Supplementary Information

for

Somatic mutations affect key pathways in lung adenocarcinoma

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Excel spreadsheets can be downloaded from http://genome.wustl.edu/supplemental/tsp_nature_2008

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A. Supplementary Methods

Section I. Gene list and sample

Gene list origins and tumor sample selection

The TSP gene list consists of 623 genes, many of which have previously been implicated as proto-oncogenes or tumor suppressor genes related to solid tumor development. Genes from selected signaling pathways and additional enzyme families also were selected for this study. In addition, some genes from regions on chromosomes 3 and 22, implicated in lung cancer by copy number analysis, were included. Protein family/domain and gene ontology annotation for the 623 TSP genes are shown in Supplementary Table 1.

To identify statistically significant recurrent mutations, we sequenced these genes in 188 lung adenocarcinomas that were selected from an initial set of 384 snap-frozen lung adenocarcinoma biopsy samples, each containing a minimum of 70% tumor cells according to pathology evaluation. These samples were anonymized, and contributed along with matched normal samples by the Dana-Farber Cancer Institute, MD Anderson Cancer Center, Memorial Sloan-Kettering Cancer Center, University of Michigan, and Washington University in St. Louis. All 384 samples were run on 250K StyI Affymetrix SNP Arrays. Analysis of Affymetrix 250K SNP array data enabled the selection of 188 tumors for re-sequencing, whereby tumors displaying LOH and/or hemizygous deletion for a minimum of 10 Mb on the array were preferentially selected. Here, copy number data were visually inspected to categorize samples based on the following criteria:

- *Pass*: presence of an uninterrupted stretch of loss of heterozygosity (LOH) or hemizygous deletion with a copy number less than 1.4 (indicating $>60\%$ tumor purity) for a minimum of 10 Mb.
- *Borderline*: presence of hemizygous deletion with a copy number between 1.4 and 1.6 (indicating 40-60% tumor purity) for a minimum of 10 Mb.
- *Fail*: absence of these qualifying events.

In addition, samples exhibiting any type of technical or protocol failure, such as mismatch between the tumor and normal sample or low quality data, were excluded. These categories, used as a proxy for stromal contamination, were later computationally formalized using a metric defined as the standard deviation of the medians of log2 copynumber ratios in each chromosome arm. The first plate of 94 samples was comprised of samples from the "Pass" and "Borderline" categories.

To test the proposition that copy number data from SNP arrays could be used as a genomic indicator for stromal contamination, as described above, we sequenced the *EGFR*, *KRAS*, and *TP53* genes by both traditional Sanger sequencing and 454 single molecule sequencing. We processed 96 samples chosen randomly from the larger set of 384. The 454 allele frequency generally tracked with both the SNP array category and the ability to detect mutations by Sanger sequencing for each sample. Yet, there were 8 samples that exhibited 454 allele frequencies above 30% (indicating $>60\%$ tumor purity) with mutations still detectable by Sanger sequencing, despite the absence of qualifying lesions on SNP arrays (data not shown). In light of these data, the second plate of 94

samples was comprised of the remaining "Pass" samples that were still available, as well as samples chosen at random from the "Borderline" and "Fail" categories (Supplementary Table 17).

Interpro analysis of 623 genes selected for TSP

Peptide sequences for each transcript were created and stored in a fasta file, which was subsequently processed with Interproscan, specifically the HMMPfam and superfamily analyses. The results were loaded into a relational database, enabling queries for protein domain, protein family, gene ontology (GO), etc.

Section II. Sequencing strategy and mutation analysis

Sequencing strategy and mutation detection

We screened 188 primary lung adenocarcinoma tumors for somatic mutations, focusing on the coding exons and splice donor and acceptor sites of 623 human genes. In total, we re-sequenced 247Mb from the full set of tumor genomes utilizing PCR amplification, followed by fluorescent terminator-based capillary sequencing. Coverage analysis demonstrates Phred Q30 coverage for greater than 90% of the target bases. Raw DNA sequence trace data were analyzed using a combination of mutation detection algorithms, including PolyScan¹, PolyPhred², PolyDhan (unpublished), PolyTedh (unpublished), and SNP detector³ to discover single nucleotide variants and small insertions and deletions (indels). Putative mutations were verified by a second round of PCR-directed sequencing, or were validated by orthogonal methods, including Sequenom genotyping, custom Illumina Golden Gate assays, Applied Biosystems Taqman and/or PCR-based pyrosequencing with the Roche 454 FLX or Biotage platforms (Supplementary Fig. 1). Orthogonal validation included the assay of the matched normal genomic DNA sample (derived from adjacent normal lung tissue or PBLs), to confirm the somatic origin of each variant.

In order to compare results from PCR-directed sequencing and associated variant discovery pipelines across the three sequencing centers (Human Genome Sequencing Center at Baylor College of Medicine, Broad Institute at MIT and Harvard, and The Genome Center at Washington University), 61 genes representing frequently mutated oncogenes and tumor suppressor genes (Supplementary Table 1) were sequenced independently at all three centers and the resulting verified and/or validated mutations were used for concordance analysis. Mutations observed independently by at least two centers were accepted as true positives and had the highest rate of validation by orthogonal methods while mutations discovered by only a single center from a single amplification attempt were likely to be false positives. Therefore, additional supporting data were generated by orthogonal validation methods or independent amplification attempts followed by manual review, to verify all reported mutations in 623 TSP genes.

