Adaptive mutations in RNA polymerase and the transcriptional terminator Rho

have similar effects on *Escherichia coli* gene expression

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ABSTRACT

Modifications to transcriptional regulators play a major role in adaptation. Here we
compared the effects of multiple beneficial mutations within and between *Escherichia
coli rpoB*, the gene encoding the RNA polymerase β subunit, and *rho*, which encodes a
transcriptional terminator. These two genes have harbored adaptive mutations in
numerous *E. coli* evolution experiments but particularly in our previous large-scale
thermal stress experiment, where the two genes characterized two alternative adaptive
pathways. To compare the effects of beneficial mutations, we engineered four
advantageous mutations into each of the two genes and measured their effects on fitness,
growth, gene expression and transcriptional termination at 42.2°C. Among the eight
mutations, two *rho* mutations had no detectable effect on relative fitness, suggesting they
were beneficial only in the context of epistatic interactions. The remaining six mutations
had an average relative fitness benefit of ~20%. The *rpoB* mutations altered the
expression of ~1700 genes; *rho* mutations altered the expression of fewer genes, most of
which were a subset of the genes altered by *rpoB*. Across our eight mutants, relative
fitness correlated with the degree to which a mutation restored gene expression back to
the unstressed, 37.0°C state. The *rho* mutations do not enhance transcriptional
termination in known *rho*-terminated regions, but the genome-wide effects of mutations
in both genes was to enhance termination. Although beneficial mutations in the two genes
did not have identical effects on fitness, growth or gene expression, they acted
predominantly through parallel phenotypic effects on gene expression and transcriptional
termination.

Key words: transcriptional termination, protein structure, relative fitness, experimental
evolution, adaptive pathways, phenotypic convergence.

INTRODUCTION

In 1975, King and Wilson famously speculated that evolutionary modifications in phenotype "… are more often based on changes in the mechanisms controlling the expression of genes than on sequence changes in proteins" (King and Wilson, 1975). The relative frequency of changes in regulatory vs. structural genes is still debated (Hoekstra and Coyne, 2007, Carroll, 2008, Wittkopp and Kalay, 2011), but it has nonetheless become clear that regulatory genes do often play a crucial role in adaptation. For example, evolutionary modifications of transcriptional regulators have modified plant phenotypes during domestication (Doebley et al., 2006, Olsen and Wendel, 2013), contributed to the shift from marine to freshwater environments for sticklebacks (Peichel and Marques, 2017), and facilitated the adaptation of microbes during laboratory evolution experiments (Conrad et al., 2011, Long et al., 2015). Microbial evolution experiments have further shown that mutations in global transcriptional regulators are often highly beneficial, occur early in the course of adaptation, and appear under different selective regimes (Long et al., 2015). The last observation is especially true in *E. coli* evolution, because experiments over a wide range of strains and growth conditions have consistently identified adaptive genetic changes within the genes that encode the RNA polymerase (RNAP) complex [e.g., (Herring et al., 2006, Conrad et al., 2009, Charusanti et al., 2010, Conrad et al., 2010, Tenaillon et al., 2012, Sandberg et al., 2014, Deatherage et al., 2017)] and the Rho transcriptional terminator [e.g., (Freddolino et al., 2012, Tenaillon et al., 2012, Herron and Doebeli, 2013, Le Gac et al., 2013, Haft et al., 2014, Lee and Helmann, 2014, Dillon et al., 2016, Deatherage et al., 2017)].

These observations raise at least three interesting topics about adaptive changes within *E. coli* transcriptional regulators. The first, which we do not address here, is why modifications of global regulators like RNAP and Rho are favored in evolution experiments, despite the fact that RNAP function and sequence is often highly conserved in nature (Long et al., 2015). The second concerns potential pleiotropic effects, because some transcriptional regulators can, in theory, affect the expression of every gene in the genome. Indeed, single adaptive mutations in the *rpoB* gene, which encodes the RNA Polymerase β subunit, alter the expression of hundreds to thousands of downstream genes (Sandberg et al., 2014, Rodríguez-Verdugo et al., 2016, Utrilla et al., 2016). These

findings raise the possibility that some of the shifts in gene expression are maladaptive.

Consistent with this view, at least two studies have shown that fitness gains after the

fixation of a beneficial *rpoB* mutation act to ameliorate negative pleiotropic effects

(Sandberg et al., 2014, Rodríguez-Verdugo et al., 2016).

A third topic is about the relative effects of different adaptive mutations, both

within the same transcriptional regulator (e.g., different mutations within *rpoB*) and

between transcriptional regulators (e.g., *rpoB* vs. *rho*). These are potentially interesting

contrasts because it has been shown that different mutations can have different effects on

fitness, pleiotropy and evolutionary contingency (Rosenblum et al., 2014), even for

different mutations within the same gene (Linnen et al., 2009). It seems likely that there

are large-scale differences in the effects of mutations to RNAP and Rho. A modification

of RNAP has the potential to affect the expression of every gene, but Rho terminates

transcription for a subset of ~20% to 50% of *E. coli* genes (Cardinale et al., 2008, Peters

et al., 2009). This begs the questions: Do adaptive mutations in *rho* affect the expression

of fewer genes? If so, are mutations in *rho* generally more beneficial, because they cause

fewer negatively pleiotropic effects? And, to what extent are these effects consistent

across different beneficial mutations within the same transcriptional regulator?

To our knowledge, the effects of adaptive mutations have not yet been compared

explicitly between different transcriptional regulators. This may be due, in part, to the

fact that a valid comparison requires that mutations in the two regulatory genes are

adaptive in the same genetic background under identical culture conditions. Fortunately,

our previous thermal adaptation experiment has yielded appropriate mutations. Our

experiment evolved 115 populations of *E. coli* independently from the same ancestral

clone (REL1206) for 2000 generations at 42.2°C (Tenaillon et al., 2012). At the end of

the experiment, we isolated one clone from each population and found that fitness had

improved ~40%, on average, relative to REL1206. We also sequenced the evolved clones

and identified over 1300 mutations. Using parallelism as a *prima facie* argument for

adaptation (Wichman et al., 1999, Fong et al., 2005, Stern, 2013), about half of the

observed 1300 mutations were adaptive, either because the same mutation occurred in

more than one clone or because mutations occurred in the same gene in different clones.

Two of the most mutated genes in our thermal stress experiment were *rpoB*,

which accumulated a total of 87 mutations in 76 of the 115 clones, and *rho,* which

accumulated 24 different nonsynonymous mutations across 43 of 115 clones. Mutations

in the two genes were found together less often than expected at random, suggesting

negative epistatic interactions (Tenaillon et al., 2012). More generally, the two genes

define alternative pathways to thermal stress adaptation. The first includes mutations in

rpoB, as well as mutations in the other RNA polymerase subunits (*rpoA*, *rpoC* and *rpoD*)

and six *rod* genes that affect cell shape. In contrast, the *rho* pathway includes mutations

of the cardiolipin synthase (*cls*) gene and the transcription factor gene *iclR*. We have

shown that these two adaptive pathways differ in some aspects of their phenotypes, such

as chemical sensitivities (Hug and Gaut, 2015) and trade-offs for growth at low

temperature (Rodriguez-Verdugo et al., 2014).

Before diving into contrasts between the effects of *rho* and *rpoB* mutations, it is

useful to briefly consider the structure and function of RNAP and Rho. RNAP consists of

a five-subunit core protein that has the catalytic activity for RNA synthesis (Ebright,

2000, Ishihama, 2000). The β subunit contributes to RNA synthesis activity and contains

regions for non-sequence-specific interactions with DNA and nascent RNA. Some of the

observed beneficial *rpoB* mutations have occurred in the contact region between the

downstream DNA duplex and RNAP (proximal active site) (Rodríguez-Verdugo et al.,

2014). Mutations in the contact region are particularly likely to play key roles in

modulating RNAP activity in the three stages of transcription: Initiation, elongation, and

termination (Ederth et al., 2006).

The Rho molecule acts to terminate RNAP transcription for a subset of *E. coli*

genes. The protein is a hexameric ring composed of six monomers (Skordalakes and

Berger, 2003) (fig. 1). Given a mature hexamer, transcriptional termination proceeds,

first, by the protein recognizing a *rho ut*ilization (*rut*) site on an elongating mRNA;

second, by binding *rut* sites and translocating mRNA through the hexamer's central

cavity (Skordalakes and Berger, 2003); until, third, it contacts RNAP while it pauses,

thereby disassociating the elongation complex (Skordalakes and Berger, 2003, Peters et

al., 2011). The *rut* sites remain difficult to predict bioinformatically, and so the genomic

targets of Rho are characterized incompletely (Ciampi, 2006, Hollands et al., 2014).

