Genetic determinants of *EGFR*-Driven Lung Cancer Growth and Therapeutic Response *In Vivo*

Giorgia Foggetti*[1], Chuan Li*[2], Hongchen Cai*[3], Jessica A. Hellyer[4], Wen-Yang Lin[3], Deborah Ayeni[1], Katherine Hastings[1], Jungmin Choi[5,6], Anna Wurtz[1], Laura Andrejka[3], Dylan Maghini[3], Nicholas Rashleigh[1], Stellar Levy[1], Robert Homer[7,8], Scott Gettinger[9], Maximilian Diehn[4,10,11], Heather A. Wakelee[4], Dmitri A. Petrov[2], Monte M. Winslow[3,12,13,#] and Katerina Politi[1,7,9,#]

[1]Yale Cancer Center, [5]Department of Genetics, [7]Pathology, [9]Medicine (Section of Medical Oncology), Yale School of Medicine, New Haven, Connecticut

[6]Department of Biomedical Sciences, Korea University College of Medicine, Seoul, Korea

[8]VA Connecticut HealthCare System, Pathology and Laboratory Medicine Service, West Haven, Connecticut

[2]Department of Biology, [3]Genetics, [4]Stanford Cancer Institute, Department of Medicine, Division of Oncology, [10]Institute for Stem Cell Biology and Regenerative Medicine, [11]Department of Radiation Oncology, [12]Pathology, [13]Cancer Biology Program, Stanford University School of Medicine, Stanford, California

* Authors contributed equally

To whom correspondence should be addressed:

Katerina Politi, PhD
Departments of Pathology and Internal Medicine (Section of Medical Oncology)
Yale Cancer Center
Yale University School of Medicine
333 Cedar Street, SHM-I 234D
New Haven, CT 06510 USA
Office Tel: 203-737-5921
Lab Tel: 203-737-6215
Fax: 203-785-7531
Email: katerina.politi@yale.edu

Monte Winslow, PhD
Departments of Genetics and Pathology
Stanford University School of Medicine
279 Campus Drive, B256
Stanford, CA 94305 USA
Office Tel: 650-725-8696
Email: mwinslow@stanford.edu

Abstract

Cancer genome sequencing has uncovered substantial complexity in the mutational

landscape of tumors. Given this complexity, experimental approaches are necessary to

establish the impact of combinations of genetic alterations on tumor biology and to uncover

genotype-dependent effects on drug sensitivity. In lung adenocarcinoma, *EGFR* mutations co-

occur with many putative tumor suppressor gene alterations, however the extent to which

these alterations contribute to tumor growth and their response to therapy *in vivo* has not

been explored experimentally. By integrating a novel mouse model of oncogenic *EGFR*-driven

Trp53-deficient lung adenocarcinoma with multiplexed CRISPR–Cas9-mediated genome editing

and tumor barcode sequencing, we quantified the effects of inactivation of ten putative tumor

suppressor genes. Inactivation of *Apc*, *Rb1*, or *Rbm10* most strongly promoted tumor growth.

Unexpectedly, inactivation of *Lkb1* or *Setd2* – which are the strongest drivers of tumor growth

in an oncogenic *Kras*-driven model – reduced *EGFR*-driven tumor growth. These results are

consistent with the relative frequency of these tumor suppressor gene alterations in human

EGFR- and *KRAS*-driven lung adenocarcinomas. Furthermore, *Keap1* inactivation reduces the

sensitivity of *EGFR*-driven *Trp53*-deficient tumors to the EGFR inhibitor osimertinib.

Importantly, in human *EGFR/TP53* mutant lung adenocarcinomas, mutations in the KEAP1

pathway correlated with decreased time on tyrosine kinase inhibitor treatment. Our study

highlights how genetic alterations can have dramatically different biological consequences

depending on the oncogenic context and that the fitness landscape can shift upon drug

treatment.

During tumor evolution, cancer cells accumulate alterations in oncogenes and tumor

suppressor genes, which contribute to many of the hallmarks of cancer[1]. Despite their extensive

genomic complexity, tumors are frequently classified based on the presence of a single

oncogenic driver mutation, while the function of co-incident tumor suppressor gene alterations

is largely ignored. There is emerging evidence that the interplay between oncogenic drivers and

tumor suppressor genes may influence tumor fitness and impact treatment response[2].

However, the combinatorially vast landscape of genomic alterations makes it difficult, except in

the most extreme cases, to glean information about the epistatic interactions between tumor

suppressor genes and oncogenes from human cancer sequencing data alone[3]. This complexity

makes inferring the relationship between genotype and therapy response even more tenuous.

Recently, high-throughput, tractable systems that combine autochthonous mouse modeling

and genome editing have been developed to directly uncover the functional consequences of

genetic alterations during tumorigenesis *in vivo*[4-10]. However, very few studies have

investigated the biological consequences of inactivating tumor suppressor genes in the context

of different oncogenic drivers *in vivo*, and existing knowledge about the role of specific genetic

alterations in tumor suppressor genes has been primarily inferred from correlative human

studies[11-13].

In lung adenocarcinoma, *EGFR* and *KRAS* are the two most frequently mutated oncogenic

driver genes and occur within a background of diverse putative tumor suppressor gene

alterations[2,11,12,14]. Among these, *TP53* is the most commonly mutated tumor suppressor gene

in both oncogenic *EGFR*- and *KRAS*-driven lung adenocarcinoma, consistent with the

importance of disrupting this pathway during lung cancer development[2,13,15-18]. Interestingly,

many other putative tumor suppressor genes are mutated at different frequencies in oncogenic

EGFR- and *KRAS*-driven lung adenocarcinomas[2,11,15]. Whether these differences are due to

different fitness effects that depend on the oncogenic context has never been tested

experimentally. Indeed, previous studies on tumor suppressor genes in lung cancer models *in*

vivo have been primarily conducted in the context of oncogenic *Kras*-driven tumors, while the

functional importance of different tumor suppressor genes in *EGFR*-driven lung tumors remains

largely unstudied (**Supplemental Fig. 1a**).

In addition to driving growth, inactivation of tumor suppressor pathways may affect the

therapeutic response to therapies. In advanced *EGFR* mutant lung adenocarcinomas, treatment

with EGFR tyrosine kinase inhibitors (TKIs) is the first-line of therapy[19-22]. Response rates to TKIs

are high, however, there is large variability in the depth and duration of response between

patients, and acquired resistance inevitably occurs[14]. Genomic alterations, including those in

RB1 and *TP53*, have been found to correlate with clinical responses to TKIs[13,17,23]. However,

given the complexity and diversity of genomic alterations in these tumors, the functional

contribution of individual genes to drug resistance remains poorly understood.

To quantify the functional importance of a panel of ten diverse putative tumor suppressor

genes on oncogenic *EGFR*-driven lung tumor growth *in vivo,* we coupled multiplexed CRISPR–

Cas9-mediated somatic genome editing and tumor barcoding sequencing (Tuba-seq) with a

novel genetically engineered mouse model of *EGFR*[L858R]-driven *Trp53*-deficient lung cancer.

Through the comparison of tumor suppressor effects in oncogenic *EGFR*- and *Kras*-driven lung

cancer models, we uncovered prevalent epistasis between the oncogenic drivers and tumor

suppressor genes, which explains the different mutational spectra of these tumor suppressor

genes in oncogenic *EGFR*- and *KRAS*-driven human lung adenocarcinomas. Moreover, we

established a direct causal link between tumor suppressor genotypes and differential responses

to osimertinib treatment in *EGFR*-driven lung adenocarcinoma that are supported by correlative

human mutational datasets.

Results

Development of a lentiviral-Cre based mouse model of oncogenic *EGFR*-driven lung

adenocarcinoma

The use of lentiviral vectors to initiate tumors in genetically engineered mouse models

of human cancer enables control of tumor multiplicity, tumor barcoding to map clonality, and

the delivery of lentivirus-encoded cDNAs, shRNAs, and sgRNAs to modify neoplastic cells[6,8,24,25].

The simplicity of viral-Cre initiated models of oncogenic *Kras*-driven lung cancer has enabled

the analysis of many genes that co-operate to drive tumor growth within these autochthonous

mouse models[26] (**Supplemental Fig. 1a**). To permit the generation of virally-initiated oncogenic

EGFR-driven *Trp53*-deficient lung tumors, we bred mice with an rtTA/tetracycline-inducible

transgene encoding the common lung adenocarcinoma-associated EGFR^{L858R} mutant (*TetO-*

EGFR^{L858R}), a Cre-regulated *rtTA* transgene (*Rosa26$^{CAGs-LSL-rtTA3-IRES-mKate}$*, abbreviated *R26^{RIK}*), and

homozygous *Trp53* floxed alleles (*p53$^{flox/flox}$*)[27-29]. In these *TetO-EGFR^{L858R};Rosa26^{RIK};p53$^{flox/flox}$*

(*EGFR;p53*) mice, lentiviral-Cre transduction of lung epithelial cells leads to the expression of

rtTA and mKate as well as the inactivation of *Trp53*. Co-incident doxycycline treatment induces

the expression of oncogenic EGFR (**Fig. 1a**).

We initiated tumors with a lentiviral-PGK-Cre vector[30] in *EGFR;p53* mice and used

magnetic resonance imaging (MRI) to monitor tumor development (**Fig. 1b**). Tumors were first

detectable in *EGFR;p53* mice 8 weeks after tumor initiation. Histological analysis of lungs 11

weeks after tumor initiation confirmed the development of multifocal lung adenocarcinomas

(**Fig. 1b**, bottom panels). Tumors stained positively for EGFR^{L858R} and mKate, as well as

surfactant protein C (SP-C) and the lung lineage-defining transcription factor NKX2.1/TTF-1 (**Fig.**

1c, top panels)[31-33]. Importantly, in this model, tumors were more focal than the diffuse tumors

that rapidly develop in the previous *CCSP-rtTA;TetO-EGFR^L858R* model[27] likely due to tumor

initiation from fewer cells in the virally initiated model (**Fig. 1b**, top right panel). Lentivirus-

induced tumors in *EGFR;p53* mice were more poorly differentiated than those typically

observed in the *CCSP-rtTA;TetO-EGFR^L858R* model (**Fig. 1b**, bottom panels) as shown by

increased prevalence of a micropapillary pattern, which is known to be highly aggressive in

human adenocarcinoma[27]. Thus, this new lentiviral-Cre-initiated model recapitulates the

genetic and histopathological features of human oncogenic *EGFR*-driven *TP53*-deficient lung

tumors.

Multiplexed quantification of tumor suppressor gene function in *EGFR*-driven lung tumors

To enable somatic genome editing in the *EGFR;p53* model, we further incorporated a

conditional *Cas9* allele (*Rosa26^LSL-Cas9-GFP*)[4] to generate *TetO-EGFR^L858R;R26^RIK/LSL-Cas9-GFP;p53^flox/flox*

(*EGFR;p53;Cas9*) mice (**Fig. 1a**). Lentiviral-Cre delivery to *EGFR;p53;Cas9* mice initiated

multifocal lung adenomas and adenocarcinomas that expressed EGFR^L858R, mKate, Cas9, and

GFP (**Figs. 1c, d**). Tumors in *EGFR;p53;Cas9* mice were histologically similar to those in the

EGFR;p53 mice (**Figs. 1b, d** and **Supplemental Fig. 1b**).

We used an improved version of our Tuba-seq approach to quantify tumor suppressor

gene function in oncogenic *EGFR*-driven lung tumors (**Methods**). Genomic integration of

barcoded lentiviral vectors uniquely tags each transduced cell and all of the neoplastic cells

within the resulting clonal tumors[8]. Each barcode encodes an 8-nucleotide sgID region specific

to the sgRNA followed by a random 15-nucleotide barcode; thus, high-throughput sequencing

of this sgID-BC region from bulk tumor-bearing lung can be used to quantify the number of cells

in each tumor of each genotype (**Methods**)[8]. With this approach, the absolute number of

neoplastic cells in each tumor is calculated by normalizing the number of reads of each unique

barcode (sgID-BC) to the number of reads from benchmark control cells added to each sample

(**Fig. 2a**, **Supplemental Fig. 9a and Methods**). Thus, Tuba-Seq enables the parallel analysis of

the impact of multiple tumor suppressor gene alterations on tumor growth *in vivo.*

To assess the function of ten diverse putative tumor suppressor genes, which are

frequently altered in human lung adenocarcinoma, we initiated tumors in *EGFR;p53* and

EGFR;p53;Cas9 mice with a pool of barcoded Lenti-sgRNA/*Cre* vectors (Lenti-sg*TS^Pool^/Cre*; **Fig.**

2a). In addition to Lenti-sgRNA/*Cre* vectors targeting each putative tumor suppressor gene, this

pool contains negative control vectors, including four Lenti-sg*Inert/Cre* vectors and a vector

with an sgRNA targeting *Trp53* (which is already inactivated by Cre-mediated recombination in

EGFR;p53;Cas9 mice, **Fig. 1a**)[8]. Lenti-sg*TS^Pool^/Cre*-initiated tumors were first detectable by MRI 4

weeks after tumor initiation in *EGFR;p53;Cas9* mice. At 11 weeks after tumor initiation, when

tumors were readily detectable in all mice, tumor-bearing lungs were collected for Tuba-seq

analysis and histology (**Fig. 2b** and **Supplemental Fig. 1e**).