Description of PCR-based sequencing pipelines

Primers were designed according to target region(s) of interest. The design process included a validation step for both primers and DNA templates to ensure quality. Each DNA template was then amplified with each primer pair for PCR-directed genomic resequencing. Dye terminator sequencing was followed by separation and detection on ABI 3730xl sequencers. The resulting data were screened for mutations through a series of automated and manual steps. A supplemental round of "confirmation" sequencing was performed in an attempt to verify putative mutations, which were then further validated utilizing an alternative genotyping and/or sequencing platform. These steps included the matched normal genomic DNA sample to establish the nature of the variant (somatic or germline). All traces were deposited in the NCBI Trace Archive

(http://www.ncbi.nlm.nih.gov/Traces/trace.cgi) under randomized trace names to prevent future identification of the individuals.

Validation approaches

Putative single nucleotide variants were validated on the Illumina Golden Gate Genotyping platform, the Sequenom MassARRAY platform or, alternatively using TaqMan, Biotage assays, or 454 re-sequencing. Putative indels verified after second pass sequencing were manually reviewed and annotated, then validated either on the Biotage pyrosequencer or the 454 FLX. Verified and validated mutations were used for downstream analysis.

454 FLX-based indel validation

Putative indels detected in 3730-based resequencing of TSP samples were validated with PCR-directed 454 sequencing. Resulting 454 reads were mapped to the human reference sequence (hg36) using BLAT and CrossMatch (unpublished). Subsequent processing of the mapped 454 reads identified the gap position, if any, and compared it to the position predicted by Sanger sequencing. The list of indels targeted from 3730 data was crossreferenced with the best alignments to determine the overall 454 sequence coverage in both normal and tumor. Target indels were then cross-referenced with 454 indels, matching up indels of the same type, of similar size (within 2 bp), and having similar chromosomal position (within 2 bp). This step was performed separately for normal and tumor. In the event that multiple 454-detected indels matched a target indel, the one with the highest number of supporting reads was retained. To determine validation status, the list of targeted indels was populated with the 454 read coverage, detected indels, and the number of indel-supporting reads. Target indels were deemed as validated when sufficient read coverage was achieved in both samples and the fraction of the reads harboring the indel exceeded a predetermined threshold. The combination of 3730 trace and 454 validation data were used to determine the status of indels.

Biotage-based indel detection

The validation process involves assay design, assay validation, and tumor sample analysis. The process begins with the PSQ Assay Design Software distributed by Biotage which identifies two amplification primers flanking the sequence of interest (one of which is biotinylated) and a sequencing primer. The assay design is validated by both PCR product generation and subsequent Pyrosequencing using human genomic DNA as a template. If the assay works on human genomic DNA, the process is repeated with the designated tumor samples. The data is analyzed by the instrument software and reviewed and assembled by the technician.

Indel annotation

Boundaries of insertion, deletion and complex rearrangements are annotated as follows (see also Reporting Mutations, "MAF file format", below) *Insertions*:

- * Start Position is the base before the insertion site
- * End Position is the base after the insertion site
- * The reference sequence is reported as "-"
- * The inserted sequence is reported on the positive genomic strand

 * When multiple alignments are possible, the position is reported as the 3' most alignment on the annotated gene's strand.

Deletions:

- * Start Position is the first base deleted
- * End Position is the last base deleted

 * The reference sequence is reported as the sequence from the Start Position to the End Position on the positive genomic strand

* The deleted sequence is reported as "-"

 * When multiple alignments are possible the position is shifted to the 3' most alignment on the annotated gene's strand.

Complex Indels and Insertions and Deletions with multiple complex alignments:

- * Start Position is the first base deleted or first base of the repeat
- * End Position is the last base deleted or the last base of the repeat

 * The reference sequence is reported as sequence deleted from the Start Position to End Position on the positive genomic strand

 * The inserted sequence is reported as the sequence that replaces the reference sequence on the positive genomic strand

Detecting dinucleotide polymorphisms in 454 sequence data

Dinucleotide polymorphisms (DNPs) were detected during the pairwise sequence comparison between read and reference sequences. A DNP event was identified as two substitutions (relative to the reference) at consecutive aligned bases within a single read. All DNP events were then combined to calculate the number of reads supporting each DNP.

Target coverage calculation

Since the position of a SNP might receive a lower quality score due to the presence of double peaks, a sliding window of 15bp was used to evaluate the coverage of the center base of each window. The center base of each window was considered covered when at least 2/3 of the window's bases, typically 10bp out of the 15bp, were covered by Phred quality scores of at least Q30.

In silico predictions of functional consequences of mutations

We used $SIFT⁴$ and PolyPhen⁵ to evaluate the potential impact on protein function for 811 missense mutations. Given the amino acid substitution and protein fasta sequence as inputs, these two programs return predictions of possible functional impact for nonsynonymous variants. PolyPhen identifies homologues via BLAST search in the NR database, while SIFT searches against the human SWALL database. SIFT predicts functional changes based on sequence homology and physical properties of amino acids while PolyPhen uses sequence, phylogenetic, and structural information to characterize the substitutions. SIFT predicted 430 missense mutations as deleterious and 297 as tolerated. PolyPhen predicted 438 mutations as probably/possibly damaging and 331 as benign. Taken together, these programs identified 579 mutations having potential

functional relevance and these have been prioritized for further functional studies (Supplementary Table 2).

Comparison of mutations with COSMIC and OMIM databases

Detected and annotated mutations were compared to the COSMIC (version 35) and OMIM (1/15/2008 download) databases to assess novelty. For each mutation, all possible matching transcripts were used to determine possible amino acid changes with respect to both residue and position within the associated protein. This change was then checked against the two databases. If both position and residue were identical, the mutation was declared a match. A match was also declared if only the position within the protein matched that of a mutation found within either database. In cases where a mutation affected a splice site, we checked to see if its genomic coordinates were present in COSMIC. (OMIM does not include genomic coordinates.) Mutations not detected by the above methods were considered novel.