However, a few hundred intergenic and intragenic Rho termination sites have been

identified experimentally (Peters et al., 2009, 2012), and these have helped to evaluate

whether *rho* mutants increase (Mori et al., 1989, Miwa et al., 1995) or decrease the

efficiency of termination (Freddolino et al., 2012, Haft et al., 2014).

Here we take advantage of a unique opportunity to compare and contrast the

effect of adaptive mutations between the *rho* and *rpoB* genes that characterize alternative

adaptive pathways. In the study, we engineer four beneficial *rho* mutations into the

REL1206 ancestor and contrast effects on fitness, growth, gene expression and

transcriptional termination to four previously-studied *rpoB* mutants (Rodriguez-Verdugo

et al., 2014, Rodríguez-Verdugo et al., 2016). In doing so, we address three sets of

questions. First, are the fitness and growth characteristics similar between *rho* and *rpoB*

mutations? Second, do the beneficial mutations influence the expression of similar

numbers and sets of genes? Third, do *rho* mutations alter its termination efficiency and, if

so, how do termination properties compare between *rho* and *rpoB* mutations? Finally, do

the mutations have a consistent predicted effect on protein stability, which is predicted to

be linked to fitness (e.g. DePristo et al., 2005)?

RESULTS

Rho mutations and relative fitnesses

We engineered four *rho* mutations - *I15N, I15F, A43T* and *T231A* – into the

ancestral REL1206 background (see Materials and Methods). Each of these substitutions

were adaptive by the criterion of parallelism, because they were observed in 15, 2, 3 and

2 independent populations, respectively, of our 42.2**°**C thermal stress experiment

(Tenaillon et al., 2012). *I15N, I15F* and *A43T* point mutations are located in the NHB

domain of the Rho monomer, while *T231A* is located in the central part of the C-terminal

domain (CTD), specifically in the Loop-CTD (fig. 1).

We assessed the relative fitness ($\overline{w}_r$) of the four *rho* mutants to REL1206 at

42.2˚C (supplementary table S1, Supplementary Material online). Relative fitness data

conveyed three observations (table 1). First, two of the four mutations (*A43T* and *T231A*)

yielded a $\overline{w}_r$ value significantly > 1.0, indicating an adaptive benefit under thermal stress.

In contrast, neither the *I15N* nor the *I15F* mutation produced a $\overline{w}_r$ value significantly

different from 1.0. *I15N* yielded an estimate < 1.0 (Rodriguez-Verdugo et al., 2014)

suggesting a slightly deleterious mutation (table 1). Second, the $\overline{w}_r$ estimates differed

significantly among the four mutations (ANOVA, $p = 2.4 \times 10^{-8}$), with *I15N* and *I15F*

forming one group and *A43T* and *T231A* forming a second, significantly different group

(Tukey-test; $p < 0.05$).

We contrasted $\overline{w}_r$ among four *rpoB* mutants (*I572L*, *I572F*, *I572N*, *I966S*)

(Rodriguez-Verdugo et al., 2014) and the four *rho* mutants. Each of the *rpoB* mutations

had $\overline{w}_r > 1.0$, with estimates ranging from $\overline{w}_r = 1.16$ to 1.26 at 42.2**°C** (table 1). Across all

mutants, comparisons again indicated heterogeneity of $\overline{w}_r$ (ANOVA, $p = 1.91 \times 10^{-08}$;

table 1), and Tukey tests grouped *I15N* and *I15F* against the remaining six mutations ($p <$

0.05 for 10 of 12 comparisons between *I15* mutations and the remaining mutations).

Altogether, $\overline{w}_r$ values were >1.00 and indistinguishable among the four *rpoB* mutations

and two of the four *rho* mutations; the two remaining *rho* mutations had demonstrably

lower $\overline{w}_r$ values and little effect on fitness.

Growth dynamics

To gain additional insights about potential differences between *rho* and *rpoB*

mutants, we measured growth curves of mutant lines at 37.0˚C and 42.2˚C (fig. 2, table 2

and supplementary table S2, Supplementary Material online) and estimated maximal

growth rates and final yields at stationery phase. At 37.0˚C, all *rho* mutants had

significantly higher final yields than at 42.2˚C (supplementary table S2, Supplementary

Material online), indicating that high temperature remains stressful even after the

introduction of putatively beneficial mutations. At 42.2˚C, the *rho* mutants had a lower

final yield than the ancestor, and there were also differences in maximum growth rate

among mutants: *I15F* and *I15N* showed somewhat lower maximum growth rate than the

ancestor but *A43T* and *T231A* had higher growth rates (fig. 2 and supplementary table S2,

Supplementary Material online), consistent with their higher $\overline{w}_r$ values.

We then contrasted growth dynamics between *rho* and the three *I572 rpoB* mutants

(Rodríguez-Verdugo et al., 2016). Similar to results with *rho*, *rpoB* mutants grew more

slowly and had lower yields at 42.2˚C compared to 37.0˚C (fig. 2 and supplementary

table S2, Supplementary Material online). At 37.0˚C, both *rho* and *rpoB* mutants grew

with similar rates relative to the REL1206 ancestor (fig. 2 and supplementary table S2,

Supplementary Material online). However, a striking difference became apparent at

42.2˚C, because the *I572 rpoB* mutants reached significantly higher final yields than the

rho mutants (table 2 and supplementary table S2, Supplementary Material online). The

only significant difference in growth rates was the contrast between *rpoB I572F* vs. *rho*

I15F contrast (table 2). Overall, growth curves indicate that: *i*) *rho* and *rpoB* mutations

differ with respect to yield, and *ii*) growth rates tend to be lower for *rho I15F* compared

to the remaining clones.

Gene expression phenotypes

To gain further insight into the phenotypic effects of *rho* mutations, we measured

gene expression at 42.2˚C using replicated RNAseq data (see Materials and Methods).

We hypothesized that expression covaries with $\overline{w}_r$, so that *I15N* and *I15F* differ more

dramatically in expression from *A43T* and *T231A* than they do from each other. To test

this hypothesis, we measured the correlation in expression across all genes for each pair

of *rho* mutants (table 3). All pairwise correlations were high ($r^2 > 0.95$), but *A43T* and

T231A had the highest correlation ($r^2 = 0.992$), while contrasts between an *I15* mutant

with either *A43T* or *T231A* had lower correlations (table 3). We also identified

differentially expressed genes (DEGs) between *rho* mutants, based on a significance cut-

off of $q < 0.001$ (see Material and Methods). Only one gene was expressed differentially

between *I15F* and *I15N*, but both *I15* mutations had > 100 DEGs between *A43T* and

T231A (table 3). These data suggest that *A43T* and *T23A* mutations have quantitatively

different effects on GE relative to the two *I15* mutations, mimicking observed differences

in fitness among clones.

Given that single *rho* mutations can confer extensive GE shifts relative to an

ancestral background (Freddolino et al., 2012, Haft et al., 2014), we compared GE

between the REL1206 ancestor at 42.2˚C and each of the four *rho* mutants. Across the

four *rho* mutants, we detected a total of 1140 DEGs compared to the 42.2˚C ancestor, but

there were more DEGs for *T231A* (1028 genes) and *A43T* (656) than for *I15F* (372) and

I15N (195) (fig. 3*A*). Among the complete set of 1140 DEGs, 141 (or 12%) were shared

among all four *rho* mutants (fig. 3*A*). Gene Ontology (GO) analysis of these 141 genes

revealed significant enrichment for down-regulation of maltose transport genes (GO:

0015768, $p = 1.04 \times 10^{-3}$) and significant up regulation of genes involved in transcription

(GO:0010467, $p = 1.12 \times 10^{-12}$) and translation (GO: 0006412, $p = 9.17 \times 10^{-37}$)

(supplementary table S3, Supplementary Material online). Interestingly, the *A43T* and

T231A mutants shared 330 DEGs that were not identified in either *I15F* or *I15N*. These

330 genes are likely candidates to contribute to $\overline{w}_r$ differences among *rho* mutants, and

they were enriched for up-regulation of purine nucleotide biosynthetic processes (GO:

0006164, $p = 1.15 \times 10^{-12}$) and down-regulation for glycerol catabolic processes (GO:

0019563, $p = 1.15 \times 10^{-12}$) (supplementary table S4, Supplementary Material online).

