Allelic Expression of Deleterious Protein-Coding Variants across Human Tissues

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Abstract

Personal exome and genome sequencing provides access to loss-of-function and rare deleterious alleles whose interpretation is expected to provide insight into individual disease burden. However, for each allele, accurate interpretation of its effect will depend on both its penetrance and the trait’s expressivity. In this regard, an important factor that can modify the effect of a pathogenic coding allele is its level of expression; a factor which itself characteristically changes across tissues. To better inform the degree to which pathogenic alleles can be modified by expression level across multiple tissues, we have conducted exome, RNA and deep, targeted allele-specific expression (ASE) sequencing in ten tissues obtained from a single individual. By combining such data, we report the impact of rare and common loss-of-function variants on allelic expression exposing stronger allelic bias for rare stop-gain variants and informing the extent to which rare deleterious coding alleles are consistently expressed across tissues. This study demonstrates the potential importance of transcriptome data to the interpretation of pathogenic protein-coding variants.

Introduction

Recent genome sequencing studies have highlighted that healthy individuals carry multiple loss-of-function and rare deleterious variants whose interpretation is expected to inform individual disease risk and facilitate precision medicine [1–3]. However, accurate interpretation of these variants remains a considerable challenge as phenotypic effects remain difficult to predict. Furthermore, even when a specific function can be ascribed to a genetic variant, the variable penetrance and trait expressivity of genetic variants may yield important differences. In this respect, an important modifier of a coding allele’s effect is its level of expression (Figure 1). This type of modification is likely to have considerable impact on interpretation of coding variant effects as genetic analyses of gene expression have reported that allele specific expression (ASE) influences at least 30% of genes for any given cell type [4,5] and variability in allelic expression of pathogenic coding alleles has already been implicated in contributing to clinical variability for several diseases [6–10]. However, the degree to which deleterious and loss-of-function coding variants, routinely found through personal exome and genome sequencing, are allelically-expressed across multiple tissue types remains unexplored.

In this study we investigated patterns of gene expression and ASE for rare deleterious and loss-of-function variants across multiple tissues using both RNA-Seq and mmPCR-Seq, a targeted and high-resolution sequencing assay for measuring allelic ratios [11]. A major advantage of mmPCR-Seq is that it uncouples a gene’s expression level, which can characteristically vary across tissues, from the power to measure allele-specific expression. Using this approach, we obtain 1000s of reads per heterozygous site per tissue to robustly quantify ASE. By comparing patterns of gene expression to allelic expression, we observed higher variability of allelic expression between tissues suggesting that expression level alone may be insufficient to predict the exposure of a damaging allele. Furthermore, we report patterns of ASE across tissues for both rare deleterious and loss-of-function protein-coding variants. These results demonstrate the extent to which regulatory variation can modify the functional impact of protein-coding variation across tissues, as well as the importance of using ASE for the interpretation of heterozygous variants in clinical sequencing analyses.

Results and Discussion

Collection of Deleterious and Loss-of-Function Variants

To map patterns of ASE for deleterious and loss-of-function coding variants, we sequenced the exome from two tissues (frontal lobe and small intestine) and RNA from ten tissues (cerebellum,
Both alleles are transcribed; this is known as bi-allelic expression (left panel). In the case of allele-specific expression (middle panel), one allele exhibits greater expression than the other allele. When only one allele of a gene is actively transcribed, gene expression is termed monoallelic expression (right panel). (

Both alleles are transcribed; this is known as bi-allelic expression (left panel). In the case of allele-specific expression (middle panel), one allele exhibits greater expression than the other allele. When only one allele of a gene is actively transcribed, gene expression is termed monoallelic expression (right panel). (Figures S1, S2, S3) and intersected this data with high-confidence variants across tissues. We demonstrate that these interactions occur for one third of such variants however large direction flips in allelic expression are infrequent.

Figure 1. Schematic of allele-specific expression. (A) The two chromosomal copies (alleles) of a gene are shown in red and blue. In most cases, both alleles are transcribed; this is known as bi-allelic expression (left panel). In the case of allele-specific expression (middle panel), one allele exhibits greater expression than the other allele. When only one allele of a gene is actively transcribed, gene expression is termed monoallelic expression (right panel). (B) RNA-Seq reads across heterozygous sites can discriminate between the two alleles and quantify the relative abundance of expression. Although the relative gene expression levels may be similar, the allelic ratios can vary. doi:10.1371/journal.pgen.1004304.g001
Differential Gene and Allele-Specific Expression