Section III. Mutation profiles, background mutation rate, as well as significantly mutated genes, protein domains, and pathways

Molecular signatures of non-synonymous and synonymous mutations

Mutation signatures may reflect histories of mutagen exposure or DNA mismatch repair defects, thereby providing insights into cancer etiology. We have identified 1,013 nonsynonymous mutations in 623 genes and another 108 synonymous mutations in a 250 gene subset. This allowed us to analyze the mutation signatures of non-synonymous and synonymous mutations in parallel. Our results show that point mutations are more common at C:G than at A:T. For non-synonymous mutations, 41% are C:G→A:T transversions, while 27% are C:G \rightarrow T:A transitions. For synonymous mutations the respective numbers are 26% and 61% (Supplementary Fig. 2a). This result indicates that transversion events, leading to non-synonymous mutations, are positively selected for in tumor cells. We then investigated the potential impact of cigarette smoke on the molecular signature by comparing non-synonymous mutations in smokers versus neversmokers. Interestingly, 43% and 13% C:G→A:T transversions are found in smokers and never-smokers respectively, even though the rates of transition and transversion at A:T are comparable for both cohorts (Supplementary Fig. 2b). This result supports the notion that C:G→A:T transversion events in non-synonymous mutations are likely induced by carcinogens in smoke and demonstrates that previous exposure to tobacco-borne carcinogens impacts the mutational signature.

Mutational signatures already have been shown to vary in different cancer types and are characterized by specific sequence contexts. Previous studies also showed that C:G \rightarrow T:A transitions at CpG sites were targets of activated carcinogens in gastric and colon cancers. We expanded our signature analysis to measure all 12 possible changes of the transcribed strand in various 5' and 3' sequence contexts and showed that a $G \rightarrow T$ transversion of the transcribed strand with a 5' flanking T and a 3' flanking G is the most commonly observed molecular change in lung cancer. This is followed by a $G \rightarrow T$ transversion with a 5' G and a 3' T (Supplementary Table 4a). Our results also showed that transition and transversion events at CpGs are not preferentially targeted in lung cancer. The sequence contexts for synonymous mutations (Supplementary Table 4b) are used for background mutation rate estimation.

The relatively large sample size used in this study allowed us to compare the mutational signatures of several frequently mutated genes in lung cancer. *KRAS* and *TP53*, already associated with cigarette smoking, are central to the hypothesis that specific carcinogens link nicotine addiction to lung cancer. Our analysis clearly shows that point mutations at C:G are not only most common in *KRAS* and *TP53* but also in three additional highly mutated genes, *STK11*, *NF1*, and *LRP1B* (Supplementary Table 4d). Furthermore, point mutations in those genes often occur at a G residue on the transcribed strand, establishing a positive relationship between cigarette consumption and $C:G \rightarrow A:T$ transversions in those genes. Our observations are generally consistent with the fact that most activated carcinogens react predominantly at G and that repair of the resulting adducts would be slower on the non-transcribed strand. A contrasting result is found in the mutational signature of *EGFR* where point mutations are found mainly at A:T and the most frequently observed sequence context is an A:T→C:G transversion flanked by 5' G:C

and 3'C:G (Supplementary Table 4d) . Hence, our mutational signature analysis supports the hypothesis that cigarette smoke-borne carcinogens do not induce *EGFR* mutations.

Statistical analysis of significantly mutated genes

Statistical tests on the observed mutations across samples attempt to identify genes that harbor mutations under selection during tumor development. The general framework is first to estimate a background mutation rate, ρ, based on mutations that were not under selection and then identify genes mutated beyond this rate. It is widely presumed that non-synonymous mutations can be under selection pressure because of their resultant changes to protein sequence and function, while synonymous mutations are not selected against because they are generally considered to be biologically silent. However, they have been implicated to have deleterious effects in some cases ⁶⁻⁹. This premise provides several convenient bases for estimating ρ, including data-driven methods and methods that use prior knowledge about highly mutable sequence contexts (Supplementary Tables 4&5 and Supplementary Information). The resulting estimates of background mutation rate ranged between 2.98e-6 and 3.30e-6. These estimates do not account for possible non-synonymous mutations that arrest cell growth, which are presumably under negative selection during carcinogenesis. Consequently, the actual rate could be lower, meaning our analysis is conservative.

Statistical treatments and analyses of cancer sequencing results are not yet standardized. There are several important aspects of this problem, each of which can be addressed in a number of possible ways. Here, we describe several procedures for each of the 3 subproblems: background mutation rate estimation, significance testing, and error analysis. (Of course, we realize additional methods are possible.) We then describe the 3 overall approaches (out of the many possible combinations of the above) that we used for analysis.

(i)Background mutation rate estimation

The number of somatic mutations in each tumor varies widely among the 188 tumors. Across the 623 sequenced genes, 25 tumors had no somatic mutations in the genes we assayed, while others contain exceptionally large numbers of mutations (Fig. 4). We calculated the synonymous mutation rate as the maximum likelihood ratio of the 108 silent mutations in 188 samples encompassing 95,738,393 covered bases over 250 genes. This yields $\rho_{SN} = 1.128e-06$. The 95% Wilson confidence interval is 0.93e-06 to 1.36e-06. (The Wilson interval is preferable to the traditional Wald interval for low values (see e.g. L.D. Brown, T.T. Cai, A. DasGupta (2001) "Interval Estimation for a Binomial Proportion" Statistical Science, 16(2) 101-133.)