Finally, to determine whether putatively beneficial mutations in *rpoB* or *rho* have

similar effects on gene expression, we identified DEGs in four *rpoB* mutants -- *I572N*,

I572F, *I572L* and *I966S* -- using previously published data (Rodríguez-Verdugo et al.,

2016). We took the union of the DEGs for the four *rpoB* mutations and found 1726 DEGs

relative to REL1206 at 42.2°C. The *rpoB* and *rho* DEG sets were remarkably overlapping

(fig. 3*B*): of the 1726 DEGs identified with *rpoB* mutations, 957 genes (or 55.4%) were

also identified as DEGs in *rho* mutants. This similarity is more impressive when one

considers that *rho* mutations altered gene expression for significantly fewer genes than

rpoB mutations (1140 vs. 1726; binomial test: $p < 2.2 \times 10^{-16}$) so that 83% (=957/1140)

of DEGs caused by *rho* mutations were also identified as DEGs in *rpoB* mutants (fig.

3*B*). These results indicate that *rho* mutants generally affect the expression of a subset of

the genes affected by *rpoB* mutants.

The DEG overlap between *rho* and *rpoB* mutations left only 183 DEGs unique to

the set of *rho* mutations (fig. 3*B*). Among these 183 DEGs, GO analyses identified up-

regulated responses to temperature stimuli (e.g., *clpB, dnaK, dnaJ, degP, grpE*; GO:

0009408, $p = 3.35 \times 10^{-2}$) (supplementary data set S1, Supplementary Material online). In

contrast, the 769 genes uniquely modified by *rpoB* mutants were enriched for up-

regulation of iron ion transport (GO: 0006826, $p = 3.2 \times 10^{-05}$) and flagellum cell motility

(GO: 00048870, $p = 7.1 \times 10^{-06}$) genes. Monosaccharide catabolic processes (GO:

0005996, $p = 2.0 \times 10^{-04}$) and cell wall biogenesis (GO: 0042546, $p = 2.94 \times 10^{-4}$) were

also unique to *rpoB* mutants, but they were not consistently up- or down-regulated

(supplementary data set S1, Supplementary Material online).

Shifts in gene expression are partially restorative

Taken in total, *rpoB* and *rho* mutants affect an overlapping gene set, but it is not a foregone conclusion that they affect expression in the same direction. Here direction refers to expression shifts in mutants relative to the stressed ancestral state (i.e., REL1206 at 42.2 ˚C) and the unstressed ancestral state (i.e., REL1206 at 37.0˚C) (Carroll and Marx, 2013). We determined directionality in two ways. First, we applied PCA to all expression data for *rho, rpoB* and ancestral replicates, and then plotted the first two principal components, PC1 and PC2. Based on the PCA, the *rpoB* mutants were intermediate on PC1 between the ancestor at 37.0˚C and 42.2 ˚C (fig. 3*C*). This position is consistent with an overall tendency of *rpoB* mutants to restore expression patterns from the stressed (42.2˚C) toward the unstressed (37.0˚C) ancestral state (Rodríguez-Verdugo et al., 2016). Expression patterns from *rho* mutants were also intermediate between the two ancestral states on PC1, but they were not restored as fully as the *rpoB* mutants (fig. 3*C*). Intriguingly, replicates from the two less fit *rho* mutants (*I15N* and *I15F*) clustered more closely to REL1206 at 42.2˚C. These clustering patterns suggest that fitness is related to restoration in PCA space; indeed, $\overline{w}_r$ and the average PC1 eigenvector were correlated across the eight mutants ($r^2 = 0.4156$; $p = 0.042$).

Second, we categorized expression of single genes into categories. Following previous studies (Carroll and Marx, 2013), genes in mutants were classified as: *i*) "restored", if expression in the mutant shifts toward the unstressed ancestral state from the stressed ancestral state; *ii*) "unrestored", if expression remains similar to the REL1206 ancestor in its stressed state; *iii*) "reinforced" if expression in the mutant is exaggerated in the mutant relative to REL1206 at both 37.0˚C and 42.2˚C and, finally, *iv*) "novel" if the two ancestral treatments did not differ in GE but the mutant differed from both. (The Materials and Methods section includes more precise quantitative definitions of these four directional categories.) The majority of genes fell into the restored category for all mutants except *rpoB I572L* (table 4). More importantly, the number of restored genes was correlated with $\overline{w}_r$ across the eight mutants (*rho* and *rpoB* mutants) at a borderline level of significance (Spearman's $r = 0.67$; $p = 0.055$). Altogether, directional

analyses show that $\overline{w}_r$ of a mutant is a function of the degree of restoration of gene

expression.

Assessing potential effects on transcriptional termination

We have shown that *rho* mutations differ in $\overline{w}_r$ and that $\overline{w}_r$ correlates with shifts

in the magnitude and direction of gene expression. However, the question of mechanism

remains – i.e. how do mutations in *rho* affect its function as a transcriptional terminator?

Previous studies have shown that *rho* mutations tend to decrease termination and therefor

increase read-through activity (Freddolino et al., 2012, Haft et al., 2014). Alternatively,

we have hypothesized that adaptive *rho* mutations increase transcriptional efficiency at

high temperature by enhancing termination (Rodriguez-Verdugo et al., 2014, Rodríguez-

Verdugo et al., 2016). We addressed this hypothesis both directly and indirectly.

Direct effects on Rho-terminated regions: The direct approach relied on a set of

178 Rho-terminated regions that were defined by Peters et al. (2009) and previously used

to analyze read-through activity of a *rho* mutation (Haft et al., 2014) (supplementary data

set S2, Supplementary Material online). The advantage of studying these regions is that

they can, in theory, examine direct (primary) effects of *rho* mutations, as opposed to

indirect (secondary) effects on downstream genes. The size of the *rho*-terminated regions

spanned from 100 to ≈ 4000 bp, with roughly half located at the 3' end of coding regions

(intergenic) and the other half within genes (intragenic). Following Haft et al. (2014), we

calculated γ, the $\log_2$ ratio of normalized RNAseq counts between each mutant at 42.2˚C

and REL1206 at 42.2˚C for each of the 178 regions (see Materials and Methods). Under

the null hypothesis that the mutant and ancestor have similar termination properties,

γ is distributed binomially. If a mutation enhances termination, we expected significantly

more than 50% of the regions to have γ < 0.0. In contrast, increased read-through results

in >50% of regions having γ > 0.0 (Haft et al., 2014). Contrary to our prediction, both

I15N and *I15F* have increased read-through activity, with 108 and 119 of 178 regions

having γ > 0.0 (binomial, $p < 0.01$). The two remaining *rho* mutations (*A43T, T231A*)

yielded no evidence of altered termination properties ($p = 1.00$; supplementary fig. S1,

Supplementary Material online).

We further examined expression dynamics of the Rho-terminated regions by

taking the ratio of expression counts for each *rho*-terminated region (RT) against the

counts from the immediate 5' upstream region (UP) of the same size. We then computed

a measure of termination efficiency for each mutant as the ratio of averages, r_{avg}, of read

counts in RT vs. UP across all 178 regions (see Materials and Methods). While not

without caveats (such as the fact that upstream and downstream regions are in different

operons in some cases), this approach allowed us to measure the strength of termination

for each mutant and for each ancestral treatment.

Bootstrapped estimates of r_{avg} are presented in fig. 4. The estimates suggest

weaker termination transcription (i.e., enhanced read-through) for REL1206 at 42.2˚C

compared to 37.0˚C; although the trend is notable, the two ancestral treatments do not

differ significantly (bootstrap; p =0.864). For the *rho* mutants, *I15N* was alone in having

a higher median estimate of r_{avg} than REL1206 at 42.2˚C (fig. 4), which verifies the

inference of increased read-through activity based on γ values. In contrast, the

r_{avg} estimates for *T231A* and *A43T* (and *I15F*, to a lesser extent) appeared to restore

termination to the level of the ancestor at 37.0˚C (fig. 4).

It has been shown previously that some rpoB mutants enhance transcriptional

termination (Jin et al. 1988). Hence for completeness we also applied analysis of Rho-

terminated regions to *rpoB* mutants. Based on γ analyses, none of the *rpoB* mutants

yielded evidence of altered termination in these regions ($p > 0.500$; supplementary fig.

S1, Supplementary Material online). However, r_{avg} estimates for *rpoB* were consistently

lower than the ancestral treatments and the *rho* mutants (fig. 4). Furthermore, the average

r_{avg} estimate between the set of *rho* and *rpoB* mutants differed significantly ($p < 0.001$),

indicating either that termination in these regions is more efficient in *rpoB* mutants or that

rpoB mutants had consistently higher expression in the upstream regions. The *rpoB*

mutations also differed significantly from the ancestors at 42.2˚C and 37.0˚C ($p<0.003$).