We next examined the sharing of gene expression and allelic effects across different tissues. Shared patterns of gene expression are detectable for tissues with shared functional roles or embryonic origins (Figure 2A, inset). For instance, the small intestine and colon, which are both digestive system organs derived from the endoderm layers, have a high degree of correlation (Spearman Correlation, \( R = 0.92 \)). Likewise, the frontal lobe and cerebellum, which are both neural tissues derived from the ectoderm, have a high degree of shared gene expression (\( R = 0.91 \)). To test the degree of correlation of allelic expression across tissues, we measured concordance of allelic ratios between pairwise tissues using the high-depth mmPCR-Seq data. Here, allelic ratios are defined as the ratio of the non-reference allele to the sum of the non-reference allele and the reference allele. We observed that the concordance of ASE between tissues does not as strongly reflect the relationships seen for shared gene expression or shared embryonic origin (Figure 2B). The range of pairwise tissue correlation for allelic effects ranges between 0.46 and 0.80, with the small intestine and colon having the most similarity (\( R = 0.80 \)).

We also compared in detail the pairwise correlation coefficients for expression and allelic ratios for tissue pairs of highly similar embryonic origin (Figure S14). We compared two neural tissues (frontal lobe and cerebellum) both derived the ectoderm and two intestinal tissues (small intestine and colon) both derived from the mesoderm. Irrespective of read depth and sequencing technology, the correlation of expression for tissues is consistently greater than the correlation of allelic effects across tissues. This observation suggests that allelic effects exhibit more variability than gene expression across tissues.

We also investigated the sharing of monoallelic expression across tissues (Figure 1). We identified five genes (\( NDN, MAP2K3, FRG1B, IGSF3, \) and \( DUSP22 \)) that showed monoallelic expression across all testable tissues (\( N \geq 5 \)) in the RNA-Seq data. Two of these genes were mono-allelically expressed across all ten tissues: \( NDN \), which is a known maternally imprinted gene [18], and \( MAP2K3 \), which has known allele-specific expression bias [19]. For all five genes, the same allele was mono-allelically expressed in all testable tissues suggesting that these genes are not imprinted in a tissue-specific manner.

Patterns of Allele-Specific Expression across Tissues

The majority of sites tested by mmPCR-Seq have equal expression of both alleles, as expected. However, many sites exhibit consistent or variable allelic patterns across different tissues (Figure S15). By comparing the mean and variance of allelic ratios as quantified through mmPCR-Seq across tissues, we stratified sites into those that exhibited no ASE, shared ASE and variable ASE across tissues. Due to the inherent nature of the binomial test, minor deviations from equal allelic expression will appear significant with high read coverage and therefore p-value significance alone is not sufficient for distinguishing between these classes. Therefore, we also took effect size (allelic ratios) into account when classifying sites as ASE. However, the definition of what constitutes a biologically important allelic effect is not easily discernable; therefore, to distinguish between each group, we accounted for previously reported definitions of ASE [20,21] and applied cutoffs based on the reproducibility of both the allelic ratio and its variance across replicates (Figure S16). Variants were classified as non-ASE sites if the allelic expression was balanced (mean allelic ratio = 0.5+/-0.15) and if there was low variance (\( \sigma^2 < 0.2 \)) of the allelic ratios for all tissues tested. Variants were classified as shared ASE sites if they had a significant p-value (\( p < 0.01 \)), an imbalanced mean allelic ratio (0.35 < mean allelic ratio < 0.65), and non-variable allelic ratios (\( \sigma^2 < 0.2 \)) across all tissues. Lastly, variants were classified as variable (tissue-specific) ASE sites if they had a significant p-value (\( p < 0.01 \)) and variable allelic ratios (\( \sigma^2 > 0.2 \)) across tissues. The reproducibility of the groups between replicates was tested at varying allelic ratio and variance cut-offs (Figure S16) and was also assessed when the pancreas and frontal lobe, two tissues that had high variability between replicates, were removed (Figure S11). The reproducibility between replicates increases as the variance cut-off increases and reaches a plateau of \( \approx 95 \% \) at a variance of 0.2. Since the greatest reproducibility is observed when the ASE cutoff is \( < 0.35 \) or \( > 0.65 \), the variance cutoff is 0.2, and the pancreas is removed, these cut-offs were chosen for Figure 3. Using these cut-offs, the reproducibility between replicates for the three groups (non-ASE, shared ASE and variable ASE) is 93.3%. The reproducibility between replicates for the classification of non-ASE and ASE (shared ASE plus variable ASE) is 95.7%. In total, for sites tested with mmPCR-Seq, 172 showed no ASE across tissues, 52 showed shared ASE, and 8 showed variable ASE (Figure 3A). These proportions are similar to those obtained with RNA-Seq (Figure S17). We then tested if sites exhibiting shared or variable ASE are more likely to be deleterious sites compared to sites exhibiting no ASE. Of the sites exhibiting no ASE, only 25.0% are deleterious. Comparatively, we find no significant enrichment in deleteriousness among sites which exhibit variable ASE compared to non-ASE sites (p = 0.423, Fisher’s exact test; not significant); however, a significantly higher proportion of shared ASE sites (42.3%) are deleterious compared to non-ASE sites (p = 0.022; Fisher’s exact test).