Putative tumor suppressor genes have distinct effects on *EGFR*-driven lung tumor growth

We used Tuba-seq to quantify the number of neoplastic cells in clonal tumors of each

genotype in the *EGFR;p53* model and used two summary statistics to describe the tumor size

distribution (percentiles within the tumor size distributions and the log-normal mean[34]

(**Methods**; **Figs. 2c-e** and **Supplemental Figs. 2a, b**)). Effects of the sgRNAs on tumor growth

were assessed by examining the significance of the differences in the tumor size distribution

compared to controls and also the magnitude of the effects. For negative controls, tumors with

each sgRNA in *EGFR;p53* mice, which lack the *Cas9* allele, had very similar size distributions (**Fig.**

2d). Furthermore, in *EGFR;p53;Cas9* mice, tumors initiated with each Lenti-sg*Inert/Cre* vector or

Lenti-sg*p53/Cre* had very similar tumor size profiles (**Figs. 2c, e**).

Inactivation of *Rb1*, *Apc*, and *Rbm10* most dramatically enhanced the growth of oncogenic

EGFR-driven *Trp53*-deficient lung tumors (**Figs. 2c, e**). While the importance of *RB1* inactivation

in *EGFR*-driven lung adenocarcinomas has begun to be investigated[23,35], very few studies have

addressed the functional importance of the APC pathway on *EGFR*-driven lung

adenocarcinomas[34]. Interestingly RBM10 is an RNA binding protein and splicing regulator that is

poorly studied in cancer in general and has not previously been implicated as a critical regulator

of *EGFR*-driven lung cancer growth[12,36-38].

Surprisingly, inactivation of either *Lkb1* or *Setd2* – which are strong tumor suppressor

genes in analogous oncogenic *Kras*-driven lung tumor models – dramatically reduced tumor

growth relative to sg*Inert* tumors[8,39,40]. These effects were consistent across multiple

percentiles within the tumor size distribution and as assessed by the LN mean of tumor sizes

(**Figs. 2c, e**). Notably, these significant effects observed with sg*Setd2*, sg*Lkb1*, sg*Smad4*, sg*Apc*,

sg*Rbm10*, and sg*Rb1* were all recaptured even after we simulated a 50% reduction in cutting

efficiency or when we used other strategies for subsampling underscoring the robustness of our

findings (**Supplemental Figs. 9b, c** and **Supplemental Figs. 10a, b**). These results suggest that in

specific contexts, inactivation of genes presumed to be tumor suppressors can have deleterious

effects on cancer growth. Other tumor suppressor genes, *Atm*, *Arid1a*, *Cdkn2a* and *Keap1*, did

not significantly alter tumor growth in the context of this experiment (**Figs. 2c, e**).

To assess tumor suppressor gene function at a later time point of tumor growth, we

initiated tumors in *EGFR;p53;Cas9* mice with 10-fold less Lenti-sg*TS^Pool/Cre* and performed

Tuba-seq after 19 weeks of tumor growth. At this time point, the histology of the tumors was

similar to that observed after 11 weeks of tumor initiation (**Supplemental Figs. 1c, d**). Tuba-seq

analysis confirmed the tumor-suppressive function of *Rbm10*, *Apc,* and *Rb1* (**Supplemental Figs.**

2a-c). Since we used a 10-fold lower viral titer for this experiment, there were proportionally

fewer tumors (**Supplemental Fig. 1f**), which limited the resolution of Tuba-seq analysis. Thus,

while inactivation of the other genes had no significant effect on tumor growth at this time

point, we cannot exclude that these genes may influence tumor growth. Interestingly, despite

the decreased statistical power, inactivation of *Cdkn2a* or *Arid1a* had a positive effect on tumor

growth at this 19-week time point (but not at the 11-week time point) suggesting a potential

role of these tumor suppressor genes during a later phase of tumorigenesis in this model

(**Supplemental Figs. 2a, b**).

Validation of *Apc* and *Rbm10*-mediated tumor suppression

We performed further experiments to confirm the role of two less-well studied tumor

suppressors, Apc and Rbm10 on the growth of *EGFR*-driven tumors. We initiated lung tumors in

EGFR;p53 and *EGFR;p53;Cas9* mice with Lenti-sg*Apc/Cre*, Lenti-sg*Neo2/Cre* (sgInert), and two

Lenti-sg*Rbm10/Cre* vectors each with a unique sgRNA targeting *Rbm10* (*N* = 3 *EGFR;p53*

mice/group and *N* = 5 *EGFR;p53;Cas9* mice/group; **Fig. 3a**). We used two sgRNAs targeting

Rbm10 to increase the power of our findings, and because the tumor suppressive role of *Rbm10*

remains entirely uncharacterized in *EGFR*-driven lung cancer. We found a large variation across

mice due to the stochastic nature of tumor progression and the low resolution of the tumor

volume measurements determined by MRI and through tumor area calculations (**Supplemental**

Figs. 3b, c). Despite this, inactivation of either *Apc* or *Rbm10* in *EGFR;p53;Cas9* mice gave rise to

tumors that were significantly larger than control tumors initiated with sg*Neo2* in

EGFR;p53;Cas9 mice. Moreover, by quantifying the size of individual sg*Apc*- or sg*Rbm10*-

initiated tumors (based on tumor diameter) in histological sections, we observed that

EGFR;p53;Cas9 tumors were larger than tumors initiated in *EGFR;p53* mice (**Figs. 3b-e**). Lenti-

sg*Apc*/Cre-initiated tumors in *EGFR;p53;Cas9* mice had more cancer cells with stabilization and

nuclear localization of β-catenin as well as increased expression of Sox9 (consistent with *Apc*

inactivation) (**Supplemental Figs. 3d, e**) [41]. Furthermore, at least 50% of Lenti-sg*Rbm10/Cre*-

initiated tumors in *EGFR;p53;Cas9* mice lacked or had lower Rbm10 protein (**Supplemental Fig.**

3f). Tumors with either *Apc* or *Rbm10* inactivation were histologically similar to tumors in

EGFR;p53 mice at this time point and had papillary/acinar or micropapillary structures with a

medium/high nuclear grade (**Supplemental Fig. 3a**). These results further confirm the

importance of these tumor suppressor pathways in constraining *EGFR*-driven tumor growth *in*

vivo. Collectively, our findings underscore the value of coupling Tuba-seq and CRISPR–*Cas9*-

mediated somatic genome editing with our virally-induced mouse model to dissect gene

function in oncogenic *EGFR*-driven lung cancer.

Oncogenic drivers shape the fitness landscape of tumor suppression

The extent to which different oncogenic drivers affect the landscape of tumor

suppression is almost entirely unknown. We approached this question by comparing the fitness

landscape of tumor suppression within the contexts of oncogenic *EGFR*- and *Kras*-driven lung

tumors. We repeated an experiment previously performed by our group in which we

inactivated the same panel of tumor suppressor genes in *Kras$^{LSL-G12D/+}$;p53$^{flox/flox}$;R26^{LSL-}*

^{Tomato};H11$^{LSL-Cas9}$ (*Kras;p53;Cas9*) mice and used library preparation methods and the analytical

pipeline identical to those used for the *EGFR;p53* and *EGFR;p53;Cas9* mice (**Supplemental Fig.**

4a)[29,30,42]. Inactivation of *Lkb1*, *Setd2,* and *Rb1* were particularly strong drivers of oncogenic

Kras-driven *Trp53*-deficient tumor growth, while inactivation of *Rbm10*, *Apc*, *Cdkn2a* and *Arid1a*

also modestly increased tumor growth (**Figs. 4a, b**). These results are largely consistent with our

previous Tuba-seq analysis of *Kras;p53;Cas9* mice, as well as other studies on these genes in

oncogenic *Kras*-driven lung cancer mouse models (**Supplemental Fig. 1a**)[9,39-41,43-47]

Inactivation of several of the tumor suppressor genes (e.g. *Rb1*) had similar effects on

EGFR- and *Kras*-driven tumors suggesting that these putative tumor suppressor genes limit lung

adenocarcinoma growth regardless of the oncogenic context in these mouse models (**Fig.4c** and

Supplemental Fig. 4b). However, inactivation of either *Lkb1* or *Setd2* greatly increased the

growth of oncogenic *Kras*-driven lung tumors but decreased the growth of oncogenic *EGFR*-

driven lung tumors (**Figs. 2c, e**, **Figs. 4a-c** and **Supplemental Fig. 4b**). Thus, the consequences of

tumor suppressor gene inactivation in specific contexts are not limited to the magnitude of

tumor-suppressive effects but can also be manifested as opposite effects (known as the sign

epistasis) even when the driving oncogenic alterations (in this case *EGFR* and *KRAS*) are

traditionally thought to be within a linear pathway.

Profound epistasis between tumor suppressor genes and oncogenic drivers drives mutational

patterns in human lung adenocarcinoma

To compare our functional data from our *in vivo* models with the spectrum of tumor

suppressor gene mutations found in human lung adenocarcinomas, we queried data from the

AACR Project GENIE database[48]. We calculated the frequency of tumor suppressor gene

mutations that occur co-incident with oncogenic *EGFR* (L858R, Exon 19 deletions, L861Q,

G719X) or oncogenic *KRAS* (at codons 12, 13 or 61) mutations and *TP53* mutations. This analysis

revealed different frequencies of mutations in several tumor suppressor genes in *EGFR/TP53*

and *KRAS/TP53* mutant human lung tumors. *RB1*, *RBM10*, and *APC* are frequently altered tumor

suppressor genes in *EGFR/TP53* mutant lung adenocarcinomas. Interestingly, *RB1* mutations are

more frequent in *EGFR/TP53* tumors compared to *KRAS/TP53* tumors (7.5% versus 3.1%).

However, *Rb1* inactivation was a major driver of tumor growth in both *EGFR* and *Kras* mutant

tumors in mice (**Figs. 2c, e** and **Figs. 4a-c**). This apparent discrepancy between mouse and

human may be related to the higher frequency of alterations in *CDKN2A* in human *KRAS/TP53*

mutant tumors (7.3%, **Fig. 4d**) that would disrupt the same cell cycle regulation pathway as *RB1*

inactivation. *LKB1/STK11* and *SETD2,* are among the most frequently mutated tumor

suppressor genes in *KRAS/TP53* mutant lung adenocarcinomas (**Fig. 4d**)[49,50]. Further supporting

a difference in the function of *LKB1* and *SETD2* in *EGFR/TP53* versus *KRAS/TP53* mutant lung

adenocarcinomas, mutations in these genes occurred at significantly higher frequencies in

KRAS/TP53 mutant tumors compared to *EGFR/TP53* tumors (**Fig. 4e**). This asymmetry in the

mutation frequency of *LKB1* or *SETD2* within oncogenic *EGFR*- or *KRAS*-driven lung tumors is

also significant when we extend our analysis to include all tumors regardless of *TP53* mutation

status (**Supplemental Fig. 4c**). Collectively, the mouse and human data indicate that the

mutational patterns can reflect the biological consequences of profound epistasis between

tumor suppressor genes and oncogenic drivers. This highlights the power of our approach in

uncovering the functional relevance of genomic combinations on tumorigenesis.

Keap1 inactivation limits the response of tumors to osimertinib

Genetically engineered mouse models have provided insight into the biology of _EGFR_-

driven lung tumors and proven valuable in studying mechanisms of resistance to EGFR TKIs,

especially on-target [51] mechanisms of resistance[27,52-54]. The TKI osimertinib was recently

approved for the first-line treatment of _EGFR_-driven lung adenocarcinomas. However,

pathways involved in modulating the depth of response and mechanisms of resistance to

osimertinib are still under investigation[55,56]. To investigate how tumor suppressor genes

influence the therapeutic response of lung tumors to EGFR inhibition, we treated

EGFR;p53;Cas9 mice with Lenti-sg_TS^{Pool}/Cre_-initiated tumors with osimertinib for two weeks

starting at 9 weeks after tumor initiation (**Fig. 5a**). Osimertinib treatment greatly reduced the

overall tumor burden relative to vehicle-treated _EGFR;p53;Cas9_ mice (**Supplemental Figs. 5a-d**).

Residual neoplastic cells were sparse, as determined by staining for EGFR^{L858R} and those cells

were not proliferating (**Supplemental Figs. 5e-f**). The overall tumor response was similar when

the 2-week treatment was started 17 weeks after tumor initiation (**Supplemental Figs. 5g-j**).