Altogether, r_{avg} and γ analyses indicate that the *rho I15N* and *I15F* mutations likely

decrease termination efficiency, but as a group the *rpoB* mutations have statistically

better termination for these same regions.

Indirect effects: In addition to assessing the properties of *rho* termination directly,

we assessed potential effects on termination indirectly by focusing on the expression of

all genes and intergenic regions (IRs). Focusing first on genes, we compared expression

data between REL1206 at 37.0˚C and 42.2˚C. Similar to Rodriguez-Verdugo et al.

(2016), we found that ~1700 of 4204 coding regions were differentially expressed ($q <$

0.001) during thermal stress, with a tendency toward lower expression at 42.2 ˚C (972

down-regulated genes vs. 695 up regulated genes; binomial $p = 1.243 \times 10^{-11}$) (fig. 5*A*).

Given this baseline, we then assessed the effect of *rho* mutants relative to REL1206 at

42.2˚C. GE was significantly biased toward higher expression in each of the mutants

relative to REL1206 at 42.2˚C at $q < 0.001$ (fig. 5*A*; binomial, $p = 1.41 \times 10^{-10}$ (*I15N*), $p =$

2.13×10^{-6} (*I15F*), $p = 8.6 \times 10^{-12}$ (*A43T*), $p = 2.2 \times 10^{-16}$ (*T231A*)). In effect, thermal

stress led to lower GE at 42.2˚C relative to 37.0˚C, and the four mutations reversed that

trend. These trends were quantitatively similar for *rpoB* mutants (fig. 5*C*).

The picture was, however, different for IRs. Among 2306 IRs (supplementary

data set S3, Supplementary Material online) we found more were up-regulated in

REL1206 at 42.2˚C relative to 37.0˚C (212 up regulated IR vs. 164 down; regulated;

binomial $p = 0.015$) (fig. 5*B*). This up-tick in the expression of IRs may indicate more

transcriptional read-through for REL1206 under thermal stress. This trend was reversed

by both *rho* and *rpoB* mutations, such that differentially expressed IRs tended to have

lower expression in the mutants relative to REL1206 at 42.2˚C [fig. 5*B*, binomial $p =$

0.0016 (*I15N*), $p = 0.0001$ (*I15F*), $p = 0.04164$ (*A43T*); fig 5*D*; $p = 0.0016$ (*I15N*), $p =$

0.0001 (*I15F*), $p = 0.04164$ (*A43T*)]. These results raise the possibility that all of the *rho*

and *rpoB* mutations enhance termination efficiency at 42.2˚C. For the *rho* mutations this

is not likely a direct effect (fig. 4) but an indirect, downstream effect.

Mutations and protein stability

Finally, we evaluated the predicted folding stability of the Rho and RpoB

proteins. Our principal goal was to assess whether changes in fitness correlated with the

direction and magnitude of shifts in the free energy of protein folding stability, as is

expected under some evolutionary models (DePristo et al., 2005, Wylie and

Shakhnovich, 2011). We hypothesized that $\overline{w}_r$ from specific mutations correlates with the

difference of the free energy of folding between ancestral and mutant proteins ($\Delta\Delta G$) at

42.2° C. To determine the free energy of folding (ΔG), we applied an approach that

combines classical Molecular Dynamics (MD) with the FoldX algorithm (see Materials

and Methods) and then measured the change in folding stability ($\Delta\Delta G$) induced by each

of the four *rho* and four *rpoB* mutations. Positive values of $\Delta\Delta G$ suggest a decrease either

in the stability of the protein fold or in the ability of the protein to fold relative to the

ancestor; negative values indicate increased stability (Guerois et al., 2002, Miller et al.,

2016). Three of four *rho* mutations (*I15F*, *A43T* and *I15N*) were destabilizing at 42.2˚C,

with $\Delta\Delta G$ values ranging between 0.50 to 1.22 kcal/mol (table 1); in contrast, the *T231A*

substitution mildly increased folding stability at 42.2˚C ($\Delta\Delta G$=-0.06). Two of the four

rpoB mutations were destabilizing at 42.2˚C (table 1). Although our sample size was

small (*n* = 4) for each gene, there was no clear trend between $\overline{w}_r$ and $\Delta\Delta G$ (table 1). For

completeness, we estimated $\Delta\Delta G$ for 16 additional *rho* mutations from our evolution

experiment, for a total of 20 $\Delta\Delta G$ estimates (supplementary table S5, Supplementary

Material online). Of these, 17 of 20 $\Delta\Delta G$ estimates were destabilizing, and there were no

differences in $\Delta\Delta G$ for mutations in different structural features (e.g., α-helices vs. β-

sheets, t-test, *p* = 0.45; NHB and CSD-like RBD, vs. non-defined regions, *p* = 0.36, see

supplementary table S5, Supplementary Material online). The only consistent effect of

mutations was toward destabilizing the wild type Rho protein at high temperature.

DISCUSSION

This study was designed to compare fitness and phenotype, as measured primarily

by gene expression, among and between adaptive mutations in *rho* and *rpoB*. We

undertook this study both because transcriptional regulators contribute substantially to

adaptive evolutionary change across many types of organisms and because mutations of

these two genes are particularly common in *E. coli* experimental evolution. However, to

our knowledge there have not yet been direct comparisons of the effect of beneficial

mutations within and between transcriptional regulators. Our comparisons reveal

substantial differences in relative fitness ($\overline{w}_r$) and growth characteristics among

mutations, but we also find broad similarities. Specifically, *rho* mutations primarily affect

the expression of a subset of the genes affected by *rpoB* mutations, mutations in both

genes tend to restore gene and IR expression to the unstressed state of the REL1206

ancestor, and the extent of restoration correlates with $\overline{w}_r$.

Heterogeneity in fitness and growth characteristics

The first major difference among beneficial mutations is in $\overline{w}_r$. Of the eight

mutations, six have $\overline{w}_r$ significantly > 1.00 and are statistically indistinguishable (table

1). Of the six advantageous mutations, the three *rpoB* codon *572* mutations are

unambiguous drivers of adaptive change, both because they have high fitness values and

because they often fix rapidly in experimental populations (Rodriguez-Verdugo et al.,

2013).

The two *rho I15* mutations have $\overline{w}_r \leq 1.0$ and thus confer no apparent advantage

under thermal stress (table 1). These two mutations are unlikely to drive adaptation as

solo mutations. They thus illustrate the potential importance of linkage and epistasis,

because *I15N* was one of the two most common nucleotide substitutions in the entire

thermal stress experiment and therefore must confer a substantial benefit in the proper

genetic background. But what is the proper background? Two possibilities stand out:

mutations in the *cls* gene or in the *iclR* gene. Knock-downs or knock-outs of the *cls* gene,

which encodes a cardiolipin synthase, are present in 14 of 17 of the clones with *rho I15F*

and *I15N* mutations; mutations within *iclR*, a transcriptional repressor, are in 10 of 17 of

clones; and either *cls* or *iclR* was mutated in all 17 clones (Tenaillon et al., 2012). *rho*

mutations have been shown to interact epistatically with mutations in other genes -- such

as *rpsL*, *metJ* and *rpsQ* -- that have a role in transcription or translation (Freddolino et al.,

2012, Haft et al., 2014). Both *rpsL* and *rpsQ* are critical to the 30S ribosomal unit

(Cabezon et al., 1975), and *metJ* represses the expression of genes involved in methionine

biosynthesis (Marincs et al., 2006).

The association between *rho* and *iclR* mutations are particularly interesting,

because *iclR* encodes a transcriptional repressor of the *aceBAK* operon, which encodes

the enzymes involved in the glyoxylate bypass (Nègre et al., 1992). Mutations in *iclR*

commonly arise in evolution experiments with *E. coli* that use glucose-limited medium

(Herron and Doebeli, 2013; Deatherage et al., 2017), perhaps because they derepress the

acetate operon improving the utilization of acetate after glucose is depleted (Spencer et

al., 2007). Interestingly, the *aceBAK* operon is up-regulated under thermal stress, but

down-regulated again in all of our *rho* and *rpoB* mutants (and significantly down-

regulated in *rho A43T*, *T231A* and *rpoB I152F*, *I572N* and *I966S*). Hence, mutations to

iclR may compensate for the effect of mutations on the *aceB*AK operon (Yamamoto and

Ishihama, 2003). It is worth noting that though *iclR* mutations are statistically more

likely to be found in the *rho* evolved lines from our thermal stress experiment, they are

also found in *rpoB* lines with the *I966S* and *I572N* mutations (Tenaillon et al., 2012). *iclR*

mutations may thus compensating for pleiotropic effects.