Next, we investigated the relationship between ASE effect sizes and direction of effect across tissues. Figure S15 highlights the range of effect sizes and directions of effect seen across tissues. By focusing on the range of allelic ratios for variants tested in three or more tissues, we further reviewed the distribution of minimum and maximum allelic ratios observed across all tested tissues (Figure S18). As expected, most sites have an allelic ratio around 0.5, and imbalanced loci show similar direction of effect. Interestingly, several sites exhibit opposing directions of effect in different tissues. For example, heterozygous sites in genes \( PCDHA13, SCRIB, \) and \( PDE4DIP \) have a major flip in direction of effect from an alternate allele ratio less than 0.2 to an alternate allele ratio greater than 0.8 across tissues. Four additional heterozygous sites have a large directional flip from an alternate allele ratio less than 0.4 to greater than 0.8, and five more heterozygous sites have a directional flip from an alternate allele ratio less than 0.2 to greater than 0.6.

To determine if gene expression level informed allelic expression level, we investigated the relationship between gene expression and allelic expression level as measured by mmPCR-Seq (Figure S19). As expected, due to the nature of mmPCR-Seq, no general pattern between absolute expression levels and ASE was observed. Four sites (circled in Figure S19) did have noticeably lower non-reference allele ratios and lower gene expression levels in the pancreas, stomach and lung; however these outliers were not enriched in any variant class and did not influence distinction of variable versus shared ASE.

Allele-Specific Expression of Rare Deleterious Variants across Tissues

By focusing on patterns of ASE for rare deleterious variants in this individual, we identified 40 sites corresponding to 40 unique genes which were quantified by mmPCR-Seq across three or more tissues. Of these genes 28 exhibited no ASE across tissues, 11 exhibited shared patterns of ASE across tissues and 1 exhibited variable ASE (Figure 3B; Figure S20). We next investigated if genes with different patterns of ASE have relevant disease
associations using the Online Mendelian Inheritance in Man (OMIM) database of heritable diseases (Table S4) [22]. Although the OMIM database serves as a catalog of genomic variants, OMIM variants serve as examples of the pathogenic consequences of deleterious alleles. Among those that exhibit shared ASE is the \textit{FMO3} gene, which encodes a monoxygenase enzyme responsible for hepatic metabolism and whose deficiency causes the rare Mendelian disorder trimethylaminuria that is manifested in a range of phenotypes (OMIM 602079; Figure S20) [23,24]. Here, the shared allelic effect is detectable in all tissues, but the strongest effect against the deleterious allele is detected in the liver (non-ref to ref allelic ratio = 0.16; Figure S20). In contrast, no ASE patterns

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Correlation of gene expression and allelic ratios across ten somatic tissues. (A) Shared patterns of gene expression were detected for tissues with shared functional roles or embryonic origins. For example, the small intestine and colon are both digestive system organs derived from the endoderm and have a high degree of pairwise correlation (Spearman Correlation, $R = 0.92$). Likewise, the frontal lobe and cerebellum, which are both vital tissues nervous system derived from the ectoderm, have a high degree of shared expression ($R = 0.91$). The hierarchical clustering was generated using pairwise Spearman correlation coefficients of FPKM expression values for all genes. (B) Shared patterns of ASE were detected by mmPCR-Seq. The concordance of ASE between tissues does not as strongly reflect the relationships seen for shared gene expression or shared embryonic origin. The allelic ratio is calculated as the alternate allele reads divided by the total reads. Each data point represents a single heterozygous site tested for ASE with a total read depth greater than 200. The plots are colored by the degree of correlation of allelic bias between the pairwise tissues. These results indicate that relationships of allelic expression across tissues are much more complex than those of total expression level.}
\end{figure}

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Allele-Specific Expression of Loss-of-Function Variants across Tissues