To quantify the impact of inactivating each tumor suppressor gene on the response to

osimertinib _in vivo_, we performed Tuba-seq on the lungs from osimertinib-treated

EGFR;p53;Cas9 mice 11 and 19 weeks after tumor initiation and compared the results to Tuba-

seq results from vehicle-treated controls (**Fig. 5b** and **Supplemental Figs. 6a, b**). Consistent with

the imaging data and histological analysis, osimertinib treatment greatly reduced tumor burden

as assessed by Tuba-seq (**Compare Figs 2c, e with Fig. 5b and Supplemental Fig. 6a**; **Methods**).

After two weeks of osimertinib treatment, inactivation of *Apc*, *Rb1* or *Rbm10* was still

associated with larger tumors while the size distribution of tumors with inactivation of *Cdkn2a*,

Arid1a, or *Atm* remained similar to that of tumors with inert sgRNAs (compare **Fig. 5b** and **Fig.**

2e, Supplemental Fig. 6a and **Fig. 2c**, **Supplemental Fig. 6b** and **Supplemental Fig. 2a**). The

striking exception was tumors with sg*Keap1*. In vehicle-treated mice, the size distribution of

sg*Keap1* tumors was almost identical to that of tumors with inert sgRNAs, however in

osimertinib-treated mice sg*Keap1* tumors were significantly larger than the tumors with inert

sgRNAs. This suggests that inactivation of *Keap1* limits responses to osimertinib (**Fig. 5b**).

Osimertinib resistance conferred by *Keap1* inactivation was also observed at 19 weeks after

tumor initiation (**Supplemental Figs. 6a, b**).

We applied an analytical approach that we previously developed and validated to

quantify the genotype-specific responses (**Fig. 5c** and **Supplemental Figs. 6c-g**; **Methods**)[57]. By

comparing the LN mean of the observed tumor size distributions in osimertinib-treated mice

with the expected tumor size distribution based on the overall drug effects, we can estimate

genotype specific drug responses (*ScoreRLM*; **Fig. 5c** and **Supplemental Fig. 6c**). At 11 weeks

after tumor initiation, following 2 weeks of osimertinib treatment sg*Rb1* tumors were 25%

smaller than expected (P = 0.04). Conversely, tumors with *Keap1* inactivation were 48% larger

than expected (P = 0.07; **Fig. 5c**). The effect of *Keap1* inactivation was even greater at 19 weeks

after tumor initiation, where tumors were 274% larger than expected (P = 0.13, **Supplemental**

Fig. 6c). Given the magnitude of the *ScoreRLM* for sg*Keap1* at both time points (*ScoreRLM* =

0.57 and 1.90 after two weeks of treatment at 11 and 19 weeks after tumor initiation,

respectively), we combined the two independent *P*-values and confirmed that *Keap1*

inactivation significantly reduced the therapeutic response to osimertinib (Fisher's method, *P*-

value = 0.05). Other statistical measures of genotype-specific responses, including relative

tumor number (*ScoreRTN*) and relative geometric mean (*ScoreRGM*) did not significantly differ

between the treated and untreated groups (**Supplemental Fig. 6d**; **Methods**). Our analytical

methods allow us to uncover when effects are more pronounced on larger tumors (*ScoreRTN*

and *ScoreRGM* have much lower sensitivity when the effects are greater on larger tumors;

Supplemental Figs. 6e-g; **Methods**). Thus, our data are consistent with the resistance conferred

by *Keap1* inactivation being more pronounced in larger tumors.

Keap1-deficient tumors have reduced sensitivity to osimertinib which correlates with clinical

outcomes

To further investigate these findings, we initiated tumors with Lenti-sg*Keap1/Cre* in

EGFR;p53 and *EGFR;p53;Cas9* mice followed by treatment with osimertinib or vehicle (**Figs. 5d,**

e). Osimertinib-treatment reduced the size and number of tumors in *EGFR;p53* mice compared

to vehicle-treated *EGFR;p53* mice (**Fig 5d** and **Supplemental Figs. 7a, b**). Conversely, osimertinib

treatment of Lenti-sg*Keap1/Cre*-initiated tumors in *EGFR;p53;Cas9* mice did not decrease tumor

size or number compared to vehicle-treated *EGFR;p53;Cas9* mice (**Figs. 5d, e** and **Supplemental**

Figs. 7a, b). Consistent with the inefficiency of CRISPR–Cas9-mediated genome editing in

somatic cells, some tumors initiated with Lenti-sg*Keap1/Cre* in *EGFR;p53;Cas9* mice retained

expression of Keap1 protein (**Fig. 5e** top panels). However, the tumors that remained in

osimertinib-treated *EGFR;p53;Cas9* mice all had medium to low/negative expression of Keap1

(**Fig. 5e**). Together, these data indicate that while *Keap1* inactivation is not positively selected

for during oncogenic *EGFR*-driven tumor growth, osimertinib treatment selects for cancer cells

expressing low/negative levels of *Keap1*, thus reducing the therapeutic response to the drug.

To correlate our findings with clinical data, we analyzed the effects of KEAP1 pathway

alterations on patient outcomes to EGFR inhibition in *EGFR/TP53* mutant lung

adenocarcinomas. Oncogenic *EGFR*-driven tumors with KEAP1 pathway inactivation have been

suggested to be less responsive to TKIs, and we confirmed this association in *EGFR/TP53* tumors

(**Figs. 6a, b**)[58]. Mutations in the *KEAP1/NFE2L2/CUL3* pathway were associated with a

significantly shorter time on EGFR TKI therapy compared with matched patients with

KEAP1/NFE2L2/CUL3 wildtype tumors (5.8 versus 14.3 months, P = 0.01; Log-rank test, **Fig. 6a**;

Supplemental Table 1). This remained significant even after adjustment for potential

confounders such as age, sex, race and smoking status (**Supplemental Table 2**). Among several

other tumor suppressor genotypes, KEAP1 pathway alterations were the most significant driver

of limited sensitivity after correction for multiple hypothesis testing (**Fig. 6b**).

We also analyzed a dataset of oncogenic *EGFR* lung adenocarcinoma patient samples

collected through the Yale Lung Rebiopsy Program (YLR) prior to first-line TKI treatment

(erlotinib, gefitinib, or afatinib) and after the development of resistance to TKIs (**Fig. 6c**;

Supplemental Table 3). Among 18 patients with *EGFR* and *TP53* mutant tumors, two had *KEAP1*

alterations at relapse (TKI-R samples). One case had an acquired missense mutation (Y206N)

that lies in a domain of KEAP1 involved in forming the complex with Cullin3 to mediate

ubiquitination and degradation of NRF2 (encoded by *NFE2L2*)[59]. The other tumor, which was

analyzed only at resistance had heterozygous loss of *KEAP1* (**Fig. 6c**). Moreover, we also

observed two cases of *NFE2L2* copy number gain (one detected prior to treatment and

maintained at resistance, the other detected only at resistance), and one case of *CUL3*

heterozygous loss at resistance. Thus, our *in vivo* functional results are consistent with human

data and support a role for inactivation of the KEAP1 pathway in reducing EGFR TKI sensitivity.

Discussion

The genomic fitness landscape of lung adenocarcinoma is combinatorially complex, with

a large number of genomic alterations in oncogenic drivers and tumor suppressor genes

occurring in various combinations[2,3]. While critical for precision medicine approaches,

dissecting the functional contribution of these co-occurring genetic alterations to tumor growth

and response to therapy is extremely challenging. Using somatic CRISPR–Cas9-mediated gene

editing and Tuba-seq[8,9], we evaluated the fitness effects of inactivation of ten tumor suppressor

genes commonly altered in lung adenocarcinoma in the contexts of oncogenic *EGFR*- and *Kras*-

driven tumors. We uncovered distinct roles for specific tumor suppressor genes on tumor

growth in the different oncogenic contexts and on sensitivity to the TKI osimertinib *in vivo*.

EGFR and *KRAS* are the most frequently mutated oncogenic drivers in lung

adenocarcinoma, collectively occurring in ~40-50% of all patients[2]. Oncogenic alterations in

these two genes are mutually exclusive, consistent with them being in the same canonical

receptor tyrosine kinase (EGFR-RAS-MAPK) signaling pathway[60,61]. For this reason, one might

anticipate that inactivating tumor suppressor pathways in *EGFR*-driven and *KRAS*-driven lung

cancers would have similar biological consequences. It is tempting to make a simplifying

assumption that tumor suppressor genes have a constant marginal effect independent of other

genomic alterations, or in other words, that the fitness landscape of tumor suppression is

smooth and that epistatic interactions are infrequent and/or small in magnitude. Here, we

tested this assumption by comparing the fitness landscape of tumor suppression in *EGFR*-driven

Trp53-deficient and in *Kras*-driven *Trp53*-deficient lung adenocarcinoma and found pervasive

epistasis between tumor suppressor genes and oncogenes. Inactivation of *Rb1*, *Rbm10* and *Apc*

had a similar effect on *EGFR* and *KRAS*-driven lung tumors (**Figs. 2c, e**, **Figs. 4a-c** and

Supplemental Figs. 4b). However, while *Lkb1* and *Setd2* were amongst the most potent tumor

suppressor genes in *Kras/p53* tumors, sg*Lkb1* and sg*Setd2* led to reduced tumor growth of

EGFR/p53 tumors (**Figs. 2c, e** and **Figs. 4a, b**). This observation is consistent with human data,

where alterations in either *LKB1* or *SETD2*, are much less common in lung tumors with

oncogenic *EGFR* than in tumors with oncogenic *KRAS* (**Figs. 4d, e** and **Supplemental Fig. 4c**).

Thus, we reveal a highly context-dependent fitness landscape of tumor suppression that

depends on the nature of the oncogenic driver. Investigation of the mechanisms that underlie

the sign epistasis of *LKB1* and *SETD2* may uncover new biological insights and vulnerabilities of

EGFR mutant tumors. More broadly, sign epistasis within seemingly similar cancer contexts,

could help identify genetic interactions for further functional investigation and should be

considered when interpreting cancer genomic data (**Figs. 4d, e** and **Supplemental Fig. 4c**).

One major advantage of autochthonous genetically engineered mouse models of human

cancer is that they can be used to study the impact of inactivation of putative tumor suppressor

genes on therapy responses *in vivo*[10,57,62]. We found that inactivation of *Keap1* decreases

sensitivity to osimertinib *in vivo* (**Fig. 5**). This finding was supported in a clinical cohort of

EGFR/TP53 mutated lung adenocarcinomas, in which patients with tumors harboring mutations

in *KEAP1/NFE2L2/CUL*3 had a significantly shorter time to treatment discontinuation with EGFR

TKIs compared with matched controls (**Figs. 6a, b** and **Supplemental Figs. 8a-d**)[17,58]. These

results are consistent with this tumor suppressor gene pathway limiting the response to

therapy and explains the presence of alterations in *KEAP1* pathway genes in TKI-resistant

human tumors. A reduced response to TKI therapy mediated by *KEAP1* inactivation may be

associated with the accumulation and transactivation of oxidative stress-related genes by

NRF2[63-65]. Indeed, we found that Keap1-deficient tumors had increased nuclear Nrf2 and Nqo1

expression relative to Keap1-proficient tumors, suggesting enhanced Nrf2 transcriptional

activity (**Supplemental Fig. 7c**)[63-65]. Alternatively, KEAP1/NRF2-dependent metabolic

reprogramming could be involved in mediating drug resistance in lung cancer[66-68]. However,

direct genetic alterations in this pathway occur in less than 10% of TKI-resistant *EGFR* mutant

lung adenocarcinomas (**Fig. 6c**)[17]. It is possible that non-genomic alterations that increase

NRF2-dependent gene expression or other mechanisms that decrease oxidative stress also

occur in TKI-resistant tumors[69-72]. Collectively, these results raise the possibility that targeting

NRF2 may reduce or delay the onset of resistance in *EGFR*-driven lung adenocarcinomas. More

broadly, our study demonstrates that our approach can be used to identify clinically relevant

pathways that modulate response to therapy *in vivo*. By uncovering the driving forces of the

heterogeneity of responses to therapy observed in patients, these types of studies could help

define high-risk versus low-risk patient populations and guide therapeutic interventions.