The non-synonymous background rate ρ_{NS} is due to *passenger* non-synonymous mutations, whose number is obviously not known. We can estimate ρ_{NS} in an expectedvalue context according to $\rho_{NS} = \rho_{SN} x R$, where *R* is the ratio of NS to SN changes. *R* is calculated by examining all possible residue changes for a single mutation based on the codon usage in all genes sequenced in this study. More specifically, each nucleotide of each codon was mutated *in silico* to determine whether a particular change would result in a NS or SN alteration. While this process is straightforward, the choice of how to

weight each hypothetical NS or SN alteration is less clear. An obvious basis for weighting is the sequence-context based mutation spectra for synonymous mutations observed in lung adenocarcinoma (Supplementary Table 4b). However, there are numerous reasonable methods for choosing the specific weights, all of which lead to some amount of variation in the final estimate of ρ_{NS} . We will describe four possible methods here, along with some caveats for each. These methods can be thought of as hierarchical in the sense that they involve increasing degrees of merging context information. (This is quite analogous, for instance, to chi-square testing when there are too few data for the initial number of categories, requiring some categories to be merged.) For example, if we consider the influence of just the two adjacent bases, Supplementary Table 4b represents the extreme case of maximizing the "resolution" of context information. Sampling zeros and data sparseness, along with the possibility that the strictly-synonymous context information itself could bias the result toward synonymous changes, raises the additional possibility of including a carefully chosen number of nonsynonymous mutations, as well. (This is something of a "bootstrap" method.)

- (1) Direct Weighting: Weight each alteration directly according to its frequency in Supplementary Table 4b ($R = 2.41$, $\rho_{NS} = 2.72e-06$). The large number of sampling zeros and low integer cell values imply unacceptably large error bars, rendering this method of little practical use. Additional data could remedy this problem.
- (2) Uniform Weighting: At the opposite extreme, we could instead give uniform weight to all alterations ($R = 3.38$, $\rho_{NS} = 3.81e-06$), but this entirely overlooks differences in context that we know actually exist in these data.
- (3) Data-Driven Weighting: Use a data-driven approach to collapse categories in Supplementary Table 4b based on using Fisher's exact test. Specifically, we are doing 2X3 table where the two columns are the two contexts being tested and the three rows represent the three possibilities of any bases could be mutated. The test evaluates whether there is enough information between two different contexts (where a "context" consists of 2 specific flanking nucleotides) of cells to consider them "statistically distinct", whereby they are not collapsed. If there is not enough information to distinguish the contexts, they are collapsed into a single one. For example, if A:A and A:C are the contexts (where the colon is the intervening base position whose mutations are being examined), then the collapsed context would be A:AC. In other words, the downstream flanking base would be either A or C, if there is insufficient information to statistically distinguish A:A from A:C. The collapsing process continues until no further moves can be made within a userchosen significance threshold. This approach is supposed to provide a non-biased pruning of categories without having to make *ad hoc* assumptions. In addition to the 108 synonymous mutations mentioned above, we included 156 nonsynonymous point mutations in this process that we reasonably felt were nondriver occurrences. Specifically, they were picked from genes that had only single non-synonymous events. For a threshold of 5%, we obtain the 18 sequence context categories shown in Supplementary Table 5a. The overall ratio *R*=2.645 was obtained by concatenating all gene sequences for analysis, while still observing proper context at exon boundaries. This resulted in an overall non-

synonymous rate estimate of $\rho_{NS} = 2.98e-06$. Gene-specific *R* values and their subsequent non-synonymous rates were obtained by running the same calculation method on individual genes (Supplementary 5b).

(4) Prior Knowledge Weighting: Take prior knowledge and additional biological intuition into account to collapse categories in Supplementary Table 5c. For example, it is well-known that CpG dinucleotides have elevated mutation rates (> 16 fold higher than A's and T's) due to cytosine deamination. Consequently, any C or G appearing in CpG is assigned a particular weight. Similarly, we assign weights to C or G not in CpG and to any A or T. Here, we used the 108 synonymous mutations discussed above, but we again relaxed the restriction on non-synonymous mutations slightly. That is, we included non-synonymous events from those genes not in the list of top 100 mutated genes (sorted by number of mutations per covered bases), which allows inclusion of indels, as there are no silent indel mutations. The resulting 4 categories are summarized in Supplementary Table 5c. The relative mutation rates are then determined directly from these data and are subsequently used as multipliers for their respective raw *in silico* mutation tallies. Finally, the resulting grand totals for non-synonymous and synonymous tallies lead to a ratio of $R = 2.93$ and a non-synonymous rate of $\rho_{\rm NS} = 3.30e-06.$

Although we feel the two latter methods described above are an improvement over those adopted in the past, background rate estimation is clearly still something of an art. For example, neither accounts for possible non-synonymous mutations that arrest cell growth. These are presumably under negative selection during carcinogenesis. Consequently, the actual rate could be lower, meaning our analysis is conservative.

(ii) Significance Testing

We used three statistical methods for testing, all based on the nature of mutation, i.e. a base position is either mutated, or it is not mutated. Each is described briefly:

- (1) Standard Test: This approach treats all mutations equally. Given a uniform probability for each position in a gene, a one-tailed binomial test was used to assess whether the observed mutation rate was significantly higher than the background mutation rate. Here, P values were obtained directly from the binomial distribution (W. Feller (1968) An Introduction to Probability Theory and Its Applications, John Wiley and Sons). One set of results shown in Supplementary Table 6a use this standard binomial test based on the overall mutation rate of 2.98e-06, as described above.
- (2) Gene-Specific Test: We also applied the method of the standard test, except where we used gene-specific background rates instead of a single, global rate. These results are furnished in Supplementary Table 6a, as well.
- (3) Category Test: Score mutations according to prevalence. This test is based on the four sequence mutation categories mentioned above (mutated C or G in a CpG dinucleotide, any other mutated C or G, any mutated A or T, and indel). In short,

convolution is used on the category-specific binomials to obtain an overall Pvalue¹⁰ (see Appendix A). Using the category-based overall rate of $3.30e-06$, this test yielded a third list of significantly mutated genes (Supplementary Table 6a).