In contrast to the two *rho I15* mutations, the *A43T* and *T231A* mutations are

capable of driving adaptive change as solo mutations, but there is a twist: they too, are

often found in *cls* and *iclR* backgrounds. All three *A43T* clones and one of two *T231A*

clones from our evolution experiment also had *cls* and *iclR* mutations, again implying the

possibility of positively epistatic interactions. Potential functional interactions between

cls and *rho*, if any, are unknown. The *cls* gene has not been identified as *rho*-terminated

(Peters et al., 2009) and is not differentially expressed in any one of our four *rho* mutants.

One possible - but purely speculative - interaction between *cls* and *rho* is through

membrane signaling. Cardiolipin plays a key role in recruiting signaling molecules to the

membrane (Romantsov et al., 2007), and *E. coli* can perceive alterations in membrane

fluidity and transfer that information to signal-transduction pathways that alter gene

expression (Los and Murata, 2004, Los et al., 2013). The potential for, and causes of,

interactions between *rho* and *cls* require further study.

The effects of mutations on growth vary, too (fig. 2). Generally speaking, the

rpoB mutants grow better at 42.2˚C than the *rho* mutants, including higher maximum

growth rates and yields (table 2 and supplementary table S2, Supplementary Material

online). The effects on maximum growth rates are not statistically significant -- probably

due in part to high variance in growth characteristics for the *rho* mutants (fig. 2 and

supplementary fig. S2, Supplementary Material online) -- but the final yields for *rpoB*

mutations are statistically higher than that of *rho* mutants. Of these two parameters, yield

is not a component of fitness (Vasi et al., 1994) and maximum growth rate is at best a

proxy for fitness (Concepción-Acevedo et al., 2015, Durão et al., 2015, Wiser and

Lenski, 2015). Nonetheless, estimated growth rates corroborate $\overline{w}_r$ estimates by

indicating that the *I15 rho* mutations are not marked improvements (if at all) over the

ancestor. Another interesting facet of growth dynamics is that the *rpoB* mutants are

robust across 37.0˚C and 42.2˚C temperature regimes, but the same mutations are

antagonistically pleiotropic at lower (< 20.0˚C) temperatures (Rodriguez-Verdugo et al.,

2014).

Mutations alter the expression of similar genes in similar directions

478   Despite differences in relative fitness and growth dynamics between *rho* and *rpoB*

mutations, there are some clear similarities with respect to gene expression. One such

similarity is that mutations in both genes act in part by restoring expression from the

stressed condition (in this case, REL1206 under thermal stress at 42.2˚C) back toward the

wild type state (in this case, REL1206 at 37.0˚C). We have detected this restoration both

as a shift in PCA space (fig. 3*C*) and as the dominant directional shift among individual

genes (table 4). Several previous studies have also shown that adaptation proceeds

through phenotypic restoration (Fong et al., 2005, Carroll and Marx, 2013, Sandberg et

al., 2014, Carroll et al., 2015, Hug and Gaut, 2015, Rodríguez-Verdugo et al., 2016), but

our study is unique in establishing a quantitative correlation between restoration and $\overline{w}_r$.

488   There is a relevant counter-example. In their study of *Methylobacterium*

extorquens, Carroll and Marx (2013) show that adaptation was accompanied by the

restoration of ancestral gene expression levels, just as we find here. In their case, growth

rates are not correlated with restoration but with reinforcement (i.e., the number of genes

that exaggerate the acclimation response to physiological stress). We do not find a

correlation between the number of reinforced genes and $\overline{w}_r$ ($r^2 = -0.48$; $p= 0.24$). Taken

together these studies suggest that relationships among fitness and the direction of

evolutionary change may vary with experimental conditions. An important goal for future

research is to uncover generalities about relationships among fitness, restoration,

reinforcement and novelty.

498   A second similarity is that the set of genes affected by mutations in *rho* and *rpoB*

overlap to a remarkable extent, such that the *rho*-affected genes are a nearly perfect

subset of *rpoB*-affected genes (fig. 3*B*). There are, of course, caveats to this observation.

One is that to compare the *rho* and *rpoB* pathways in this way, we have taken the union

of DEGs among *rho* and *rpoB* mutants. In reality, different mutations are associated with

different DEG sets (fig. 3*A*); the pattern is recognizable primarily because we have

studied multiple mutants in each gene. A second caveat is to recognize that the number of

DEGs is an imperfect metric, because it varies with statistical power and can be non-

transitive across pairwise comparisons. Finally, RNAseq approaches are also not without

caveats. RNAseq measures relative RNA amounts of expression across genes within a

sample, making it difficult to contrast absolute levels of expression between samples.

Nonetheless, the overarching impression is that *rho* mutations mostly affect a smaller

subset of the genes altered by *rpoB* mutations.

The common set of genes affected by the *rho* and the *rpoB* mutations provides

insights into the physiological response to thermal stress. Mutations in *rho* and *rpoB* up-

regulate functions related to cellular growth, including purine and pyridine biosynthesis,

amino acid biosynthesis, ribosome biogenesis, nitrogen assimilation, translation and the

regulation of translation. Mutations in *rho* and *rpoB* also down-regulate a common set of

genes, particularly those associated with carbohydrate transport and amino acid

degradation. The shared patterns between *rho* and *rpoB* mutations are consistent with the

view that long-term acclimation to thermal stress leads to the down-regulation of growth-

related pathways, potentially resulting in energy conservation and enhanced survival

(Rodríguez-Verdugo et al., 2016) and that adaptation adjusts to support growth in the

stressful environment (Gunasekera et al., 2008).

Although there is a considerable overlap of genes affected by *rho* and *rpoB*

mutations, some functional categories were altered predominantly by one of the two

pathways. For example, *rho* mutants are enriched for DEGs that respond to temperature

stimuli, such as *clpB*, *dnaK*, *dnaJ*, *degP* and *grpE*. For reasons not fully understood, the

rpoB mutations do not up-regulate these temperature response genes (Gunasekera et al.,

2008, Rodríguez-Verdugo et al., 2016). In contrast, *rpoB* but not *rho* mutations enhance

the expression of iron transport and flagellum biogenesis. This last observation is

particularly interesting, because the up-regulation of flagellar genes is unlikely to have

been adaptive in our evolution experiment and because two studies have shown that these

are later down-regulated by subsequent adaptive mutations in populations (Gunasekera et

al., 2008). This example of flagellar genes raises an important point: for all of these

gross-scale effects on GE, it is difficult to distinguish between directly adaptive shifts vs.

negatively pleiotropic shifts.

Potential impacts on transcription termination

Genome sequencing uncovers the type and potential function of adaptive

mutations in evolution experiments (Long et al., 2015, Tenaillon et al., 2016), but the gap

from 'potential function' to an established molecular mechanism remains a chasm for all

but a few exceptions [e.g., (Blount et al., 2012, Quandt et al., 2015)]. With respect to

thermal stress it is known that the speed of RNAP increases with increasing temperature

(Ryals et al., 1982). We have therefore hypothesized that adaptive *rpoB* mutations slow

RNAP transcription under thermal stress, leading to increased termination efficiency.

rpoB mutations have been shown to increase termination previously (Jin et al., 1988).

The effects of our *rpoB* mutations on the expression of IRs (fig. 5c) and *rho*-terminated

regions (fig. 4) are consistent with our increased termination efficiency hypothesis.

Termination efficiency may require a balance (or 'kinetic coupling') between Rho

and RNAP activity (Jin et al., 1992). Under this model, when RNAP increases in speed,

Rho must match the increase to maintain efficient termination. We predicted, then, that

adaptive *rho* mutants translocate along RNA more quickly, leading to increased

termination efficiency relative to REL1206 at 42.2˚C. Improved termination efficiency is

possible, in theory, because at least one *rho* mutation (*L3F*) has been shown to increase

termination (Mori et al., 1989). Despite this prediction, transcriptomic analyses of *rho*

terminated regions indicate that two *rho* mutants (*A43T* and *T231A*) had little detectable

direct effect on termination, and the two without a detectable fitness benefit (*I15F* and

I15N) exhibited weaker termination (i.e., enhanced read-through) (fig. 4).