This study provides insight into the complex interplay between tumor suppressor genes

and other co-occurring mutations in *EGFR*-driven lung adenocarcinoma tumorigenesis and thus

has significant clinical implications. By evaluating interactions between co-occurring alterations

in these models, we have avoided confounding factors pervasive in human genomic data (*i.e.,*

tumor mutation load, mutation frequency, passenger mutations) and environmental factors

such as smoking, a condition that is more often, but not exclusively associated with *KRAS*-driven

tumors. Our data provide clear quantitative data on mutual exclusivity and synergistic biological

effects of genetic alterations. Notably, other oncogenic drivers (e.g. an *ALK* rearrangement) also

have a unique spectrum of co-occurring tumor suppressor gene alterations further suggesting

wide-spread interactions between tumor suppressor gene pathways and oncogenic drivers

(**Supplemental Fig. 11**). Future *in vivo* Tuba-seq studies should investigate tumor models driven

by other oncogenes to uncover a broader understanding of the genetic interactions between

diverse oncogenes and large panels of tumor suppressor genes. Precise mapping of the fitness

consequences of combinations of genetic alterations during tumor evolution will help uncover

the biological and clinical relevance of specific alterations during carcinogenesis and identify

pathways that can be exploited as therapeutic targets to prevent or overcome resistance to

TKIs.

Acknowledgements

G.F was supported by an American Italian Cancer Foundation (AICF) postdoctoral

fellowship. C.L. is the Connie and Bob Lurie Fellow of the Damon Runyon Cancer Research

Foundation (DRG-2331). H.C. was supported by a Tobacco-Related Disease Research Program

Postdoctoral Fellowship (28FT-0019). D.A. was supported by NIH F31 CA203488. K.H. was

supported by NIH F32 CA210516. This work was supported by NIH R01 CA231253 (to M.M.W

and D.P), NIH R01 CA234349 (to M.M.W and D.P.), NIH R01 CA120247 (to K.P.) and NIH P50

CA196530 (to K.P.). The authors would like to acknowledge the American Association for Cancer

Research and its financial and material support in the development of the AACR Project GENIE

registry, as well as members of the consortium for their commitment to data sharing.

Interpretations are the responsibility of study authors. We thank members of the Politi,

Winslow and Petrov Laboratories for helpful feedback and support in particular, Jacqueline

Starrett and Emily Forrest for editing, Fernando de Miguel for creating resources to help with

the WES analysis. We also thank Henning Stehr for providing the sequencing data from the

STAMP cohort and the Bosenberg Laboratory for sharing their Leica M205 FA

stereomicroscope.

Author contributions

G.F. designed and performed *in vivo* experiments, analyzed the data and wrote the

manuscript. C.L. performed sequencing analysis, developed and performed statistical analyses,

and wrote the manuscript. H.C. designed sgRNAs, generated Lenti-sgRNA/*Cre* vectors, tested

sgRNA cutting efficiency, produced lentivirus, and wrote the manuscript. J.A.H. evaluated and

analyzed the Stanford Solid Tumor Actionable Mutation Panel (STAMP) cohort of lung cancer

patients at Stanford University School of Medicine and wrote the manuscript. W.L. performed

in vivo experiments, D.A. and K.H. developed the models used for the study. J.C. generated the

pipeline for the WES data of the Yale Rebiopsy program (YLR) cohort at the Yale Cancer Center.

A.W. coordinates the YLR program. L.A. prepared the libraries for Tuba-seq. D.M. developed the

pipeline to analyze the GENIE data. N.R. and S.L. maintained the Yale mouse colony and imaged

mice included in this study. R.H. performed the histological analysis of all the mouse lung tumor

samples. S.G. conceptualized and leads the Yale Rebiopsy Program at the Yale Cancer Center

with K.P.. M.D. conceptualized and analyzed the STAMP cases. H.W. supervised the analysis of

the STAMP cohort. D.A.P. conceptualized, supervised the project and wrote the manuscript.

M.M.W. and K.P. designed the experiments, conceptualized, supervised the project and wrote

the manuscript. All the authors have revised and approved the submitted version.

Methods

Mice and tumor initiation

$TetO\text{-}EGFR^{L858R}$; $p53^{flox/flox}$; $Rosa26^{CAGs\text{-}LSL\text{-}rtTA3\text{-}IRES\text{-}mKate}$, $Rosa26^{CAGs\text{-}LSL\text{-}Cas9\text{-}GFP}$, $Kras^{LSL\text{-}G12D}$,

$Rosa26^{LSL\text{-}tdTomato}$, and $H11^{LSL\text{-}Cas9}$ mice have been described[4,25,27-30,42,73,74]. *EGFR*;*p53* and

EGFR;*p53*;*Cas9* were on a mixed BL6/129/FVB background and *Kras*;*p53*;*Cas9* mice were on a

mixed BL6/129 background. Approximately equal numbers of males and females were used for

each experiment and the number of mice used for each experiment is listed in each figure

legend. Lung tumors were initiated by intratracheal administration of Lentiviral-*Cre* vectors as

previously described[26]. Tumor burden was assessed by magnetic resonance imaging,

fluorescence microscopy, lung weight, and histology, as indicated. Doxycycline was

administered by feeding mice with doxycycline-impregnated food pellets (625 ppm; Harlan-

Teklad). Osimertinib (from AstraZeneca, Cambridge, UK) was resuspended in 0.5% (w/v)

methylcellulose (vehicle) and was administered orally (*per os*, 25 mg/kg 5 days a week). All

animals were kept in pathogen-free housing under guidelines approved by either the Yale

University Institutional Animal Care or the Stanford University Institutional Animal Care and Use

Committee guidelines.

Production, purification, and titering of lentivirus

The barcoded vectors in the Lenti-sg*TS^Pool/Cre* have been previously described

(**Supplemental Table 4**)[8]. The second Lenti-sg*Rbm10/Cre* vector used in the validation

experiments was generated by site-directed mutagenesis (**Supplemental Table 5**). Briefly,

Lentiviral-U6-sgRNA*/Cre* vectors contain an 8-nucleotide defined sequence (sgID) that identifies

the sgRNA followed by a 15-nucleotide random barcode (BC) to uniquely tag each tumor[8]. To

avoid barcode-sgRNA uncoupling driven by lentiviral template switching during reverse

transcription of the pseudo-diploid viral genome, each barcoded Lenti-sgRNA*/Cre* vector was

generated separately[75,76]. We cultured HEK293T cells in Dulbecco's Modified Eagle Medium

with 10% Fetal Bovine Serum and transfected them with individual barcoded Lenti-sgRNA*/Cre*

plasmids (*sgLkb1, sgp53, sgApc, sgAtm, sgArid1a, sgCdkn2a, sgKeap1, sgNeo1, sgNeo2, sgNeo3,*

sgNT1, sgRb1, sgRbm10, sgRbm10#2 unbarcoded*, sgSetd2,* or *sgSmad4*) along with pCMV-VSV-

G (Addgene #8454) envelope plasmid and pCMV-dR8.2 dvpr (Addgene #8455) packaging

plasmid using polyethylenimine. We treated the cells with 20 mM sodium butyrate 8 hours

after transfection, changed the culture medium 24 hours after transfection, and collected

supernatants 36 and 48 hours after transfection. Subsequently, we removed the cell debris with

a 0.45 μm syringe filter unit (Millipore SLHP033RB), concentrated each lentiviral vector by

ultracentrifugation (25,000 g for 1.5 hours at 4°C), resuspended the virus in PBS, and stored the

virus at -80°C. To determine the titer of each vector, we transduced $Rosa26^{LSL-YFP}$ mouse

embryonic fibroblasts (a gift from Dr. Alejandro Sweet-Cordero/UCSF), determined the

percentage of YFP-positive cells by flow cytometry, and normalized the titer to a lentiviral

preparation of known titer. Lentiviral vectors were thawed and pooled immediately prior to

delivery to mice. All these plasmids are available at

https://www.addgene.org/Monte_Winslow/.

Lentiviral titers and time of analysis

Anticipated growth rates were determined by monitoring tumor development through

magnetic resonance imaging in pilot experiments and the analysis time points were selected to

ensure that tumors were detectable by MRI such that their response to treatment could be

evaluated. Viral titers used in the experiments were chosen to balance the total tumor burden

across mice at the time of analysis after tumor initiation. For analysis of tumor growth 11 weeks

after tumor initiation, the Lenti-sgTS^{Pool}/Cre titer administered to $EGFR;p53$ mice was 2×10^6

infectious units (ifu)/mouse, while for $EGFR;p53;Cas9$ mice we used 1×10^6 ifu/mouse. We

reasoned that using a higher viral titer in the control $EGFR;p53$ mice would increase our

confidence that any differences observed between $EGFR;p53$ and $EGFR;p53;Cas9$ mice were

due to inactivation of tumor suppressor genes in the latter model. For the 19-week time point

in $EGFR;p53;Cas9$ mice we initiated tumors with 1×10^5 ifu/mouse. Two weeks before collection,

mice were treated with either vehicle or osimertinib. For the validation experiments in which

we used a single vector to initiate tumors (Lenti-sgApc/Cre, Lenti-sg$Rbm10$/Cre, Lenti-

sg*Rbm10*#2/*Cre* or Lenti-sg*Neo2/Cre* (sg*Inert*)) we used $1x10^5$ ifu/mouse and analyzed the mice

after 14 weeks of tumor growth (**Supplemental Table 5**). For the validation with Lenti-

sg*Keap1/Cre* virus ($1x10^5$ ifu/mouse), both *EGFR;p53* and *EGFR;p53;Cas9* mice were treated 15

weeks after tumor initiation and lungs were collected after two weeks of treatment with either

vehicle or osimertinib. *Kras;p53;Cas9* were analyzed 14 weeks after tumor initiation with

$2.2x10^4$ ifu/mouse.

Magnetic resonance imaging

All procedures were performed in accordance with protocols approved by the Yale

University IACUC and in agreement with the NIH Guide for the Care and Use of Laboratory

Animals. Respiratory gated, gradient-echo MR images of mice were collected with a 4T (31-cm

bore) small-animal Bruker horizontal-bore spectrometer (Bruker AVANCE). All data were

collected as previously described[52]. Tumor volume was quantified by calculating the area of

visible lung opacities present in each image sequence per mouse using BioImage Suite 3.01[77].

Isolation of genomic DNA from mouse lungs and preparation of sgID-BC libraries

Genomic DNA was isolated from bulk tumor-bearing lung tissue from each mouse as

previously described[8]. Briefly, three benchmark control cell lines (~$5x10^5$ cells per cell line)

carrying unique sgID-BCs, were added ("spiked-in") to each sample prior to lysis to enable the

calculation of the absolute number of neoplastic cells in each tumor from the number of sgID-

BC reads. Following homogenization and overnight protease K digestion, genomic DNA was

extracted from the lung lysates using standard phenol-chloroform and ethanol precipitation.

sgID-BC sequencing libraries were prepared by PCR amplifying the sgID-BC region from

total genomic DNA. To enable the identification and subsequent computational elimination of

index hopped reads after high-throughput sequencing, the sgID-BC region of the integrated

Lenti-sg*RNA-BC/Cre* vectors was PCR amplified using unique dual indexing primer pairs. To

increase the sequence diversity at each position and reduce the amount of PhiX required to

achieve high sequencing quality, we added 6-9 Ns before the sequence-specific primers[57]. PhiX

is control DNA (with a diverse sequence) that is added to Illumina sequencing samples when

the diversity of the product to be sequenced is low (often the case with amplicon sequencing

like what we are doing to analyze barcodes). Since we are performing amplicon sequencing

with the possibility of less than random sequence diversity at each position, we add 5%-15%

PhiX to ensure good sequencing quality. We used a single-step PCR amplification of sgID-BC

regions, which we have found to be a highly reproducible and quantitative method to

determine the number of neoplastic cells in each tumor. For each mouse, we performed eight

100 μl PCR reactions per sample (4 μg DNA per reaction, 32 μg per mouse) using Q5 High-

Fidelity 2x Master Mix (New England Biolabs, M0494X). The PCR products were purified with

Agencourt AMPure XP beads (Beckman Coulter, A63881) using a double size selection protocol.

The concentration and quality of the purified libraries were determined using the Agilent High

Sensitivity DNA kit (Agilent Technologies, 5067-4626) on the Agilent 2100 Bioanalyzer (Agilent

Technologies, G2939BA). The libraries were pooled based on lung weight (to have sequencing

depth more evenly distributed across samples), cleaned up and size-selected using AMPure XP

beads, and sequenced on the Illumina®HiSeq 2500 platform to generate paired-end 150 bp

reads (Admera Health).

Quantification of tumor sizes from sgID-BC sequencing data

A diagram describing the analysis steps that are part of the Tuba-seq method in more

detail are summarized in **Supplemental Fig. 9a**. We used stringent filtering to identify the sgID-

BC region that minimizes PCR and sequencing error, as previously described[57]. Specifically, we

required no mismatch in the barcode region between the forward and reverse reads and

removed all spurious tumors with the barcodes within two nucleotides from that of another

larger tumor. The absolute number of cells in each tumor was calculated by scaling its sgID-BC

read number with the mean read number of three spiked-in cell lines with a known absolute

cell number of 5×10^5.