In all three of these scenarios, we are testing multiple hypotheses (one per gene). Therefore, we control the false discovery rate using the standard Benjamini and Hochberg False Discovery Rate (FDR) procedure. We used an FDR cutoff of 0.1 which bounds the expected fraction of false positives at 10%.

(iii) Error Analysis

Error analysis is important in any problem where only a single, main analysis method is used because it is typically the only avenue for assessing uncertainty. As with the above issues, there are many possibilities for handling this aspect of the problem.

- (1) No formal error handling. Use calculated values of background rate exclusively. Usually, this is acceptable only if an alternate method of assessing accuracy is available, for example using several independent testing methods.
- (2) Determine confidence intervals, say at 95%, and re-calculate results at low and high values. In this particular problem, this involves estimating not only the intervals on the synonymous rate and the NS/SN ratio, but also subsequently using error propagation analysis to arrive at an overall interval.
- (3) Use Monte Carlo methods to sample the distribution of possible background rates and assess error from sampling statistics.

(iv) Main Methods Used for Analysis

It is easy to see from the above that there are many possibilities for an overall statistical method and that these span various levels of sophistication. We chose 3 of these methods for analyzing our results.

- (1) Data-driven weighting to determine background mutation rate with the standard binomial test for assessing statistical significance
- (2) Data-driven weighting using the gene-specific significance test
- (3) Prior-knowledge weighting using the category-specific test

The first two methods are related, while the third is clearly independent of the others. This observation, coupled with the fact that the resulting analyses from the three methods are quite similar, suggested placing somewhat less emphasis on an extremely formalized error analysis. For example background rates from the data-driven and prior-knowledge

approaches, 2.98e-06 and 3.30e-06 respectively, are quite close in value. In fact, when considering statistical uncertainty, their ranges overlap substantially. For example, the 95% confidence interval on the latter value, $2.56e-06 < \rho_{NS} < 4.04e-06$ includes the lower estimate by a large margin. This suggested using these two background rates to directly assess rate sensitivity *in lieu* of using confidence intervals on just a single rate.

Distribution of non-synonymous mutations in protein functional domains

We further characterized the distribution of non-synonymous mutations in protein functional domains and found that 645 mutations were within known conserved Pfam domains. An examination of the various functional domains within those driver genes found non-uniform mutation rates, but when we compared the protein domain mutation rates against the estimated background genomic mutation rate, we found that the RAS (71 mutations), P53 DNA binding (54 mutations), protein tyrosine kinase (104 mutations), protein kinase (103 mutations), and protein phosphatase (7 mutations) domains comprised the top mutated driver protein domains. In addition, fibronectin type III repeat domain (fn3, 25 mutations), Furin-like cysteine rich region (involved in receptor aggregation, 8 mutations), and receptor_L_binding domains (16 mutations) also had mutation rates significantly above background (Supplementary Table 6b). This result suggests that mutations within a group of functional domains are positively selected during carcinogenesis and are excellent candidate mutations for therapeutics.

Concurrence and mutual exclusion analysis

Positive correlations between mutations in two genes across tumors may suggest that the mutations (and their associated pathways) function synergistically to promote carcinogenesis, while negative correlation of mutations in two genes may imply that the alteration of either gene (or its associated pathway) is sufficient, wholly or in part, for carcinogenesis. We performed two slightly different permutation tests for mutation correlation between genes (i.e. concurrence or exclusion of mutations). In both tests, we take inter-individual differences of gene mutation prevalence into consideration. FDR corrections have been applied (Supplementary Table 7a-c).

Test 1: we kept the number of samples mutated in a given gene and the number of genes mutated in a given sample the same as observed in the data and randomly permuted the observed mutations across samples and genes. For each permutation, we recorded the number of samples with concurrent and exclusive mutations (Xc and Xe, repectively) for each pair of genes and compared them with the numbers observed in the original data (Nc and Ne). We repeated this process 10,000,000 times and summarize the frequencies of Xc>=Nc and Xe>=Ne, respectively. These frequencies are used as empirical p-values under the null hypothesis (no correlation between genes) (Supplementary Table 7a $\&$ 7b).

Test 2: we kept the number of mutations in a given gene and sample the same as observed in the data and randomly permuted the observed mutations across samples and genes. The rest of the analysis is the same as above and we performed 1,000,000 permutations (Supplementary Table 7c).

Analysis of significantly mutated pathways

We examined the distribution of mutations found in the 623 TSP genes within KEGG pathways (release 45). KEGG pathway maps are hierarchically classified, having 5 categories in the top level, 24 subcategories in the second, and 215 individual pathways in the third. We mapped TSP genes to KEGG pathways both by blast (cutoff: P_value \le e-10) and by name matching and were able to place 389 genes onto the pathways. NF1 and KRAS were added to the mTOR pathway based on the literature. We used two approaches to test mutation association on all three levels and to determine whether the genes within specific pathways were mutated more often than the genes outside of the pathways. We evaluated the total number of mutations from all genes examined within each pathway, the number of genes mutated, and the total sequenced coding length of genes in all 188 tumors in the pathway.

In one approach, we created a two-way contingency table by counting mutations in all tested genes within and outside of the pathway. Fisher's exact test was then performed to assess significance of pathway mutation enrichment (Supplementary Table 12).

In another approach, we counted both the total number of base pairs within each pathway that were successfully sequenced and the total number of NS mutations observed in each pathway. A one-tailed binomial test was again performed to check for significance of the observed mutation rate in the pathway. The Benjamini and Hochberg False Discovery Rate and Bonferroni correction procedures were applied according to the total number of pathways tested (Supplementary Table 12). Of those pathways deemed to be significant by this process, we further assessed significance in terms of the number of mutated genes. This step disqualifies pathways having just one or two highly-mutated genes.

