth of *in silico* simulated sample (10M default)
- j<- desired number of repeats

#### For j=1:5

For i=1:N

```
s <- sample[i]
```

```
U <- get reads from s
```
For f in 1:F

h <- new *in silico* sample

For d in (10,15,20) #desired numbers of altered arms

t <- copy of s

For a in 1:d #select alteration types and spike-in to t

r, r\_type <- weighted random selection where the weights  $[p(r)]$ are the likelihood that an arm is gained or loss in cancer

u\_all <- get all Reads that that map to chr arm r

if r\_type== gain

t <- add 50% of u\_all reads

else (r\_type == loss)

t <- subtract 50% of u\_all reads

Endif

h\_normal<-randomselect (1-f)\*rho reads from s

h\_aneuploid<-randomselect f\*rho reads from t

h<-h\_normal+h\_aneuploid

End

End

End

End

End

**Fig. S7**. Pseudocode to Generate *in silico* simulated samples with multiple arm alterations that were used in the Genome Wide Aneuploidy SVM training set.