Summary statistics for tumor size distributions

As sequencing depth and PCR efficiency vary across libraries, we focused on tumors that

we can repeatedly identify with high confidence, which are tumors over 500 cells as quantified

by comparing technical replicates. We used multiple summary statistics to describe the

truncated distribution of tumor sizes for all tumors larger than 500 cells. Percentiles and LN

means were calculated as two summary statistics. Percentiles are a nonparametric summary of

the distribution by taking the 50th, 60th, 70th, 70th, 90th, and 95th percentile of the distribution.

The LN mean calculates the maximum likelihood estimator of the mean tumor sizes assuming a

log-normal distribution of tumor sizes. For both of these metrics, we normalized to the

corresponding value of the average of inert tumors to represent the relative growth advantage

of inactivating the gene.

Quantification of treatment responses of inert tumors to osimertinib

We quantified the treatment effect of osimertinib by comparing the tumor size

distributions of the vehicle- and osimertinib-treated groups. We used two ways to quantify

treatment effect. The first way is to calculate the total number of neoplastic cells of tumors

carrying the inert control sgRNAs in each mouse and taking the fold change of the average of

the total number of neoplastic cells as an approximation of the drug effect.

$$Drug\ effect = \frac{Average\ neoplastic\ cell\ number\ in\ osimertinib - treated\ mice}{Average\ neoplastic\ cell\ number\ in\ vehicle - treated\ mice}$$

This calculation of tumor burden is very intuitive and relevant in the clinical setting, but this

measure is quite variable due to the large variations in the sizes of the largest tumors. The

second way assumes that each neoplastic cell, regardless of the size of the tumor harboring it,

has an equal probability of being killed by osimertinib treatment (K). To make sure that we are

evaluating tumors that are large enough to be repeatedly identified, we focus on tumors that

are over 1,000 cells in the vehicle-treated mice. We estimated the tumor size reduction after

treatment with osimertinib for the tumors with the inert control sgRNAs by matching the

distribution of tumor sizes in vehicle- and osimertinib-treated mice. Specifically, we used the

binary search algorithm to find the proportion of neoplastic cells remaining after treatment

with osimertinib (S) between $K = 1$ (100% cells were killed by osimertinib) and $K = 0$ (0% of cells

were killed by osimertinib), such that the median tumor number of tumors with the inert

control sgRNAs across the vehicle-treated mice, upon simulated reduction to K, matches the

median tumor number of tumors with the inert control sgRNAs larger than 1,000 cells across all

osimertinib-treated mice.

Estimation of genotype-specific treatment responses

We calculated the expected size distribution of tumors after treatment assuming no

genotype-specific treatment responses by reducing all tumors in the vehicle-treated mice by

the estimated drug effect (K). Then we calculated the genotype-specific treatment response for

each sg*TS* by comparing the relative LN mean of all tumors in the osimertinib-treated mice and

the relative LN mean of all tumors calculated from the expected distribution after treatment.

The genotype-specific treatment response is calculated as the log2 ratio of the observed

relative LN mean by the expected LN mean, and we named it as *ScoreRLM*. We focus on tumors

with the inert control sgRNAs that are over 1,000 cells in untreated mice and take out

comparable proportions of tumors with each sgRNA from each vehicle- and osimertinib-treated

mice based on the estimated treatment effect and the proportion of tumors carrying each sg*TS*.

The *ScoreRLM* is calculated as:

$$647 \quad RLM_{i,j} = Log_2 \left(\frac{LN\ mean_{i,osimertinib} / LN\ mean_{Inert,osimertinib}}{LN\ mean_{i,vehicle} / LN\ mean_{Inert,vehicle}} \right)$$

$$648 \quad ScoreRLM_{i,j} = 2^{RLM_{i,j}} - 1$$

where LN mean$_{i,osimertinib}$ is the LN mean for tumors containing sgID *i* in osimertinib-treated

group, LN mean$_{Inert,osimertinib}$ is the LN mean for all tumors containing one of the four inert

sgIDs in the osimertinib-treated group. Similarly, LN mean$_{i,vehicle}$ is the LN mean for tumors

containing sgID *i* in vehicle-treated group and LN mean$_{Inert,vehicle}$ is the LN mean for all tumors

containing one of the four inert sgIDs in the vehicle-treated group. When tumors are larger

than expected, the *ScoreRLM* will be positive, indicating resistance conferred by gene

inactivation, while when tumors are smaller than expected, the *ScoreRLM* will be negative,

indicating sensitivity conferred by tumor suppressor gene inactivation. Although the metric on

the log2 scale results in the first formula with good statistical properties ranging from $-\infty$ to $+$

∞ and centered on 0. To make it more directly interpretable by readers, we converted it to the

linear scale as shown in the second formula. On the linear scale the metric ranges from -1 to $+$

∞, a value of 0.5 means the tumors are 50% larger than expected and a value of -0.5 means

that the tumors are 50% smaller than expected.

Apart from *ScoreRLM* that compares the relative LN mean in the vehicle- and

osimertinib-treated group, we can similarly compare the relative tumor number (*ScoreRTN*) and

relative geometric mean (*ScoreRGM*) for the observed and expected distribution of tumor sizes

following the same logic as shown below:

666
$$ScoreRGM_{i,j} = Log_2\left(\frac{\text{geometric mean}_{i,\text{osimertinib}} / \text{geometric mean}_{\text{Inert,osimertinib}}}{\text{geometric mean}_{i,\text{vehicle}} / \text{geometric mean}_{\text{Inert,vehicle}}}\right)$$

667
$$ScoreRGM_{i,j} = 2^{RGM_{i,j}} - 1$$

669
$$RTN_{i,j} = Log_2\left(\frac{\text{tumor number}_{i,\text{osimertinib}} / \text{tumor number}_{\text{Inert,osimertinib}}}{\text{tumor number}_{i,\text{vehicle}} / \text{tumor number}_{\text{Inert,vehicle}}}\right)$$

670
$$ScoreRTN_{i,j} = 2^{RTN_{i,j}} - 1$$

where the geometric mean and tumor number were calculated from inert tumors that are over

1,000 cells in the vehicle-treated mice and the corresponding proportions for other sgIDs in the

vehicle-and osimertinib-treated groups considering the proportion of sgIDs and the

treatment[57].

The standard deviation of the genotype-specific responses, represented by any of the

three metrics, is estimated by bootstrapping mice in both the vehicle- and osimertinib-treated

groups and then bootstrapping tumors with the same sgID in each bootstrapped mouse. Such a

two-step bootstrap process allows us to control for both variations of tumor size across mice

and within the same mouse. For each run of bootstrap, we re-estimated the drug effect,

estimated the expected tumor size profile between the vehicle- and osimertinib-treated mice.

We estimated the standard deviation based on the scores on the log2 scale and then plotted

the values on the linear scale, because the latter ranges from -1 to $+\infty$ with no genotype-

specific responses located at 1.

Power analysis for three metrics in identifying genotype-specific treatment responses

686   We calculated the sensitivity and specificity for the three metrics, when 1) the

genotype-specific treatment responses to osimertinib only occur in large tumors, while smaller

tumors respond similarly to sg*Inert* tumors, 2) the genotype-specific treatment responses are

uniform across all tumor sizes such that all sg*TS* tumors have increased or reduced sensitivity to

osimertinib relative to sg*Inert* tumors (**Supplemental Figs. 6e, f**). Specifically, we used all ten

vehicle-treated mice at 11 weeks for simulation. We first applied a drug effect of K = 75% (75%

of cells are expected to be killed by osimertinib assuming no genotype-specific treatment

responses) to all tumors. Then we apply the preassigned genotype-specific treatment responses

to all tumors to generate the simulated distributed tumor sizes. For the first scenario of size-

dependent genotype-specific treatment response, the preassigned genotype-specific responses

only occur in tumors with over 10,000 cells, and they are assigned to be four-fold higher than

expected, i.e., these tumors do not respond at all to osimertinib considering that 75% of tumor

cells are expected to be killed without any genotype-specific treatment responses. For the

second scenario of uniform responses, all tumors with the sg*TS* are assigned to be 50% larger

than expected, i.e., reduced in size by 62.5% instead of 75% after treatment by osimertinib. The

same sample sizes of ten vehicle- and ten osimertinib-treated mice were generated from

bootstrapping mice and then bootstrapping tumors from each mouse prior to and after the

simulated effects of drug responses and genotype - specific responses, respectively. To

calculate the false discovery rate, we also simulated another scenario where no preassigned

genotype-specific responses exist and all tumors, regardless of genotypes, were reduced in size

uniformly by 75% by osimertinib. The therapeutic sensitivity was calculated as the probability of

re-identifying the preassigned genotype-specific treatment responses given the cutoff of *P*-

values, while specificity was calculated as the probability of falsely identifying genotype-specific

treatment responses without any input signal of genotype-specific treatment responses given

the cutoff of *P*-values. A total of 100 runs of simulations of the 11 tumor suppressor genes

(including Tp53; 1,100 cases) were performed for each scenario. We further plotted the

receiver operating characteristic[78] curves for the three metrics by varying the cutoff for the *P*-

values.

Histology and immunohistochemistry

The auxiliary lobe of the right lung was collected for each experimental mouse from the

mice transduced with the Lenti-sg*TS^Pool^/Cre* pool whereas, both the auxiliary and left lobes were

collected for the validation experiments with individual sgRNAs (sg*Apc*, sg*Rbm10*, sg*Rbm10#2*

and sg*Neo2*). Right and auxiliary lobes were collected for the experiment with Lenti-

sg*Keap1/Cre* virus. Lung lobes were fixed in 4% paraformaldehyde overnight at room

temperature, placed in 70% ethanol, and paraffin-embedded and sectioned (Histology @ Yale).

Four micrometer sections were used for hematoxylin and eosin (H&E) staining and

immunohistochemistry. Tumor sizes were determined by measuring the longest diameter for

each tumor in H&E stained sections. Tumor size and tumor area were quantified using ImageJ.

The limited tissue collected for histological analysis reduced the number of tumors initiated

with Lenti-sg*Rbm10/Cre* that could be measured. *P*-values were calculated from the Mann-

Whitney U test. The following antibodies were used for immunohistochemistry: anti-mutant

EGFR^L858R^ (1:200, CST #3197), anti-SP-C (1:200, AB40876), anti-TTF-1/Nkx2-1 (1:200, AB76013),

anti-phospho-histone H3 (1:200, CST #9701), anti-Ki-67 (1:400, CST #9027), anti-mKate (1:2500,

Evrogen #AB233), anti-Cas9 (1:500, Novus Biologicals #7A9-3A3, NBP2-36440), anti-β-catenin

(1:500, CST #8814), anti-Rbm10 (1:200, AB224149), and anti-Keap1 (1:500, AB227828). Rbm10

expression in tumors was binned as High (over 75% of positive nuclei), Medium (between 25

and 75% of positive nuclei) or Low/negative (positive nuclear staining below 25%). Keap1 levels

in tumors were binned as High (over 75% of positive cells), Medium (between 25 and 75% of

positive cells) or Low/negative (positive staining below 25%). *P*-values were calculated using the

Chi-squared test.

Analysis of human lung tumor data using GENIE data

The AACR Project GENIE is a registry that contains CLIA-/ISO-certified genomic data

collected from the records of more than 9,000 patients who were treated at each of the

consortium's participating institutions[48]. Data from GENIE version 4.1-public were accessed

through the Synapse Platform. We generated a comprehensive list of all missense, nonsense,

and frameshift mutations for all screened genes across all participating centers in the GENIE

project, documenting these mutations at the gene and amino acid levels. Based on the sets of

genes included in the different screening panels that contribute to Project GENIE, we annotated

all lung adenocarcinoma within the database as being wild-type, mutated, or not screened for

each gene. From this complete catalog of mutations in each tumor, we determined the rates of

co-occurrence of known oncogenic *KRAS* mutations (G12X, G13X, Q61X) or *EGFR* mutations

(L858R, Exon 19 deletions, L861Q, G719X) with missense, nonsense, or frameshift mutations in

our set of ten tumor suppressor genes. Furthermore, we determined the frequency of co-

incident tumor suppressor gene mutations in tumors with oncogenic *KRAS* and inactivating

TP53 mutations (*KRAS/TP53*) and in tumors with oncogenic *EGFR* and inactivating *TP53*

mutations (*EGFR/TP53*). A similar analysis was also performed on tumors with *ALK-*

rearrangements and *TP53* mutations using GENIE version 7.0 (**Supplemental Fig. 11**). A pipeline

for this analysis is publicly available at www.github.com/dgmaghini/GENIE, which allows users

to input OncoTree codes of interest, generate mutational profiles for the corresponding GENIE

tumors, and identify the co-occurrence of up to two background mutations (for example, *EGFR*

and *TP53*) with mutations in other genes of interest.