Section IV. Integrated analyses – mutation, copy number, gene expression, and clinical features

SNP array data pre-processing

The dChip software was used to read Affymetrix 250k Sty array CEL files and to export background-subtracted probe values using the PM-only option. For each probe set (i.e. each SNP), the log₂ value of the average of PM intensities across 12 probes was used as the basic measurement, *S*. For each array, *S* values for 238,304 SNPs were scaled to have a mean of 0 and a variance of 1 by normalization. For each SNP and each sample pair, DNA copy number was estimated based on the difference of *S* between tumor and normal samples (i.e. the log₂ ratio of the tumor and normal intensities).

Gene-based DNA copy number analyses

For genes having greater than 10 SNPs, all SNPs within the gene were used to compute the gene's copy number. For genes with fewer than 10 SNPs, the average intensity of the 10 SNPs closest to the most centrally localized SNP, within or outside of the gene, was used to calculate the copy number. This approach minimizes the risk of higher variability associated with a small number of SNPs. DNA copy numbers are log transformed for plotting.

Tumor RNA extraction and gene expression array and data analysis

For each tumor RNA used for expression analysis, serial 50 um frozen tissue sections were homogenized in Trizol reagent and used for RNA isolation according to the manufacturer's protocol. An H/E stained serial section from each tumor was reviewed to ensure representation of at least 70% neoplastic cellularity. Isolated RNA was quantified by Nanodrop fiberoptic spectrophotometry and RNA integrity was assessed using Agilent Bioanalyzer and RNA Nano assay. One ug of total RNA was convereted to biotinylated cRNA using the Affymetrix single cycle target preparation method, following the manufacturer's protocol and standard reagents. Biotinylated cRNA was fragmented and hybridized to Affymetrix U133Plus2 human GeneChip expression microarrays following the manufacturerer's recommendations. Arrays were washed, stained, and scanned using standard protocols. All target preparation and array hybridization was performed by the Siteman Cancer Center GeneChip facility. Data quality of each array was assessed by reviewling internal poly-A control probe sets and 3':5' probe intensity signal ratios for housekeeping genes. Arrays which passed all QC metrics were transferred to the Siteman Cancer Center Bioinformatics Core at Washington University for data annotation and distribution. The gene expression data were preprocessed using MAS 5.0. Then, the gene expression levels were log transformed and the mean value across all samples was subtracted. The resulting values were divided by standard deviation to obtain normalized gene expression values. The average value was used where multiple probes were available, and the single value was used when only a single probe was available for a given gene.

DNA copy number and Gene expression correlation analysis

To detect the association between DNA copy number and expression level of each gene, Pearson's correlation coefficients and P-values were calculated. Standard FDR and Bonferroni corrections were applied.

DNA copy number and gene expression

Our previous study described the DNA copy number analysis for TSP tumors based on SNP array data¹¹. In this study, RNAs from 75 tumor samples were hybridized to the Affymetrix U133Plus2 gene expression array (see Methods). Further pathological analysis suggests that 7 out of 75 tumors are not typical lung adenocarcinomas and likely belong to other types of lung cancers. Statistically significant correlation (FDR ≤ 0.05) between DNA copy number and gene expression level was observed for 2,112 of the 8,046 genes examined. The distribution of Pearson correlation coefficients between DNA copy number and gene expression is shown in supplementary Fig. 3. Further analysis identified 2,096 genes with positive correlation and only 16 genes with negative correlation between DNA copy number and gene expression level. The causes of expression change for many genes in cancer cells are still largely unknown. Our analysis suggests that DNA copy number alterations may be an important factor for driving altered gene expression in lung adenocarcinoma. Notable examples having strong correlation are the adjacent genes *ANKRD10* and *ING1*, two cyclin-dependant kinases *CDK6* and *CDK8*, PIK3 kinase *PIK3CA*, cyclin *CCNE1*, and the zinc finger protein *MYNN* (Supplementary Table 9a). *CDK8* has been shown as a colorectal cancer oncogene that regulates b-catenin activity (Nature, in press). Strong positive correlations also have been found in highly mutated genes such as *NF1*, *KRAS*, *EGFR*, *APC*, and *RB1* (Supplementary Table 9b). Interestingly, we have also identified genes showing discordant changes between DNA copy number and gene expression (data not shown). Notably, several members of the melanoma antigen (*MAGE*) and solute carrier families, having minimal copy number variations, showed drastic gene expression changes across 75 lung adenocarcinoma tumor samples. This is consistent with the notion that regulation of gene expression is a complex process that can be controlled at several steps and by multiple mechanisms in cancer. Besides copy number changes, changes in methylation status, transcription regulation, transcript stability and many other factors can have a significant impact on the gene expression levels in lung cancer cells.

Correlation between mutation and gene expression

To detect the association between gene expression and mutation of each gene, Pearson's correlation coefficient and P-values were calculated. Standard FDR and Bonferroni corrections were applied.

Correlation between mutation and DNA copy number

To detect the association between DNA copy number and mutation of each gene, Pearson's correlation coefficient and P-values were calculated. Standard FDR and Bonferroni corrections were applied.

Correlation between mutation and clinical association analysis

Each gene of each sample was assigned either 1 or 0 according to whether it harbored any mutations. For any two genes, a two-way table was obtained by counting the numbers of 0 and 1 entries over the entire sample set, after which Fisher's exact test was performed to determine their mutation correlation. To establish correlations between mutations and clinical features, Pearson's correlation coefficient and Fisher's exact test were applied (quantitative and qualitative clinical traits, respectively).