Loss-of-function alleles that introduce premature stop codons have been identified to exhibit patterns of allelic expression indicating nonsense-mediated decay (NMD) [1]. We sought to test the extent of this impact across different tissues. Indeed, comparison of ASE data using mmPCR-Seq for nonsense (stop-gained) and control sites indicates considerable reduction in the expression of the nonsense allele across all tissues (Figure 4A and Table S5). We also observed lowered expression of rare, deleterious alleles at heterozygous sites compared to control sites ($p<0.05$, student’s t-test). This observation has been previously reported in a single cell-type, with a possible explanation for this phenomenon being that lowly-expressed alleles can better tolerate the fitness impact of deleterious protein-coding alleles [23,26]. Furthermore, we identified that rare (MAF<5%) nonsense alleles exhibited even stronger evidence of nonsense-mediated decay than common alleles (Figure 4B). To ensure that genotype errors and mappability did not affect this observation, we compared RNA allelic bias to DNA allelic bias from exome-sequencing. Nonsense variants were removed from the analysis if the alternative allelic ratio was below 0.2 in both tissues. This filtration step ensures that genotyping and mappability of non-reference variants did not influence our observation that rare nonsense variants have decreased allelic expression compared to common nonsense variants. This observation suggests that harbor rare nonsense variants are either considerably unlikely to be expressed or altered transcripts are being efficiently degraded by the NMD machinery.

In conclusion, despite the feasibility of sequencing individual genomes, the functional impact of potentially pathogenic protein-coding variants remains difficult to ascertain by DNA sequencing or computational prediction methods alone. The incorporation of transcriptome data can enhance the interpretation of such variants by providing insight into their patterns of ASE. We demonstrate the advantage of ASE for interpretation of pathogenic protein-coding allele by generated high resolution measurements of ASE for these variants across multiple tissues. Such data enables us to identify the extent to which these alleles are modified by regulatory effects and the extent to which this effect is detectable across tissues. We highlight as many as 1/3 of all deleterious alleles are imbalanced and that nonsense alleles show characteristic and consistently lower expression across multiple tissues. Ultimately, by coupling interpretation of personal genomes with their corresponding transcriptomes, these results highlight that it may be possible to better understand the impact of pathogenic protein-coding variants within different tissues of an individual.

Materials and Methods

Collection of Tissue Samples

In order to investigate the differential allelic effects of divergent tissues in a single individual, we obtained the genomic DNA and RNA for ten somatic tissues (cerebellum, frontal lobe, pancreas, stomach, small intestine, colon, heart, lungs, liver, and skeletal muscle) from Biochain Institute, Inc (Newark, CA, USA). The samples were collected post-mortem from a healthy 25-year-old male with no significant medical history.

Whole Exome Sequencing

Genomic DNA from the frontal lobe and small intestine were prepared for exome sequencing. The enrichment of targeted regions (consensus coding sequence definition of exons and flanking introns, ~50 Mb) was performed using the Agilent...
SureSelect Human All Exon 50 Mb Kit (Agilent Technologies, Santa Clara, CA, USA) following the manufacturer’s recommended protocol. Paired-end libraries were constructed using the Illumina Paired End Sample Prep Kit following the manufacturer’s instructions and sequencing was carried out using the Illumina HiSeq 2000 platform (Illumina, San Diego, CA, USA). Exome sequence data was processed through a pipeline based on Picard (http://picard.sourceforge.net/) with base quality score recalibration and local realignment at known indels and BWA [27], for mapping reads to the human reference genome (build hg19). GATK version v2.3-13 [28] was used for SNP calling, with the default filters, and the additional parameters: -T UnifiedGenotyper; –downsample_to_coverage 75; –genotype_likelihoods_model BOTH; -contamination 0.0; -nct 1. For ASE detection (described below), we filtered for heterozygous variants that were present in both the frontal lobe and small intestine.

Whole Transcriptome Sequencing
Paired-end RNA-Seq libraries were prepared using the Illumina TruSeq RNA Sample Preparation kit. PolyA+ RNA was isolated using Sera-Mag oligo(dT) beads (Thermo) and fragmented with the Ambion Fragmentation Reagents kit. Complementary DNA (cDNA) synthesis, end repair, A-base addition and ligation of the Illumina-indexed adaptors were performed according to Illumina’s protocol. Each sample was barcoded and all samples were sequenced on one lane of the Illumina HiSeq 2000 platform (2×100-nt read length). In total, we obtained 13.3±3.7 (mean ± SD) million paired end reads per sample. We assessed the sequence quality using the publicly available software FastQC. For each sample, we examined per-base quality scores across the length of the reads to ensure that >95% of the reads had >Q60 for bases 1–100. Reads were mapped by TopHat (version 2.0.0) to the known transcriptome (-G option; Gencode version 7 annotations) the human reference genome (hg19) using default parameters [29]. Cufflinks (version 2.0.2) was used to quantify gene expression for known transcripts (-G option; Gencode version 7 annotations) using the default parameters [30].