Stanford cohort of *EGFR* mutant lung adenocarcinomas

Patients with lung cancer who were evaluated at the Stanford Cancer Center and had

their tumors analyzed using the Stanford Solid Tumor Actionable Mutation Panel (STAMP)[6]

were included in the analysis. This retrospective study was conducted under a molecular

analysis protocol approved by the Stanford University Institutional Review Board. All STAMP

cases performed between 2015 and 2019 were included; during this time, there were two

different assays used, with one covering 198 genes (302 kb) and the other covering 130 genes

(232 kb). STAMP was done as the standard of care and thus at the discretion of the treating

physician and could have occurred at the time of diagnosis or at the time of progression.

From the available STAMP cases, patients were selected if they had stage IV non-small

cell lung cancer (NSCLC) and had a pathogenic *EGFR* and *p53* mutation. Patients were excluded

if they had incomplete data or were lost to follow up prior to analysis of the primary endpoint,

if they elected not to receive treatment or if they received adjuvant tyrosine kinase inhibitor

therapy for early-stage disease. Within this cohort, patients were further selected for the

presence of at least one of the tumor suppressor genes investigated in the preclinical setting

(*KEAP1, LKB1/STK11, SETD2, SMAD4, RB1, APC, ARIDIA* and/or *CDKN2A*). To ensure that there

was enough power to conduct an analysis, genes were analyzed individually if there were at

least 8 patients with tumors with a mutation of that gene who met inclusion criteria. Due to

small numbers, patients with tumors with *LKB1* (*N* = 1), *SETD2* (*N* = 0) and *SMAD4* (*N* = 1)

mutations were not analyzed separately. However, as the two patients with tumors harboring

LKB1 and *SMAD4* mutations were also *EGFR/P53* mutant, they were included as part of the

control arm. Univariate analysis of time to treatment failure was completed on cases with stage

IV, *EGFR/P53* mutant NSCLC who were treated with a tyrosine kinase inhibitor [13] and had

mutations in either *KEAP1*-pathway component *(KEAP1, NFE2L2, CUL3), RB1, APC, ARIDIA* or

CDKN2A. Mutations that were significant on univariate analysis were identified and multivariate

analyses accounting for 1) co-founding variables and 2) co-mutations were run. Demographic

data including sex, age at diagnosis, smoking history, and ethnicity were extracted

(**Supplemental Tables 1, 2**). For each tumor suppressor, patients were matched 1:3 with a

wildtype cohort on the basis of sex, smoking history, ethnicity, age and treatment type. Time to

Treatment Failure [79] was determined by subtracting the date of discontinuation of TKI due to

progression, toxicity or death, from the date of initiation of TKI and reported in months.

Statistical analysis was performed using Prism 8 and R studio. The Kaplan-Meier method was

used to estimate TTF. Comparison of survival curves was made using the Log-rank test.

Significance was defined as $P < 0.05$. Hazard ratios (HR) were generated from multivariate

regression analysis performed in R and reported with a 95% confidence interval (CI).

Yale cohort of *EGFR* mutant lung adenocarcinomas

Patients with *EGFR*-mutant lung adenocarcinoma were consented and enrolled to a Yale

University IRB approved protocol allowing the collection and analysis of clinical data, archival

and fresh tissue, blood and the generation of patient-derived xenografts. Patients who received

targeted therapy (erlotinib, gefitinib, or afatinib) as first line therapy, either alone or in

combination with other therapies such as chemotherapy or cetuximab, were included

(**Supplemental Table 3**). For genomic studies, formalin-fixed paraffin embedded tissue was

macro-dissected to enrich for tumor material. All of the tumor samples (N = 29) analyzed had

matched normal tissue and cancer cell purity >20% as assessed by the LOH (Loss of

Heterozygosity) events from the whole exome sequencing data.

<u>Whole Exome Sequencing</u>

DNA was extracted from and analyzed as previously described[80]. Briefly, genomic DNA

was captured on the NimbleGen 2.1M human exome array and subjected to 74-bp paired-end

reads on the Illumina HiSeq2000 instrument. The mean coverage for normal was 109.1x and the

mean coverage for tumor was 189x with 92.78% and 95.56% for the bases covered at least 20

independent sequence reads, respectively. Sequence reads were mapped to the human

reference genome (GRCh37) using the Burrow-Wheeler Aligner-MEM (BWA-MEM) program.

Sequence reads outside the targeted sequences were discarded and the statistics on coverage

were collected from the remaining reads using in-house per scripts.

<u>Somatic Mutation Calling</u>

For all matched tumor-normal pairs, somatic point mutations and indels were called by

MuTect2 using Bayesian classifiers. For all somatic mutations called, we extracted base

coverage information in all samples and considered the mutations that were supported by at

least two independent sequence reads covering non-reference alleles and present in more than

5% of all sequencing reads. Identified variants were further filtered based on their presence in

repositories of common variations (1000 Genomes, NHLBI exome variant server and 2,577 non-

cancer exomes sequenced at Yale) and annotated using ANNOVAR program[81]. All somatic indels

were visually inspected to remove the false positive calls.

<u>Somatic Copy Number Variation Analysis</u>

Copy number analysis was performed as previously described[80]. Briefly, copy number

variants were identified from the whole exome sequencing data using EXCAVATOR software

that normalizes the non-uniform whole exome sequencing data taking GC-content, mappability,

and exon-size into account[82]. The Hidden Markov Model was utilized to classify each copy

number variant segment into five copy number states (homozygous deletion, heterozygous

deletion, normal copy number, homozygous copy gain or multiple copy gain). Tumor purity was

estimated from LOH using in-house per scripts.

Data availability

The datasets generated during and/or analyzed in the current study will be made available

in the NCBI Gene Expression Omnibus database (GSE146550) and dbGAP. GENIE genomic

data analysis is publicly available at www.github.com/dgmaghini/GENIE. All other data

supporting the findings are available upon request.

Code availability

The code is available at https://github.com/lichuan199010/Tuba-seq-analysis-and-

[summary-statistics](https://github.com/lichuan199010/Tuba-seq-analysis-and-summary-statistics).

References
844

1   Hanahan, D. & Weinberg, R. A. Hallmarks of cancer: the next generation. *Cell* **144**, 646-
674, doi:10.1016/j.cell.2011.02.013 (2011).
2   Skoulidis, F. & Heymach, J. V. Co-occurring genomic alterations in non-small-cell lung
cancer biology and therapy. *Nat Rev Cancer* **19**, 495-509, doi:10.1038/s41568-019-
0179-8 (2019).
3   van de Haar, J. *et al.* Identifying Epistasis in Cancer Genomes: A Delicate Affair. *Cell*
177, 1375-1383, doi:10.1016/j.cell.2019.05.005 (2019).

4   Platt, R. J. *et al.* CRISPR-Cas9 knockin mice for genome editing and cancer modeling.
Cell **159**, 440-455, doi:10.1016/j.cell.2014.09.014 (2014).
5   Chen, S. *et al.* Genome-wide CRISPR screen in a mouse model of tumor growth and
metastasis. *Cell* **160**, 1246-1260, doi:10.1016/j.cell.2015.02.038 (2015).
6   Chuang, C. H. *et al.* Molecular definition of a metastatic lung cancer state reveals a
targetable CD109-Janus kinase-Stat axis. *Nat Med* **23**, 291-300, doi:10.1038/nm.4285
(2017).
7   Winters, I. P. *et al.* Multiplexed in vivo homology-directed repair and tumor barcoding
enables parallel quantification of Kras variant oncogenicity. *Nat Commun* **8**, 2053,
doi:10.1038/s41467-017-01519-y (2017).
8   Rogers, Z. N. *et al.* A quantitative and multiplexed approach to uncover the fitness
landscape of tumor suppression in vivo. *Nat Methods* **14**, 737-742,
doi:10.1038/nmeth.4297 (2017).
9   Rogers, Z. N. *et al.* Mapping the in vivo fitness landscape of lung adenocarcinoma
tumor suppression in mice. *Nat Genet* **50**, 483-486, doi:10.1038/s41588-018-0083-2
(2018).
10   Winters, I. P., Murray, C. W. & Winslow, M. M. Towards quantitative and multiplexed
in vivo functional cancer genomics. *Nat Rev Genet* **19**, 741-755, doi:10.1038/s41576-
018-0053-7 (2018).
11   Campbell, J. D. *et al.* Distinct patterns of somatic genome alterations in lung
adenocarcinomas and squamous cell carcinomas. *Nat Genet* **48**, 607-616,
doi:10.1038/ng.3564 (2016).
12   Cancer Genome Atlas Research, N. Comprehensive molecular profiling of lung
adenocarcinoma. *Nature* **511**, 543-550, doi:10.1038/nature13385 (2014).
13   Blakely, C. M. *et al.* Evolution and clinical impact of co-occurring genetic alterations in
advanced-stage EGFR-mutant lung cancers. *Nat Genet* **49**, 1693-1704,
doi:10.1038/ng.3990 (2017).
14   Politi, K. & Herbst, R. S. Lung cancer in the era of precision medicine. *Clin Cancer Res*
21, 2213-2220, doi:10.1158/1078-0432.CCR-14-2748 (2015).
15   Jordan, E. J. *et al.* Prospective Comprehensive Molecular Characterization of Lung
Adenocarcinomas for Efficient Patient Matching to Approved and Emerging Therapies.
Cancer Discov **7**, 596-609, doi:10.1158/2159-8290.CD-16-1337 (2017).
16   Jamal-Hanjani, M. *et al.* Tracking the Evolution of Non-Small-Cell Lung Cancer. *N Engl*
J Med **376**, 2109-2121, doi:10.1056/NEJMoa1616288 (2017).
17   Yu, H. A. *et al.* Concurrent Alterations in EGFR-Mutant Lung Cancers Associated with
Resistance to EGFR Kinase Inhibitors and Characterization of MTOR as a Mediator of
Resistance. *Clin Cancer Res* **24**, 3108-3118, doi:10.1158/1078-0432.CCR-17-2961
(2018).
18   Scheffler, M. *et al.* K-ras Mutation Subtypes in NSCLC and Associated Co-occuring
Mutations in Other Oncogenic Pathways. *J Thorac Oncol* **14**, 606-616,
doi:10.1016/j.jtho.2018.12.013 (2019).
19   Lynch, T. J. *et al.* Activating mutations in the epidermal growth factor receptor
underlying responsiveness of non-small-cell lung cancer to gefitinib. *N Engl J Med* **350**,
2129-2139, doi:10.1056/NEJMoa040938 (2004).
20   Paez, J. G. *et al.* EGFR mutations in lung cancer: correlation with clinical response to
gefitinib therapy. *Science* **304**, 1497-1500, doi:10.1126/science.1099314 (2004).

21 Pao, W. *et al.* EGF receptor gene mutations are common in lung cancers from "never
smokers" and are associated with sensitivity of tumors to gefitinib and erlotinib. *Proc*
Natl Acad Sci U S A **101**, 13306-13311, doi:10.1073/pnas.0405220101 (2004).
22 Soria, J. C. *et al.* Osimertinib in Untreated EGFR-Mutated Advanced Non-Small-Cell
Lung Cancer. *N Engl J Med* **378**, 113-125, doi:10.1056/NEJMoa1713137 (2018).
23 Offin, M. *et al.* Concurrent RB1 and TP53 Alterations Define a Subset of EGFR-Mutant
Lung Cancers at risk for Histologic Transformation and Inferior Clinical Outcomes. *J*
Thorac Oncol, doi:10.1016/j.jtho.2019.06.002 (2019).
24 DuPage, M. *et al.* Endogenous T cell responses to antigens expressed in lung
adenocarcinomas delay malignant tumor progression. *Cancer Cell* **19**, 72-85,
doi:10.1016/j.ccr.2010.11.011 (2011).
25 Caswell, D. R. *et al.* Obligate progression precedes lung adenocarcinoma
dissemination. *Cancer Discov* **4**, 781-789, doi:10.1158/2159-8290.CD-13-0862 (2014).
26 DuPage, M., Dooley, A. L. & Jacks, T. Conditional mouse lung cancer models using
adenoviral or lentiviral delivery of Cre recombinase. *Nat Protoc* **4**, 1064-1072,
doi:10.1038/nprot.2009.95 (2009).
27 Politi, K. *et al.* Lung adenocarcinomas induced in mice by mutant EGF receptors found
in human lung cancers respond to a tyrosine kinase inhibitor or to down-regulation of
the receptors. *Genes Dev* **20**, 1496-1510, doi:10.1101/gad.1417406 (2006).
28 Dow, L. E. *et al.* Conditional reverse tet-transactivator mouse strains for the efficient
induction of TRE-regulated transgenes in mice. *PLoS One* **9**, e95236,
doi:10.1371/journal.pone.0095236 (2014).
29 Jonkers, J. *et al.* Synergistic tumor suppressor activity of BRCA2 and p53 in a
conditional mouse model for breast cancer. *Nat Genet* **29**, 418-425,
doi:10.1038/ng747 (2001).
30 Chiou, S. H. *et al.* A conditional system to specifically link disruption of protein-coding
function with reporter expression in mice. *Cell Rep* **7**, 2078-2086,
doi:10.1016/j.celrep.2014.05.031 (2014).
31 Puglisi, F. *et al.* Prognostic value of thyroid transcription factor-1 in primary, resected,
non-small cell lung carcinoma. *Mod Pathol* **12**, 318-324 (1999).
32 Tan, D. *et al.* Thyroid transcription factor-1 expression prevalence and its clinical
implications in non-small cell lung cancer: a high-throughput tissue microarray and
immunohistochemistry study. *Hum Pathol* **34**, 597-604, doi:10.1016/s0046-
8177(03)00180-1 (2003).
33 Tanaka, H. *et al.* Lineage-specific dependency of lung adenocarcinomas on the lung
development regulator TTF-1. *Cancer Res* **67**, 6007-6011, doi:10.1158/0008-
5472.CAN-06-4774 (2007).
34 Nakayama, S. *et al.* beta-catenin contributes to lung tumor development induced by
EGFR mutations. *Cancer Res* **74**, 5891-5902, doi:10.1158/0008-5472.CAN-14-0184
(2014).
35 Zehir, A. *et al.* Mutational landscape of metastatic cancer revealed from prospective
clinical sequencing of 10,000 patients. *Nat Med* **23**, 703-713, doi:10.1038/nm.4333
(2017).
36 Bechara, E. G., Sebestyen, E., Bernardis, I., Eyras, E. & Valcarcel, J. RBM5, 6, and 10
differentially regulate NUMB alternative splicing to control cancer cell proliferation.
Mol Cell **52**, 720-733, doi:10.1016/j.molcel.2013.11.010 (2013).