Our results have at least three implications. First, they imply that a direct shift in

Rho termination efficiency – at least as measured here – is not a requirement for

adaptation via the *rho* pathway. Second, they unfortunately provide few insights into

structure-function relationships, because the free energy of folding ($\Delta\Delta G$) bears no

discernible relationship with read-through properties or with fitness (table 1,

supplementary table S5), despite predictions regarding the latter (DePristo et al., 2005,

Tokuriki and Tawfik, 2009, Wylie and Shakhnovich, 2011, Bershtein et al., 2012,

Serohijos and Shakhnovich, 2014). The only discernible structural pattern was a tendency

toward destabilization of the Rho protein (supplementary table S5, Supplementary

Material online), which is not surprising given that ~70% of all possible mutations on

globular proteins yield $\Delta\Delta G > 1$ (Guerois et al., 2002, Schymkowitz et al., 2005) and that

beneficial *rpoB* mutations are known to destabilize the β subunit of RNAP (Utrilla et al.,

2016).

Third, there remains the remarkable result that all of our *rho* and *rpoB* mutations

tend torestore gene expression to that of the unstressed ancestor (fig. 2*C*), typically by

increasing gene expression (fig. 5*A* and 5*B*) in a similar set of genes (fig. 2*B*). At the

same time, all eight mutations tend to reduce expression of IR regions (fig. 5*B* and 5*D*).

The latter result is consistent with our hypothesis of enhanced termination efficiency in

rho mutants. Analyses of *rho*-terminated regions suggest that this is not a *direct* effect of

the *rho* mutations but rather an *indirect*, downstream effect. Given the substantial overlap

in differentially expressed genes (fig. 2*B*) and intergenic expression patterns (fig. 5*B* and

5*D*), *rpoB* mutations appear to cause a similar effect on transcription termination. For

rpoB we cannot easily determine whether the effect is direct – i.e., due to a modification

of RNAP - or downstream and indirect. Despite our observations, we still do not know

how, exactly, enhanced termination efficiency translates to increased fitness and the

restoration of gene expression. We can, however, draw several conclusions from our

study of *rh*o and *rpoB* mutants: that these beneficial mutations differ in relative fitness,

that their fitness is correlated with their effects on gene expression, and that they all,

somehow, tend to effect the same sets of genes and simultaneously increase expression of

genes while decreasing expression of IR regions. Finally, and perhaps most importantly,

these observations show that alternative adaptive pathways encompass substantial

phenotypic convergence.

MATERIALS and METHODS

The construction of *rho* mutants

The *I15F, A43T and T231A rho* mutations were introduced into the REL1206

ancestral strain using the pJk611 recombineering plasmid, as previously described

(Rodriguez-Verdugo et al., 2014). Briefly, the pJk611 plasmid was introduced into

REL1206, electroporating 2 μl of plasmid (80 ng of plasmid in total) into 50 μl of

competent cells using an Eppendorf Electroporator 2510 set at 1.8 kV. After

electroporation, 1 ml LB was added to the electroporated cells, and they were incubated

at 30°C for 2 h under constant shaking (120 rpm). Thereafter 100 μl of cells were plated

on LB agar plates containing 100 μg/ml ampicillin to select ampicillin-resistant

transformants. The ancestral strain carrying the pJk611 plasmid was grown overnight at

room temperature (~20°C) in 25 ml LB with 100 μg/ml ampicillin and 1mM $_L$-arabinose

(Sigma) until it reached and OD_{600} of 0.6. Electrocompetent cells were made by washing

the culture five times with ice-cold water.

To construct each mutant, two oligos of 70 bp were electroporated into cells

(supplementary table S6, Supplementary Material online); one oligo introduced the

desired single mutation in *rho* and the second oligo incorporated the change that produces

an Arabinose positive (Ara+) phenotype. Two μl of each oligo (10 μM) was

electroporated into 50 μl of cells. After electroporation 1 ml LB was added, and the cells

were incubated at 37.0˚C for 3 h with shaking, followed by 500 μl spread onto minimal

medium agar (MA) plates supplemented with $_L$-arabinose. The plates were incubated 48 h

at 42.2°C, after which 188 single colonies were selected and grown on TA agar plates

overnight at 37.0˚C. We subsequently performed colony PCR, followed by Sanger

sequencing to amplify the *rho* gene fragment surrounding the putative mutation

(supplementary table S6, Supplementary Material online). PCR conditions were 10 min

at 94˚C followed by 30 cycles of 20 s at 94˚C, 30 s at 60˚C, and 1 min at 68˚C ending

with an extension step of 5 min at 68˚C. For each mutation, we isolated multiple lines

with the mutation of interest, such that biological replicates were independently derived.

Relative fitness competitions

We estimated $\overline{w}_r$ by competing mutants against the ancestral REL1206 strain.

Briefly, both competitors were revived in LB broth and grown separately overnight at

37.0ºC under constant shaking (120rpm). After cultures were revived, they were

subcultured by 1:10000 dilution in 10 ml DM25 media for 24 hours at 37.0°C and 120

rpm and inoculated 1:100 into 9.9 ml of fresh DM25 and incubated at 42.2°C for another

day in order to acclimate cells to high temperature. Although the clones had evolved at

42.2°C in DM25, it is common practice in thermal stress studies to allow clones to

recover from freezing under less stressful conditions (Bennett and Lenski, 1993,

Rodriguez-Verdugo et al., 2014).

629   Once revived, the two competitors were mixed at a 1:1 volumetric ratio and

diluted 100-fold into 10 ml of fresh DM25 and incubated one day at the assay

temperature. The initial and final densities were estimated by plating the culture onto

tetrazolium-arabinose (TA) agar plates, counting the number of Arabinose+ colonies of

the REL1206 ancestor and the number of Arabinose- clones of the mutants and evolved

clones. Relative fitness assays were performed on three biological replicates for each

mutation and for three technical replicates for each biological replicate; thus each

mutation was tested against the ancestor a total of nine times.

637   ANOVA analyses were based on the *avo* package in R. With ANOVA, we first

638   tested for the effects specific to different biological replicates within a mutation using a

639   model of Fitness~Mutant*Replicate. Given that there were no differences among

640   biological replicates, the model was simplified to Fitness~Mutant.

642   **Growth curves**

643   To obtain the growth parameters of *rho* mutants, we first revived them in LB

broth and incubated them overnight at 37.0°C. The overnight cultures were then diluted

10,000 fold into 10 ml DM25 and incubated for 1 day at 37°C. The following day, the

acclimated cultures were dilute 100-fold into 10 ml DM25 and incubated for 1 day at the

assay temperature (either 37.0°C or 42.2°C). Cell densities were measured every hour

during the lag phase and every ~15 minutes during exponential phase. Cell densities were

quantified using an electronic particle counter (Coulter Counter model Multisizer 3

equipped with a 30 μm diameter aperture tube). For this, 50 μl of the growing culture was

diluted in 9.9 ml of Isoton II (Beckman Coulter) diluent and 50 μl of this dilution was

counted electronically. Three independent growth replicates were performed per mutant.

Estimations of the cell growth parameters were performed as per (Rodríguez-Verdugo et

al., 2016). Briefly, we estimated the maximum growth rate by fitting a linear regression

to the natural logarithm of the cell density over time during the exponential phase. We

estimated the final yield from the cell counts at the end of the exponential phase. Three

estimates of maximum growth rate and final yield were obtained for each mutant. The

exponential phase was confirmed by linear regression (Zwietering et al., 1990). Statistical

differences between *rho* and *rpoB* mutants were assessed by two sample *t*-tests.

Statistical analyses (fitting of the linear regression to the exponential phase using the *lm*

function and *t*-test analyses) were performed in R version 3.0.2 (Team, 2013). Graphs for

fig. 2 were constructed with the function stat-smooth in the ggplot2 R package version

3.2.3 (Team, 2013)

RNA Harvesting and Sequencing

To harvest cells for RNA sequencing (RNAseq), we revived cells as described

above and then cultivated populations at 42.2˚C until the mid-exponential phase of

population growth. The mid-exponential phase was determined by electronic counts

using an electronic particle counter (Coulter Counter model Multisizer 3 equipped with a

30 µm diameter aperture tube) and linear regression. For each of the single *rho*

mutations, at least two biological replicates were grown to mid-exponential for RNA

harvesting.