Targeted Allelic Sequencing by mmPCR-Seq
To quantify allele-specific expression at lowly expressed site, we applied a high-throughput method that couples microfluidics-based multiplex PCR and deep sequencing (mmPCR-Seq) [11]. We designed primers and applied this technique to 74 deleterious nonsynonymous variants, 50 nonsense variants, and 205 control
variants. The control sites are common (MAF>0.05), non-deleterious variants. First, multiplexed PCR reactions were carried out using the Fluidigm Access Array for each sample. Then, the PCR products were indexed using barcoded adaptor primers via a single PCR reaction for each tissue sample. All indexed samples were pooled and purified using a Qiagen RNeasy. Six picomoles were loaded into one lane of an Illumina MiSeq for deep sequencing. The sequence reads were mapped to the human reference genome (hg19) using the Spliced Transcripts Alignment to a Reference (STAR, version 3.2) aligner [31]. Since we targeted together specific heterozygous sites in the genome, the default parameters were modified (minimum score and match filters lowered from 0.66 to 0.3) to increase the number of mapped reads.

**Allele-Specific Expression**

Allele-specific expression was determined on a per-heterozygote-site per-tissue basis using the pipeline depicted in Figure S4 and available online (http://montgomerylab.stanford.edu/resources.html). First, mapped reads were sorted using the Samtools (version 0.1.7) [32]. Next, Samtools mpileup was used to call variants from the aligned reads using a list of known heterozygous sites from the individual. Heterozygous sites with a base quality score (MAQ) below 10, individual allele read depth below 5 and a total (both alleles) read depth below 20 were filtered out. Next, we calculated the reference to non-reference allele mapping ratio for each tissue. To test for ASE, we performed a binomial statistical test for each heterozygous site in each tissue modifying ρ to be the empirical probability of observing a reference versus non-reference allele across all sites. A significance cut-off of 0.05 and 0.01 were used for the RNA-Seq and mmPCR-Seq data, respectively.

**Data Access**

The raw mmPCR-seq data has been submitted to the NCBI Gene Expression Omnibus (GEO) [http://www.ncbi.nlm.nih.gov/geo/] under accession number GSE51769. The code for ASE detection pipeline can be found online (http://montgomerylab.stanford.edu/resources.html).

**Supporting Information**

**Figure S1** Base quality distribution for RNA-Seq reads. The base quality distribution for the 100-bp paired-end RNA-Seq reads from the Illumina Hi-Seq 2000 platform. The mean quality score at each base position for each tissue sample is plotted for reads from the Illumina MiSeq for deep sequencing. The y-axis shows the percentage of ASE sites remaining after each quality control step. The reference to non-reference mapping ratio for each sample and tissue was plotted to identify high-confidence sites. The x-axis shows the distribution of ASE sites from RNA-Seq data required quality control filters to identify high-confidence sites. The reference to non-reference mapping ratio for each sample and tissue was plotted to identify high-confidence sites.

**Figure S2** Mapping RNA-Seq reads. For all tissues except the stomach, ~90% of the reads mapped uniquely to the human genome. Reads under 20 bp were unmapped and reads that mapped to multiple regions of the genome (multi-mapping reads) were discarded for future analysis.

**Figure S3** Reference mapping bias distributed by base quality scores. The reference to non-reference mapping bias for each tissue exhibits no distinct patterns with respect to specific tissue sample or base quality scores.

**Figure S4** Pipeline for the detection of allele-specific expression.

**Figure S5** Distribution of allele-specific expression for RNA-Seq. Density plots illustrate the distribution of the alternate allele ratio for each tissue for all heterozygous sites that are expressed. The alternate allele ratio was calculated from RNA-Seq reads as the fraction of alternate allele reads divided by the total reads. In ASE analyses using RNA-Seq reads, it is important to evaluate if mapping bias exists that results in the favoring of reads harboring the reference allele at heterozygous sites. In the absence of mapping bias, the average allelic ratio is expected to be 0.5, assuming that ASE is exhibiting in a minor fraction of heterozygous sites.