37 Hernandez, J. *et al.* Tumor suppressor properties of the splicing regulatory factor
RBM10. *RNA Biol* **13**, 466-472, doi:10.1080/15476286.2016.1144004 (2016).

38 Zhao, J. *et al.* Functional analysis reveals that RBM10 mutations contribute to lung
adenocarcinoma pathogenesis by deregulating splicing. *Sci Rep* **7**, 40488,
doi:10.1038/srep40488 (2017).

39 Walter, D. M. *et al.* Systematic In Vivo Inactivation of Chromatin-Regulating Enzymes
Identifies Setd2 as a Potent Tumor Suppressor in Lung Adenocarcinoma. *Cancer Res*
77, 1719-1729, doi:10.1158/0008-5472.CAN-16-2159 (2017).

40 Ji, H. *et al.* LKB1 modulates lung cancer differentiation and metastasis. *Nature* **448**,
807-810, doi:10.1038/nature06030 (2007).

41 Sanchez-Rivera, F. J. *et al.* Rapid modelling of cooperating genetic events in cancer
through somatic genome editing. *Nature* **516**, 428-431, doi:10.1038/nature13906
(2014).

42 Jackson, E. L. *et al.* Analysis of lung tumor initiation and progression using conditional
expression of oncogenic K-ras. *Genes Dev* **15**, 3243-3248, doi:10.1101/gad.943001
(2001).

43 Schuster, K. *et al.* Nullifying the CDKN2AB locus promotes mutant K-ras lung
tumorigenesis. *Mol Cancer Res* **12**, 912-923, doi:10.1158/1541-7786.MCR-13-0620-T
(2014).

44 Schmitt, A. *et al.* ATM Deficiency Is Associated with Sensitivity to PARP1- and ATR
Inhibitors in Lung Adenocarcinoma. *Cancer Res* **77**, 3040-3056, doi:10.1158/0008-
5472.CAN-16-3398 (2017).

45 Efeyan, A. *et al.* Limited role of murine ATM in oncogene-induced senescence and p53-
dependent tumor suppression. *PLoS One* **4**, e5475, doi:10.1371/journal.pone.0005475
(2009).

46 Ho, V. M., Schaffer, B. E., Karnezis, A. N., Park, K. S. & Sage, J. The retinoblastoma gene
Rb and its family member p130 suppress lung adenocarcinoma induced by oncogenic
K-Ras. *Oncogene* **28**, 1393-1399, doi:10.1038/onc.2008.491 (2009).

47 Walter, D. M. *et al.* RB constrains lineage fidelity and multiple stages of tumour
progression and metastasis. *Nature* **569**, 423-427, doi:10.1038/s41586-019-1172-9
(2019).

48 Consortium, A. P. G. AACR Project GENIE: Powering Precision Medicine through an
International Consortium. *Cancer Discov* **7**, 818-831, doi:10.1158/2159-8290.CD-17-
0151 (2017).

49 Skoulidis, F. *et al.* Co-occurring genomic alterations define major subsets of KRAS-
mutant lung adenocarcinoma with distinct biology, immune profiles, and therapeutic
vulnerabilities. *Cancer Discov* **5**, 860-877, doi:10.1158/2159-8290.CD-14-1236 (2015).

50 Arbour, K. C. *et al.* Effects of Co-occurring Genomic Alterations on Outcomes in
Patients with KRAS-Mutant Non-Small Cell Lung Cancer. *Clin Cancer Res* **24**, 334-340,
doi:10.1158/1078-0432.CCR-17-1841 (2018).

51 Gealy, R., Zhang, L., Siegfried, J. M., Luketich, J. D. & Keohavong, P. Comparison of
mutations in the p53 and K-ras genes in lung carcinomas from smoking and
nonsmoking women. *Cancer Epidemiol Biomarkers Prev* **8**, 297-302 (1999).

52 Pirazzoli, V. *et al.* Afatinib plus Cetuximab Delays Resistance Compared to Single-Agent
Erlotinib or Afatinib in Mouse Models of TKI-Naive EGFR L858R-Induced Lung
Adenocarcinoma. *Clin Cancer Res* **22**, 426-435, doi:10.1158/1078-0432.CCR-15-0620
(2016).

53   Pirazzoli, V. *et al.* Acquired resistance of EGFR-mutant lung adenocarcinomas to
afatinib plus cetuximab is associated with activation of mTORC1. *Cell Rep* **7**, 999-1008,
doi:10.1016/j.celrep.2014.04.014 (2014).
54   Starrett, J. H. G., A.; Cuomo, M.E.; Poels, K.; van Alderwerelt van Rosenburgh I.;
Nagelberg, A.; Farnsworth, D.; Price, K.S.; Khan, H.; Asthtekar, K.D.; Gaefele, M.; Ayeni,
D.; Stewart, T.F.; Kuhlmann, A.; Keack, S.; Unni, A.M.; Homer, R.; Lockwood, W.W.;
Michor, F.; Goldberg, S.B.; Lemmon, M.A.; Smith, P.D.; Cross, D.A.; Politi, K. Drug
sensitivity and allele-specificity of first-line osimertinib resistance *EGFR* mutations.
Under Revision (2020).
55   Ramalingam, S. S. *et al.* Osimertinib As First-Line Treatment of EGFR Mutation-Positive
Advanced Non-Small-Cell Lung Cancer. *J Clin Oncol* **36**, 841-849,
doi:10.1200/JCO.2017.74.7576 (2018).
56   Ramalingam, S. S. *et al.* Overall Survival with Osimertinib in Untreated, EGFR-Mutated
Advanced NSCLC. *N Engl J Med*, doi:10.1056/NEJMoa1913662 (2019).
57   Li, C. L., W.; Rizvi, H.; Cai, H; McFarland, C.D.; Rogers, Z.N.; Yousefi, M.; Winters, I.P.;
Rudin, C.M.; Petro, D.A.; Winslow, M.M. Quantitative *in vivo* analyses reveal a complex
pharmacogenomic landscape in lung adenocarcinoma. *BioRxiv [**Preprint**] January 29,*
2020. Available from: https://doi.org/10.1101/2020.01.28.923912 (2020).
58   Hellyer, J. A. *et al.* Impact of KEAP1/NFE2L2/CUL3 mutations on duration of response
to EGFR tyrosine kinase inhibitors in EGFR mutated non-small cell lung cancer. *Lung*
Cancer **134**, 42-45, doi:10.1016/j.lungcan.2019.05.002 (2019).
59   Cleasby, A. *et al.* Structure of the BTB domain of Keap1 and its interaction with the
triterpenoid antagonist CDDO. *PLoS One* **9**, e98896,
doi:10.1371/journal.pone.0098896 (2014).
60   Gainor, J. F. *et al.* ALK rearrangements are mutually exclusive with mutations in EGFR
or KRAS: an analysis of 1,683 patients with non-small cell lung cancer. *Clin Cancer Res*
19, 4273-4281, doi:10.1158/1078-0432.CCR-13-0318 (2013).
61   Unni, A. M., Lockwood, W. W., Zejnullahu, K., Lee-Lin, S. Q. & Varmus, H. Evidence that
synthetic lethality underlies the mutual exclusivity of oncogenic KRAS and EGFR
mutations in lung adenocarcinoma. *Elife* **4**, e06907, doi:10.7554/eLife.06907 (2015).
62   Kersten, K., de Visser, K. E., van Miltenburg, M. H. & Jonkers, J. Genetically engineered
mouse models in oncology research and cancer medicine. *EMBO Mol Med* **9**, 137-153,
doi:10.15252/emmm.201606857 (2017).
63   Yamadori, T. *et al.* Molecular mechanisms for the regulation of Nrf2-mediated cell
proliferation in non-small-cell lung cancers. *Oncogene* **31**, 4768-4777,
doi:10.1038/onc.2011.628 (2012).
64   Krall, E. B. *et al.* KEAP1 loss modulates sensitivity to kinase targeted therapy in lung
cancer. *Elife* **6**, doi:10.7554/eLife.18970 (2017).
65   Park, S. H. *et al.* Resistance to gefitinib and cross-resistance to irreversible EGFR-TKIs
mediated by disruption of the Keap1-Nrf2 pathway in human lung cancer cells. *FASEB*
J, fj201800011R, doi:10.1096/fj.201800011R (2018).
66   DeNicola, G. M. *et al.* NRF2 regulates serine biosynthesis in non-small cell lung cancer.
Nat Genet **47**, 1475-1481, doi:10.1038/ng.3421 (2015).
67   Romero, R. *et al.* Keap1 loss promotes Kras-driven lung cancer and results in
dependence on glutaminolysis. *Nat Med* **23**, 1362-1368, doi:10.1038/nm.4407 (2017).
68   Galan-Cobo, A. *et al.* LKB1 and KEAP1/NRF2 Pathways Cooperatively Promote
Metabolic Reprogramming with Enhanced Glutamine Dependence in KRAS-Mutant

Lung Adenocarcinoma. *Cancer Res* **79**, 3251-3267, doi:10.1158/0008-5472.CAN-18-
3527 (2019).

69   Wang, J. *et al.* Nestin regulates cellular redox homeostasis in lung cancer through the
Keap1-Nrf2 feedback loop. *Nat Commun* **10**, 5043, doi:10.1038/s41467-019-12925-9
(2019).

70   Jain, A. *et al.* p62/SQSTM1 is a target gene for transcription factor NRF2 and creates a
positive feedback loop by inducing antioxidant response element-driven gene
transcription. *J Biol Chem* **285**, 22576-22591, doi:10.1074/jbc.M110.118976 (2010).

71   Wang, Q. *et al.* CDK20 interacts with KEAP1 to activate NRF2 and promotes
radiochemoresistance in lung cancer cells. *Oncogene* **36**, 5321-5330,
doi:10.1038/onc.2017.161 (2017).

72   Marcar, L. *et al.* Acquired Resistance of EGFR-Mutated Lung Cancer to Tyrosine Kinase
Inhibitor Treatment Promotes PARP Inhibitor Sensitivity. *Cell Rep* **27**, 3422-3432
e3424, doi:10.1016/j.celrep.2019.05.058 (2019).

73   Madisen, L. *et al.* A robust and high-throughput Cre reporting and characterization
system for the whole mouse brain. *Nat Neurosci* **13**, 133-140, doi:10.1038/nn.2467
(2010).

74   Nakada, D., Saunders, T. L. & Morrison, S. J. Lkb1 regulates cell cycle and energy
metabolism in haematopoietic stem cells. *Nature* **468**, 653-658,
doi:10.1038/nature09571 (2010).

75   Hill, A. J. *et al.* On the design of CRISPR-based single-cell molecular screens. *Nat
Methods* **15**, 271-274, doi:10.1038/nmeth.4604 (2018).

76   Annunziato, S. *et al.* Modeling invasive lobular breast carcinoma by CRISPR/Cas9-
mediated somatic genome editing of the mammary gland. *Genes Dev* **30**, 1470-1480,
doi:10.1101/gad.279190.116 (2016).

77   Papademetris, X. *et al.* BioImage Suite: An integrated medical image analysis suite: An
update. *Insight J* **2006**, 209 (2006).