To harvest RNA, 80 ml of culture from the mid-exponential phase was filtered

through a 0.2 µm cellulose membrane (Life Science, Germany). Then cells were washed

with Qiagen RNA-protect Bacteria Reagent and pelleted for storage at -80˚C prior to

RNA extraction. Cell pellets were thawed and incubated with lysozyme (Sigma-Aldrich),

for 5 minutes at room temperature ~20˚C. Total RNA was isolated and purified using

RNeasy Mini Kit (Qiagen). An on-column DNase treatment was performed for 30 min at

room temperature. RNA quality was assessed by running an Agilent RNA-Nano chip on

a bioanalyzer. rRNA was depleted using the Ribo-Zero^{TM} rRNA Removal kit for Gram-

Negative Bacteria (Epicentre Biotechnologies, Medion, WI, USA). cDNA libraries were

constructed using TruSeq RNA v2 kit (Illumina, San Diego, CA, USA). After

amplification, the samples were quantified by qPCR using the KAPA Library

Quantification Kit code KK4822 for the Illumina Genome Analyzer platform (Kapa

Biosystems, Wilmington, MA, USA). Libraries were sequenced on an Illumina Hiseq

2000 platform to generate 100 bp single-end reads.

RNAseq data for *rpoB* mutations and the REL1206 ancestor were generated

previously, using identical protocols (Rodríguez-Verdugo et al., 2016).

RNAseq data and DEG analysis

We gathered three sets of RNAseq data. First, we generated data for four *rho*

mutants, with two replicates each. Second, we used the REL1206 data from Rodriguez-

Verdugo et al. (2016), representing states of both thermal stress (42.2°C) and normal

laboratory conditions (37.0°C). Finally, we also used data from *rpoB* single mutants from

(Rodríguez-Verdugo et al., 2016). The *rpoB* data can be accessed at the NCBI's

Sequence Read Archive (SRA) under the BioProject Number PRJNA291128. The *rho*

data generated for this study have BioProject Number PRJNA339971 and SRA accession

number SRP083065.

For all RNAseq data, sequence reads were filtered to a quality cut-off of 20.

Filtered reads were mapped to the *E. coli* B REL606 reference genome (NCBI:

NC_012967.1 GI:254160123) using BWA aligner (Li and Durbin, 2010) using default

parameters. Statistics about mapping are provided in supplementary table S7 of the

Supplementary Material online. Unique matching reads to the 4204 annotated coding

regions were retained for further analyses, as were reads that mapped to 2306 non-coding

intergenic regions (IRs) of the REL606 reference (supplementary data set S3,

Supplementary Material online). IRs were defined as the sequence that extends from the

3' end of a coding region to its neighboring coding region. IRs were analyzed if they

exceeded 1 bp in length and had a minimum coverage of at least 1 read in at least one of

the ancestors and *rho* mutants replicates. Note, however, that similar trends were

obtained when IRs were defined as $\geq$100 bp in length.

Coding regions and IRs counts were obtained from SAM files using HTSeq-count

tool (Anders et al., 2015) from HTSeq, at

http://www.huber.embl.de/users/anders/HTSeq/doc/count.html using intersection-

nonempty counting mode. Differential gene expression analysis was performed with

DESeq version 1.18.0 (Anders and Huber, 2010). The FDR was determined using

Benjamini-Hochberg adjusted *p*-values. Genes with *q* values <0.001 were considered as

differentially expressed.

718   Gene Ontology enrichment analysis was performed through the Gene Ontology

719 Consortium (http://geneontology.org/page/go-enrichment-analysis) with Bonferroni

720 correction for multiple testing. Principal component analysis (PCA) was applied to

721 RNAseq data using the *plotPCA* function in DESeq version 1.18.0 (Anders and Huber,

722 2010) with the default parameters (`ntop=500`).

724 **Identification and analysis of rho-terminated genome regions**

725   To evaluate the effects of each *rho* mutation on the transcription termination

726 activity, we evaluated the gene expression of a set of previously defined Rho dependent

727 terminated regions (Peters et al., 2009). Because these Rho-terminated regions were

728 originally defined in *E. coli* K-12, it was necessary to first determine their coordinates in

729 our REL606 genome. To do so, we utilized the start positions and lengths of the regions

730 as defined by Peters et al. (2009) located the closest gene to the start of the Rho-

731 terminated region in *E. coli* K-12, noting the position of the Rho-terminated region

732 relative to the closest gene. We then located this gene in the REL606 genome and used

733 the relative position information from K-12 to assign our Rho-terminated regions in

734 REL606. In the few cases where gene orientation was not preserved across strains,

735 coordinates were determined in an orientation-dependent manner (supplementary data set

736 S2, Supplementary Material online). The number of read counts of each region was

737 obtained from SAM files using the HTseq-count tool (Anders et al., 2015) and

738 normalization was performed with DEseq based on a complete gff file that included the

739 putatively Rho-terminated regions and their 5' upstream region of the same size (Anders

740 and Huber, 2010). Five of 183 regions had no reads and were discarded. Normalized gene

741 counts were averaged among replicates to calculate the ratio γ , the $\log_2$ ratio of mutant to

742 ancestral counts.

743   For each of the 178 *rho* termination regions, we also compared read counts

744 between the termination region and its immediate upstream 5' region of the same length.

745 Thus, for each of the i=10 treatments (i.e., 8 mutants and 2 control temperatures), the data

746 consisted of paired upstream and downstream counts from j=178 regions. For each clone

747 i, we estimated termination efficiency by bootstrap resampling across the j regions,

748 keeping the 5' and termination regions paired. For each of 1000 resamplings, we

calculated the ratio of averages, r_{avg}, across the j samples (fig. 4). To test for differences

among a set of i treatments, we bootstrapped under the null hypothesis of homogeneity

by resampling across the i treatments for each of the j regions. For each of 1000 datasets

resampled under the null hypothesis, we calculated r_{avg}, for each of the i treatments.

Bootstrap resamplings were performed in R version 3.0.2 (Team, 2013).

Directions of evolutionary change

GE was classified into one of four directions of evolutionary change, as described

previously (Carroll and Marx, 2013, Rodríguez-Verdugo et al., 2016). The four directions

classify GE in a mutant relative to REL1206 at 42.2˚C and to REL1206 at 37.0˚C.

Briefly, a gene had *novel* expression if the mutant differed significantly ($q < 0.001$) from

both ancestral treatments (42.2˚C and 37.0˚C), but GE did not differ between the two

ancestral treatments (i.e. Anc42≈Anc37 & Anc37≠Mutant & Anc42≠Mutant).

Restoration occurred when the mutant GE levels fell between those of the two ancestral

treatments and when GE differed significantly between the ancestral treatments and also

between the mutant and REL1206 at 42.2˚C [i.e., (Anc42>Mut>Anc37 or

Anc42<Mut<Anc37) & Anc42 ≠ Anc37 & Anc42 ≠ Mutant]. *Reinforced* expression

occurred when GE differed significantly between the ancestral treatments and between

the mutant and REL1206 at 42.2˚C, but GE in the mutant did not fall between the

ancestral treatments [i.e., Anc42 ≠ Anc 37 & Anc42 ≠ Mutant & (Mut>Anc42>Anc37

or Mut<Anc42<Anc37)]. Finally, *unrestored* expression occurred when GE did not differ

significantly between the mutant and REL1206 at 42.2˚C, but the two ancestral

treatments differed significantly from each other (i.e., Anc42 ≠ Anc 37 & Mut≈Anc42).

Estimates of free energy of folding.

We calculated two values: ΔG, the free energy of folding, and ΔΔG, the

difference of ΔG between the REL1206 protein and mutant proteins. We focused on

folding free energy differences of the Rho hexamer and *rpoB*. To calculate ΔΔG, we used

an approach that combines classical molecular dynamics with FoldX (Guerois et al.,

2002, Miller et al., 2016), which improves the calculation of ΔΔG compared to using

FoldX alone (Miller et al., 2016). To perform the calculations, we downloaded the X-ray

crystal structures from the Protein Data Brank (PDB): (1) Rho transcription protein

bound to RNA and ADP-BeF3 (PDB ID: 3ICE) (Thomsen and Berger, 2009) and (ii)

SigmaS-transcription initiation complex with 4-nt nascent RNA (PDB ID: 5IPL) (Liu et

al., 2016). The PDB file 3ICE was modified to remove all but the six chains of Rho

hexamer. Out of all the six chains in the X-ray crystal structure, chain C had least missing

residues. MODELLER v9.15 software (Sali and Blundell, 1993) was then used to rebuild

the coordinates of the missing residues for chain C and complete chain C was used as a

template to fill gaps in the other chains of the hexamer. The final hexamer structure had

2484 residues. The chain C of 5IPL PDB file was used to obtain the structure of *rpoB*

which had 1342 residues.

The software package GROMACS 5.0.7 (Van Der Spoel et al., 2005) was used

for 10 ns long Rho hexamer and *rpoB* Molecular Dynamics simulations with the

AMBER99SB forcefield (Hornak et al., 2006). We followed the standard energy

minimization, thermalization and equilibration protocol (Miller et al., 2016) before

carrying out the final production run. During the 10 ns production simulation snapshots

were saved every 1 ns giving 10 snapshots of Rho hexamer protein and *rpoB* for the

further analysis.