**Figure S6** Quality control filtering of ASE sites. The identification of ASE sites from RNA-Seq data required quality control filter to identify high-confidence sites. The x-axis shows the reference to non-reference mapping ratio for each sample and the y-axis shows the percentage of ASE sites remaining after each quality-control filter. The base quality and read depth filters resulted in a modest (~10%) reduction in ASE sites. The p-value (p<0.05), bi-allelic expression, and intragenic location filters removed over 50% of the sites for each tissue. The proportion of sites removed after each filter shows no correlation with the reference to non-reference mapping bias for the RNA-Seq samples.

**Figure S7** Selection of LoF sites for mmPCR-Seq testing. Rare and deleterious nonsynonymous SNPs were selected for testing by mmPCR-Seq. Rare and deleterious nsSNPs are defined as SNPs not observed in dbSNP, 1000Genomes, or ESP, and annotated as damaging and deleterious by SIFT and POLYPHEN. The nonsense variants selected for testing were identified as variants that affect every full transcript in the gene.

**Figure S8** mmPCR-Seq reads by tissue. Two technical replicates of mmPCR-Seq were performed for each tissue. Since we have observed very high concordance of allelic ratios between technical replicates using mmPCR-Seq, the reads from each replicate were merged.

**Figure S9** Mapping mmPCR-Seq reads. The total reads generated per tissue from the mmPCR-Seq experiments were mapped to the reference genome using the STAR aligner. For every tissue sample, approximately 98% of the reads mapped uniquely to the reference genome.

**Figure S10** Correlation of effect size for mmPCR-Seq technical replicates. Two technical replicates of mmPCR-Seq were performed and the ASE effect size was quantified. For each tissue, the effect size for each technical replicate was plotted to demonstrate the correlation between technical replicates for mmPCR-Seq.

**Figure S11** Variance of effect size for mmPCR-Seq technical replicates. The absolute difference in effect size (allelic ratio) between the two replicates for each tissue is plotted at varying read depth. At higher read depths, there is less variability between replicates. However, even at low read depths (~200), the variability is low for most tissues, except for the pancreas and frontal lobe, which are known to have low RNA quality post-mortem.
allelic ratios across tissues; the deleterious allele is underexpressed with the Mendelian disease Muckle-Wells Syndrome (OMIM 602079), exhibits decreased expression of the deleterious allele across tissues. In contrast, gene \( FMO3 \), which is associated with the Mendelian disease Muckle-Wells Syndrome (OMIM 191900), exhibited no ASE across tissues. The gene \( PCDHA13 \), which encodes a protocadherin, is an example of a gene with variable ASE across tissues; the deleterious allele is underexpressed in certain tissues and overexpressed in other tissues.

Figure S18 Distribution of effect size and direction of effect for ASE across different tissues. The minimum and maximum alternate allele ratio observed in any tissue for each mmPCR-Seq site tested in at least three tissues are plotted to demonstrate the range of allelic effects observed across tissues.

(TIF)

Figure S19 Relationship of ASE effect size and gene expression. The relationship between ASE effect size (measured by mmPCR-Seq) and gene expression level (measured by RNA-Seq) across all tissues was examined. There is no correlation between allelic effect size and gene expression level. Four lowly expressed sites had low allelic ratios (circled) but were not enriched in any class of variants or influenced calling of variable ASE within the study.

(TIF)

Table S1 Identification of high-confidence heterozygous and homozygous variants.

(PDF)

Table S2 Identification of high-confidence common and rare variants.

(PDF)

Table S3 Identification of high-confident RNA-Seq ASE sites by quality-control filtering. To identify high-confident ASE sites, we implemented several quality control filters. We only kept ASE sites which met the following criteria: 1) base quality (BQ) greater than 10; 2) minimum sequencing depth of 10 reads; 3) calculated p-value less than 0.05 from the binomial test; 4) bi-allelic expression; and 5) intragenic location.

(PDF)

Table S4 OMIM genes associated with Mendelian disease phenotypes harboring rare deleterious nsSNP variants.

(PDF)

Table S5 Allelic imbalance of deleterious nsSNPs, nonsense variants, and control sites across tissues.

(PDF)

Author Contributions

Conceived and designed the experiments: SBM KRK JBL. Performed the experiments: RZ KSS MHT RP ML. Analyzed the data: KRK RZ XL DGM. Contributed reagents/materials/analysis tools: MS DGM JBL SBM. Wrote the paper: KRK DGM MS JBL SBM.

References