B. Supplementary Figures

Supplemtary Fig. 1

Shared and Center-Specific Genes

Supplementary Fig. 2

Supplementary Figure 3

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Tumor 16802: amplification of G12V mutant allele
Matched normal 16801

Supplementary Fig. 6

Tumor 17731: amplification of G13C mutant allele
Matched normal 17794

Supplementary Fig. 7

C. Supplementary Figure Legends

Supplementary Figure 1. Sequencing and mutation detection flow chart. 188 primary lung adencarcinoma samples were screened for mutations in the coding exons as well as splice donor and acceptor sites of 623 human genes. Detected putative somatic mutations were subjected to verification $(2nd$ round of PCR amplification and sequencing), orthogonal validation, and manual review.

Supplementary Figure 2. Mutational signatures in lung adenocarcinoma. a) For nonsynonymous mutations, 41% are C:G→A:T transversions, while 27% are C:G \rightarrow T:A transitions. For synonymous mutations the respective numbers are 26% and 61%. This result suggests that C:G→A:T transversion events, leading to non-synonymous mutations, are positively selected for in tumor cells. b) 43% and 13% C:G \rightarrow A:T transversions are found in smokers and never smokers respectively, suggesting that C:G→A:T transversion events in non-synonymous mutations are likely induced by carcinogens in smoke.

Suppelemntary Figure 3. Statistical analysis of correlation between DNA copy number alterations and gene expression changes in 75 lung adenocarcinoma samples.

Supplementary Figure 4. Focal copy number changes of significant genes in primary lung adenocarcinoma samples described in Weir et al. A, focal amplifications of *NRAS*. Upper panel, sample Daffy35T. Lower panel, sample Daffy20T. B, focal amplifications of *KDR*. Upper panel, sample 17048. Lower sample, Daffy93T. C, focal deletion in *NF1* in sample Daffy85T. Mutated genes of interest are indicated by blue bars in the figure; locations of neighboring genes indicated by black bars.

Supplementary Figure 5. Focal amplifications of *EPHA3*. Two primary lung adenocarcinoma samples from the set described in Weir et al.¹¹ show high-level, focal amplification of the *EPHA3* gene, indicated by a blue bar on the figure, as assessed by Affymetrix 250K StyI SNP array data. The positions of neighboring genes are indicated by black bars. The green bar indicates the location of the centromere of chromosome 3. Upper panel, sample 16678. Lower panel, sample 99-43.

Supplementary Figure 6. Lung adenocarcinomas display amplification of mutant alleles of *EGFR* and *KRAS*.

Supplementary Figure 7. Mutation distributions in individual cancer genomes. a) Tumors with higher grade displayed a higher mutation rate than tumors from lower grade. b) Tumors with higher stage displayed a higher mutation rate than tumors from lower stages.

D. Supplementary Tables

Supplementary Table 1. Protein family/domain and GO ontology analysis for the 623 TSP genes.

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Supplementary Table 2. Annotation of somatic mutations found in 188 lung adenocarcinomas. Excel spreadsheet can be assessed at http://genome.wustl.edu/supplemental/tsp_nature_2008.

Supplementary Table 3a. Top genes with higher frequencies of nonsense, splice site, and frame-shift mutations in 188 lung adenocarcinomas according to Fisher's exact test .

Total number of Missense/In_Frame_Indels in all genes tested: 831 Total number of Nonsense/Splice_site/Frame_Shift_Indels in all genes tested: 182

Supplementary Table 3b. Recurrent somatic mutations at 28 sites across seven genes.

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	A:A	A:C	A:G	A: T	C:A	C: C	C:G	C: T	G:A	G:C	G:G	G: T	T:A	T:C	T:G	T:T
A > C	Ω		0			າ							Ω			
A > G	0							8					0	5		
A > T							17									
C > A		8	8	ົ	ּ			ົ			5	11	◠	6	ົ	
C > G	5		З			ົ	5	6					8	6		
C > T	з	5	6		11	13	17	3	4	8	6		14	8	5	
G > A	8	Δ	9	4	10		10	6	12	12		14	9		6	15
G > C	9	3	3		8		4	ົ	6	5	3	8	6	າ		
G > T	24	14	18	13	15	20	19	15	24	14	27	20	6	14	43	
T>A	0		5	3	ົ	∩	Δ	⁰	ົ	n	5					
T>C							6	ົ	4							
T>G							12									

Supplementary Table 4a. Signature analysis of all 12 possible changes of the transcribed strand in various 5' (before colon) and 3' (after colon) sequence contexts for nonsynonymous mutations found in 623 TSP genes in lung adenocarcinomas.

Supplementary Table 4c. Signature analysis of all 12 possible changes of the transcribed strand in various 5' (before colon) and 3' (after colon) sequence contexts for 108 synonymous mutations and 156 non-synonymous point mutations from genes with only one mutation.

	A:A	A:C	A:G	A: T	C:A	C: C	C:G	C: T	G:A	G:C	G:G	G: T	T:A	T:C	T:G	T:T
A > C	0															
A > G																
A > T																
C > A																
C > G																
C > T	h.					õ										4
G > A															٠h	5
G > C															ົ	
G > T									h.							
T>A																
T>C																
T > G																

Supplementary Table 4d. Signature analysis of nonsynonymous mutations in individual genes.

Supplementary Table 5a. Collapsed categories shown in Supplementary Table 4b based on using Fisher's exact test (P < 0.05). A total of 18 categories were considered to be statistically distinct.

Supplementary Table 5b. Gene-based background mutation rates.

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Supplementary Table 5c. Collapsed categories shown in Supplementary Table 4b based on CpG context. Relative mutation rates measured for each category are shown as well.