78   Skoulidis, F. *et al.* STK11/LKB1 Mutations and PD-1 Inhibitor Resistance in KRAS-
Mutant Lung Adenocarcinoma. *Cancer Discov* **8**, 822-835, doi:10.1158/2159-8290.CD-
18-0099 (2018).

79   Reck, M. *et al.* Pembrolizumab versus Chemotherapy for PD-L1-Positive Non-Small-
Cell Lung Cancer. *N Engl J Med* **375**, 1823-1833, doi:10.1056/NEJMoa1606774 (2016).

80   Choi, M. *et al.* Genetic diagnosis by whole exome capture and massively parallel DNA
sequencing. *Proc Natl Acad Sci U S A* **106**, 19096-19101,
doi:10.1073/pnas.0910672106 (2009).

81   Wang, K., Li, M. & Hakonarson, H. ANNOVAR: functional annotation of genetic variants
from high-throughput sequencing data. *Nucleic Acids Res* **38**, e164,
doi:10.1093/nar/gkq603 (2010).

82   Xu, D., Olman, V., Wang, L. & Xu, Y. EXCAVATOR: a computer program for efficiently
mining gene expression data. *Nucleic Acids Res* **31**, 5582-5589,
doi:10.1093/nar/gkg783 (2003).

1079

Fig. 1 | Lentiviral Cre-mediated lung tumor initiation in *EGFR;p53* and *EGFR;p53;Cas9* mice. a, Schematic of the *TetO-EGFR^L858R^*, *R26^LSL-RIK^*, and *p53^flox^* alleles in *EGFR;p53* mice, prior to and following Cre-mediated recombination. Conditional expression of oncogenic EGFR^L858R^ is under the control of a tetracycline response element (*TetO*), which is induced by rtTA in the presence of doxycycline (Dox). Lentiviral-Cre inactivates *Trp53* and enables the expression of the reverse tetracycline-regulated transactivator (*rtTA3*) and mKate (from the *R26^LSL-RIK^* allele). Cre also allows expression of Cas9 and GFP (from the *R26^LSL-Cas9-GFP^* allele) in *EGFR;p53;Cas9* mice. **b**, MRI showing tumor development 11 weeks after tumor initiation in *EGFR;p53* mice (top left panel) with 2×10^6 ifu Lenti-Cre. The dashed red line surrounds the heart (H) and red arrows indicate areas of tumor. Hematoxylin and eosin (H&E) staining shows lung adenocarcinoma development. Scale bars = 1.2 mm and 100 μm in the top and bottom panels, respectively. Images are from a representative mouse ($N = 5$). **c**, Immunostaining for EGFR^L858R^, mKate and Cas9 in tumors in *EGFR;p53* and *EGFR;p53;Cas9* mice. The dashed lines indicate areas of tumor. Scale bars = 200 μm. **d**, MRI and H&E showing tumor development 16 weeks after tumor initiation in *EGFR;p53;Cas9* mice with 1×10^5 ifu Lenti-Cre. Tumors are positive for GFP in *EGFR;p53;Cas9* mice and lungs are indicated by the white dashed line. H&E image scale bars = 1.2 mm and 100 μm in top and bottom right panels, respectively. GFP image scale bar = 2.5 mm.

Fig. 2 | Multiplexed somatic CRISPR–Cas9-mediated genome editing uncovers tumor suppressor gene effects on *EGFR*-driven lung tumors. a, Experimental strategy. Tumors were allowed to develop for either 11 weeks in *EGFR;p53;Cas9* and *EGFR;p53* mice or 19 weeks in *EGFR;p53;Cas9* mice after intra-tracheal administration of Lenti-sg*TS^Pool^/Cre*. Whole lungs were collected for tumor barcode deep sequencing (Tuba-seq) and histology. The number of neoplastic cells in each tumor (tumor size) was calculated from barcode sequencing of bulk tumor-bearing lungs. Barcode read number was normalized to benchmark control cells that have known barcodes and were added at a known number to each sample (Methods). **b**, MRI, H&E, and GFP images showing tumor development in *EGFR;p53;-Cas9* mice 11 weeks after tumor initiation with 1x10⁶ ifu of Lenti-sg*TS^Pool^/Cre*. H&E image scale bars = 1.2 mm and 100 μm in top and bottom right panels, respectively. Lungs are indicated by the white dashed lines. GFP image scale bar = 2.5 mm. Images are from a representative mouse (*N* = 10). **c**, Relative log-normal (LN) mean size of tumors with each sgRNA in *EGFR;p53* (*N* = 5) and *EGFR;p53;-Cas9* mice (*N* = 10) 11 weeks after tumor initiation (normalized to the tumors with inert sgRNAs). *P*-values were calculated from bootstrapping. *P*-values < 0.05 and their corresponding means are highlighted in *EGFR;p53;Cas9* mice for sgRNAs that positively (red) and negatively (green) affect tumor growth when the effects are equal to or differ >10% compared to the size of tumors with inert sgRNAs. **d**, Relative size of tumors at the indicated percentiles of each genotype in *EGFR;p53* mice 11 weeks after tumor initiation with the Lenti-sg*TS^Pool^/Cre*. These mice lack the *R26^LSL-Cas9-GFP^* allele; therefore, all sgRNAs are functionally inert. 95% confidence intervals are shown. Percentiles calculated from bootstrapping that are significantly different from the tumors with inert sgRNAs are in color. **e**, Relative size of tumors of each genotype in *EGFR;p53;Cas9* mice 11 weeks after tumor initiation with the Lenti-sg*TS^Pool^/Cre*. The relative size of tumors at the indicated percentiles were calculated from the tumor size distribution of all tumors from ten mice. 95% confidence intervals are shown. Percentiles were calculated from bootstrapping and are in color if significantly different from the tumors with inert sgRNAs.

Fig. 3 I *Apc* and *Rbm10* inactivation enhances the growth of oncogenic *EGFR*-driven lung tumors *in vivo*. a, Experimental strategy for tumor suppressor gene validation. Tumors were initiated in *EGFR;p53* and *EGFR;p53;Cas9* mice with Lenti-sg*TS/Cre* vectors carrying sg*Apc*, sg*Rbm10*, sg*Rbm10#2*, or sg*Neo2* as a control (*EGFR;p53 N* = 3 mice/group, *EGFR;p53;Cas9 N* = 5 mice/group, 1x10⁵ ifu/mouse). **b-e**, H&E and GFP images show that *Apc* (**c**) and *Rbm10* (**d, e**) inactivation enhances tumor growth compared to the controls (**b**). The histology of the left and auxiliary lobes was analyzed. Lungs are indicated by the white dashed lines. Scale bars = 1.2 mm and 2.5 mm for histology and GFP images, respectively. Tumor size was calculated by measuring the longest diameter of each tumor. The number of tumors studied are reported on the X-axis. *P*-values were calculated using a one-tailed Mann-Whitney U test. Horizontal lines show the median and whiskers indicate the minimum and the maximum of the data set. The box represents values in the first and the third quartile. The panels on the bottom right of the H&E images show nuclear accumulation of β-catenin (**c**) and absence of Rbm10 protein expression (**d, e**) reflective of *Apc* and *Rbm10* inactivation in tumors in *EGFR;p53;Cas9* mice, respectively.

Fig. 4 | Dramatic differences in the effects of tumor suppressor genes in oncogenic *EGFR*- versus *Kras*-driven lung cancer. a, Relative size of tumors of each genotype in *Kras^{G12D};p53^{flox/flox};R26^{LSL-Tomato};H11^{LSL-Cas9}* (*Kras;p53;Cas9*) mice 14 weeks after tumor initiation with Lenti-sg*TS^{Pool}*/*Cre* relative to tumors with inert sgRNAs. The relative size of tumors at the indicated percentiles was calculated from the tumor size distribution of all tumors from six mice. 95% confidence intervals are shown. *P*-values were calculated from bootstrapping. Percentiles that are significantly different from the tumors with inert sgRNAs are in color. **b**, LN mean for tumors with each sgRNA in *Kras;p53;Cas9* mice 14 weeks after tumor initiation (normalized to the inert tumors). *P*-values were calculated by bootstrapping and significant values are highlighted in red when *P* < 0.05 and the effects are >10% compared to the size of tumors with inert sgRNAs. **c**, The relative effect of inactivating each tumor suppressor gene on tumor sizes (comparison to tumors with inert sgRNAs) at the indicated percentile in the *EGFR;p53;Cas9* (*N* = 10) and *Kras;p53;Cas9* (*N* = 6) models. *Lkb1* and *Setd2* inactivation greatly increased tumor size only in the *Kras;p53;Cas9* model. Error bars indicate the standard deviation. **d**, The frequency of tumor suppressor gene alterations that co-occur with *EGFR* or *KRAS* and *TP53* mutations in human lung adenocarcinomas (LUADs, data from AACR Project GENIE). **e**, *LKB1* and *SETD2* alterations co-occur significantly more frequently in *KRAS^{onc};TP53^{mut}* than in *EGFR^{onc};TP53^{mut}* human lung adenocarcinomas. The frequency of *RBM10* and *APC* alterations were not significantly different between in *KRAS^{onc};TP53^{mut}* and *EGFR^{onc};TP53^{mut}* tumors. The odds ratios represent the strength of the observed frequencies of tumor suppressor gene alterations that co-occur in *KRAS^{onc};TP53^{mut}* cases compared to *EGFR^{onc};TP53^{mut}* cases. *P*-values were calculated using a Fisher's exact test.

Fig. 5 | Identification of genotype-specific responses to osimertinib treatment. a, Experimental strategy. Tumors were initiated with Lenti-sg*TS^Pool^/Cre* in *EGFR;p53;Cas9* mice for nine or 17 weeks and were treated for two weeks with either vehicle or osimertinib (25 mg/kg, 5 days/week). **b,** Relative size of the tumors at the indicated percentiles for each genotype in *EGFR;p53;Cas9* mice after treatment with osimertinib. 95% confidence intervals are shown. *P*-values were calculated from bootstrapping. Percentiles that are significantly different from the tumors with inert sgRNAs are in color. **c,** Estimate of the genotype-specific treatment response (*ScoreRLM*) calculated by comparing the LN mean of tumors treated with osimertinib to the LN mean of vehicle-treated tumors in *EGFR; p53;Cas9* mice 11 weeks after tumor initiation (Methods). Error bars indicate the standard deviation. *P*-values were calculated from bootstrapping. **d,** H&E staining of tumor bearing-lungs in *EGFR;p53* and *EGFR;p53;Cas9* mice with Lenti-sg*Keap1/Cre* initiated tumors (*N* = 8 mice/group). Scale bars = 1.2 mm. **e,** Immunostaining of Lenti-sg*Keap1/Cre* initiated tumors in *EGFR;p53;Cas9* mice for EGFR^L858R^ and Keap1 after vehicle or osimertinib treatment (*N* = 4 mice/treated-group). Tumors are still detectable after two weeks of treatment with osimertinib and mostly express medium or low/negative levels of Keap1 compared to tumors treated with vehicle in *EGFR;p53;Cas9* mice (bar graph). The dashed lines indicate areas of tumors and the level of Keap1 is indicated with a label (high or low/negative). Scale bars = 200 μm. *P*-values were calculated using a Chi-squared test.

Fig. 6 | *KEAP1* inactivation correlates with reduced therapeutic response to TKIs in human *EGFR*-driven lung adenocarcinomas. a, Kaplan-Meier curve showing time to TKI treatment failure for patients with *EGFR/TP53* lung adenocarcinomas that do or not have mutations in the *KEAP1/NFE2L2/CUL3* axis. Time to treatment failure is the time from the initiation of TKI treatment to the date of discontinuation of TKI due to progression, toxicity or death. The *P*-value was calcuated using the Log rank test. **b**, Forest plot of the time on treatment hazard ratios for tumors with *KEAP1*, *RB1*, *APC*, *ARIDA* or *CDKN2A* alterations in *EGFR/TP53* mutant lung adenocarcinomas. Hazard ratios were calculated from multivariate regression analysis, 95% confidence intervals are shown. **c**, *KEAP1, NFE2L2*, and *CUL3* alteration frequency in oncogenic *EGFR* and *TP53* mutant lung tumors in the Yale Lung Rebiopsy Program dataset (Methods). OncoPrint of oncogenic *EGFR* samples prior to first-line TKI (erlotinib, gefitinib, afatinib) treatment (PRE-TKI, left panel) (*N* = 22), and at acquired resistance to TKIs (TKI-R, right panel) (*N* = 27). In each row, the percentage and the type of alterations in each gene are indicated for each patient. For the TKI-R samples, known resistance mechanisms such as acquisition of T790M in *EGFR*, are reported. Cases with paired PRE-TKI and TKI-R samples are indicated by the patient number highlighted in red.