Fold X was used to analyze the starting structure and all 10 snapshots (total 11

snapshots) captured during molecular dynamics simulations (Guerois et al., 2002).

Before, analyzing all 11 snapshots using FoldX, we first extracted chain C from each of

the snapshots in case of Rho hexamer and *rpoB* and later only the monomer structures -

i.e. chain C - were used for folding free energy calculations. We started by minimizing

monomer structure using the *RepairPDB* command of FoldX to further minimize the

potential energy. All single amino acid mutations were then generated using *BuildModel*.

Finally, protein folding stabilities were estimated using *Stability* on the *rho* monomer and

rpoB structure. For each mutation we then estimated ΔΔG by averaging across all 11

individual snapshots estimates. The molecular graphics package VMD was used to

produce fig. 1(Humphrey et al., 1996).

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FIGURE LEGENDS

FIG. 1.

A schematic of the Rho protein, showing each of its six hexamers (A-F) and the location

of the single-mutations (red spheres) produced for this experiment. Mutations in *I15* and

A43 are located in the N-terminal domain (NTD) (gray); the mutation in *A231* in the C-

terminal domain (CTD) (green).

FIG. 2.

Growth curves for the mutants and ancestor at 37.0°C and 42.2°C. Each line corresponds

to a local polynomial regression fitting of three replicates with its 95% confidence

interval (see table 2 and supplementary table S2).

FIG. 3.

(A) A Venn diagram of the number of genes that exhibit significant DEG between *rho*

mutants. *(B)* A Venn diagram of the number of genes that differ in expression between

the four *rho* mutants and REL1206 at 42.2˚C and all four *rpoB* mutants and REL1206 at

42.2˚C. *(C)* A PCA plot of the RNAseq data, including replicated data from REL1206 at

37.0˚C (light blue dots), REL1206 at 42.2˚C (dark blue dots); replicated data from each

of the four *rho* mutations (light and dark green dots); and replicated data from each of the

four *rpoB* mutations (pink dots). The *x*-axis represents restoration along PC1, where

smaller values reflect greater restorative effects.

FIG. 4.

A graph of bootstrap estimates of the ratio of averages ($\bar{r}_{avg}$) that measures the ratio of

counts between *rho* terminated sites (RT) and their upstream 5' regions (UP) across 178

loci. Lines in the boxplots represent the median bootstrap-based estimate of $\bar{r}_{avg}$ based on

1,000 resamplings (see Material and Methods). The boxes represent the upper and lower

quartiles of bootstrap replicates. Anc37 represents the REL1206 ancestor at 37.0°C and

Anc42 is the ancestor at 42.2°C.

FIG. 5.

Genome-wide expression patterns of genic and intergenic regions at 42.2°C. Histograms

showing the number of coding regions that are up or down regulated compared to

REL1206. *(A)* The first pair of histograms shows REL1206 at 37.0˚C vs. 42.2˚C. Up- or

down-regulation is relative to the first of the listed pair. For example, the first pair of

histograms show that REL1206 at 42.2˚C has ~700 and ~1000 genes that are expressed at

higher and lower levels, respectively, than REL1206 at 37.0˚C. The remaining

histograms compare *rho* mutants at 42.2˚C to REL1206 at 42.2˚C. The bars with three,

two and one asterisks indicate $p < 0.0001$, $p < 0.001$ and $p < 0.01$ respectively, a dot

indicates $p < 0.05$. *(B)* Similar histograms as in *A*, but based on intergenic regions (IRs).

(C) and *(D)* are identical to *(A)* and *(B)* but based on the *rpoB* mutants.

873 **Table 1.** Relative fitness measured at 42.2°C for four *rho* mutants and four *rpoB* mutants,

874 along with their estimated ΔΔG values, as predicted by molecular modeling.

	Relative Fitness			Estimated ΔΔG values	
Mutant[1]	Mean	± 95% CI	*p*-value[2]	Location[3]	ΔΔG at 42.2°C (kcal/mol) ± S.E.[4]
rho I15F	1.008	0.117	0.837	α2 NHB [*]	1.22 ± 0.25
rho I15N	0.945	0.184	0.396	α2 NHB [*]	0.50 ± 0.35
rho A43T	1.237	0.093	< 0.05	α3 NHB [*]	1.17 ± 0.39
rho T231A	1.266	0.104	< 0.05	Loop - CTD [**]	-0.06 ± 0.45
rpoB I572F	1.155	0.047	< 0.05	Rif [+]	-0.327 ± 0.59
rpoB I572L	1.229	0.099	< 0.05	Rif [+]	-0.421 ± 0.26
rpoB I572N	1.184	0.067	< 0.05	Rif [+]	0.803 ± 0.52
rpoB I966S	1.258	0.106	< 0.05	Eco flap - βi9 [++]	1.405 ± 0.34

[1] *rho* data from this study, based on nine replicated measures. *rpoB* data include that from

(Rodriguez-Verdugo et al., 2014) plus three additional replicates, for a total of six

replicates

[2] $p < 0.05$ rejects the null hypothesis that $\overline{w}_r = 1.0$, indicating that the mutation is

beneficial ($\overline{w}_r > 1.0$) relative to the REL1206 ancestor.

[3] Location of mutation in the Rho protein: NH B=N-terminal helix bundle * Mutations

located in the NTD= N-terminal and **CTD= C-terminal domain. Location of mutations

in the RNAP protein: [+]RNA polymerase, β subunit, Rif= Rif-binding regions in the fork

domain, [++] RNA polymerase, β subunit, Eco flap domain, β subunit insert 9.

[4] Errors are calculated with 95% confidence interval. $\Delta\Delta G$ value for *rho* and *rpoB* W.T.

is zero.

Table 2. *P*-values for statistical comparisons of maximum growth rate and yield of *rho*
and *rpoB* mutants at 42.2°C

rpoB \ rho	I15N [1]	I15F	A43T	T231A
Maximum growth rate				
I572N	0.138	0.471	0.440	0.127
I572F	0.177	**0.045** [2]	0.732	0.157
I572L	0.203	0.092	0.995	0.175
Final Yield [3]				
I572N	**0.001**	**8 x 10^{-4}**	**0.002**	**0.010**
I572F	**3 x 10^{-4}**	**4 x 10^{-4}**	**0.001**	**0.004**
I572L	**7 x 10^{-5}**	**4 x 10^{-5}**	**1 x 10^{-4}**	**0.002**

[1] Entries correspond to significant values from two-sample *t*-tests. The null hypothesis is
that the mean values of parameters are equal. Numbers in bold correspond to *P*-values
<0.05.

[2] *rpoB I572F* had a significantly higher maximum growth rate compared with the *rho*
mutant *I15F* at 42.2°C (see fig. 2 and supplementary table S2, Supplementary Material
online).

[3] In every case, r*poB* mutants had a significantly higher final yield compared with the *rho*
mutants at 42.2°C (fig. 2 and supplementary table S2, Supplementary Material online).

Table 3. Comparisons of gene expression between single *rho* mutants. The cells above

the diagonal report the Pearson correlation coefficient in gene expression across all genic

regions (*n*=4204). The cells below the diagonal indicate the number of genes significantly

different via DEseq (*q* <0.001).

	I15N	*I15F*	*A43T*	*T231A*
I15N		0.991	0.962	0.955
I15F	1		0.969	0.964
A43T	149	190		0.992
T231A	419	552	16	

917 **Table 4.** The direction of gene expression for genes within *rho* and *rpoB* mutants.

Mutant [1]	Restored [2]	Unrestored	Reinforced	Novel	Total [3]
rho I15F	762	886	19	4	1671
rho I15N	802	857	8	16	1683
rho A43T	1115	544	7	32	1698
rho T231A	1250	405	12	46	1713
rpoB I572F	1092	644	1	59	1796
rpoB I572L	563	1174	0	6	1743
rpoB I572N	1165	569	3	53	1790
rpoB I966S	1308	428	1	39	1776

[1] *rho* data from this study. *rpoB* data from (Rodriguez-Verdugo et al., 2014).

[2] The number of genes was counted as restored, unrestored, reinforced and novel using

the rules elaborated in the Material and Methods.

[3] The total tallies the number of genes that differ at $q < 0.001$ from either REL1206 at

37.0˚C or REL1206 at 42.2˚C or both. The total differs significantly between *rho* and

rpoB mutations (t-test; $p = 0.0016$).

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