Supplementary Table 6a. Significantly mutated genes (FDR < 0.1) identified using three different approaches. Significantly mutated genes in lung adenocarcinomas ranked by P_value. Fixed background mutation rate (BMR) of 2.98E-06, gene-based BMRs, and category-based BMR of 3.30E-06, were used for the calculation.

	# of	Covered			
Pfam domain	mutations	length	P value	FDR	Bonferroni
P ₅₃	54	332196	9.46E-73	2.21E-70	2.21E-70
Ras	71	1107696	3.02E-67	3.53E-65	7.06E-65
Pkinase_Tyr	104	12298020	8.27E-20	6.45E-18	1.94E-17
Pkinase	103	18050256	1.65E-09	9.65E-08	3.86E-07
Recep_L_domain	16	1668876	6.49E-05	0.00276	0.015189
P53 tetramer	4	71064	7.08E-05	0.00276	0.016562
fn 3	25	3825048	0.000333	0.01113	0.077909
Furin-like	8	617016	0.000644	0.018828	0.150626
NESP ₅₅	4	138180	0.000864	0.022456	0.202104
LdI recept b	16	2162376	0.001063	0.024866	0.248662
MAM	3	88548	0.002516	0.053514	0.588659
ig	15	2224980	0.003539	0.069002	0.828019
LdI recept a	14	2125716	0.005741	0.103346	
Y phosphatase	7	737148	0.007404	0.116746	
TGFb propeptide	3	131412	0.007484	0.116746	
Ephrin Ibd	8	1005048	0.011798	0.17254	
CXCXC	$\overline{2}$	60348	0.014356	0.197613	

Supplementary Table 6b. Pfam domains have significantly higher mutation rates above background (2.98e-06)

Supplementary Table 7a. Permutation analysis of concurrence among mutations in lung adenocarcinoma (P < 0.1) by keeping the number of mutated samples in a given gene and the number of genes mutated in a given samples as constant.

Supplementary Table 7b. Permutation analysis of mutual exclusion among mutations in lung adenocarcinoma (P < 0.1) by keeping the number of mutated samples in a given gene and the number of genes mutated in a given samples as constant.

PDGFRA	STK ₁₁	6	34		40	2.367546	35.26491	0.043273	
KRAS	NF1	60	13	4	65	7.359486	58.28103	0.044014	
EGFR	LTK	30			36	2.154057	31.69189	0.061911	
CDKN2A	STK ₁₁	9	34		41	3.49261	36.01478	0.069095	
EGFR	PTPRD	30	10		38	3.499732	33.00054	0.072	
LRP1B	STK ₁₁	16	34		44	5.958087	38.08383	0.076116	
APC	TP53		64	4	67	6.53659	61.92682	0.094491	
EGFR	PIK3C3	30			35	.80596	31.38808	0.098305	

Supplementary Table 7c. Permutation analysis of concurrence and mutual exclusion among mutations in lung adenocarcinoma (P < 0.1) by keeping the number of mutations in a given gene and sample as constant.

Supplementary Table 8. Mutations in a set of genes show positive correlation with the overall mutation rate.

Supplementary Table 9a. Top 100 genes showing strong correlation between DNA copy number and gene expression. 75 samples have been used for this analysis.

Supplementary Table 9b. Highly mutated genes showing strong correlation between DNA copy number and gene expression. 75 samples have been used for this analysis.

Supplementary Table 10a. Correlation between mutation and copy number change in 188 lung adenocarcinomas.

*Genes with ≥4 mutations used for the analysis

* *STK11, LTK, PTCH1, ZMYND10, PRKCG, LMTK3,* and *ERBB2* were not included in this analysis because there are no SNPs in those genes on affy 250k sty array.

Supplementary Table 10b. Correlation between mutation and gene expression in 41 lung adenocarcinomas.

**PTCH1* and *KIAA1804* were not included in the analysis because there are no expression probes for those genes.

Supplementary Table 11. Copy number variations and mutations found in genes from MAPK signaling, Wnt signaling, P53 signaling, cell cycle, and mammalian target of rapamycin (mTOR) pathways. Excel spreadsheet can be assessed at http://genome.wustl.edu/supplemental/tsp_nature_2008.

Supplementary Table 12. Pathways significantly mutated in lung adenocarcinoma (mTOR pathway has been modified based on the literature and cancer type-specific pathways are not included). Fisher's exact test and binomial test were used. Background mutation rate of 2.98E-06 was used. See supplementary for details. Some cancer type-specific pathways are not shown.

Supplementary Table 13a. Some highly mutated genes display copy number variations. CN > 2.5 is used for assigning amplifications and CN < 1.5 is used for assigning deletions.

NRAS 3 5 3 1 0
** NTRK1 is not from focal amplification region

Supplementary Table 13b. Some highly mutated genes display copy number variations. CN>3 is used for assigning amplifications and $CN < 1.5$ is used for assigning deletions.

** NTRK1 is not from focal amplification region.

Supplementary Table 14. Samples with at least two consecutive LOH events in STK11.

Supplementary Table 15a. Clinical information for samples used for SNP array, gene expression array, and DNA re-sequencing experiments and analyses.

Note: Some samples with incomplete clinical information. *C: current smoker; *F: former smoker.

Supplementary Table 15b. Clinical information for 188 lung adenocarcinomas sequenced (including major subtype). Missing missing values for major subtype are coded as 99. Excel spreadsheet can be assessed at http://genome.wustl.edu/supplemental/tsp_nature_2008.

Supplementary Table 16. Tumors with no somatic mutations but with copy number variations (Amp: CN>2.5; Del: CN < 1.5) in the focal regions reported in Weir et al.¹¹

Supplementary Table 17. copy number data were visually inspected to categorize samples into three categories: pass, borderline, and fail.

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