Investigation of the global translational response to oxidative stress in the model archaeon
***Haloferax volcanii* reveals untranslated small RNAs with ribosome occupancy**

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Abstract

Oxidative stress induces a wide range of cellular damage, often causing disease and cell death. While many organisms are susceptible to the effects of oxidative stress, haloarchaea have adapted to be highly resistant. Several aspects of the haloarchaeal oxidative stress response have been characterized, however little is known about the impacts of oxidative stress at the translation level. Using the model archaeon *Haloferax volcanii*, we performed RNA-seq and ribosome profiling (Ribo-seq) to characterize the global translation landscape during oxidative stress. We identified 281 genes with differential translation efficiency (TE). Downregulated genes were enriched in ribosomal and translation proteins, in addition to peroxidases and genes involved in the TCA cycle. We also identified 42 small noncoding RNAs (sRNAs) with ribosome occupancy. Size distributions of ribosome footprints revealed distinct patterns for coding and noncoding genes, with 12 sRNAs matching the pattern of coding genes, and mass spectrometry confirming the presence of seven small proteins encoded in these sRNAs. However, the majority of sRNAs with ribosome occupancy had no evidence of coding potential. Of these ribosome-associated sRNAs, 12 had differential ribosome occupancy or TE during oxidative stress, suggesting that they may play a regulatory role during the oxidative stress response. Our findings on ribosomal regulation during oxidative stress, coupled with potential roles for ribosome-associated noncoding sRNAs and sRNA-derived small proteins in *H. volcanii*, revealed additional regulatory layers and underscore the multifaceted architecture of stress-responsive regulatory networks.

Importance: Archaea are found in diverse environments, including as members of the human microbiome, and are known to play essential ecological roles in major geochemical cycles. The study of archaeal biology has expanded our understanding of the evolution of eukaryotes, uncovered novel biological systems, and revealed new opportunities for applications in biotechnology and bioremediation. Many archaeal systems, however, remain poorly characterized. Using *Haloferax volcanii* as a model, we investigated the global translation landscape during oxidative stress. Our findings expand current knowledge of translational regulation in archaea and further illustrate the complexity of stress-responsive gene regulation.

Introduction

Since the advent of oxygenic metabolism, oxidative stress has affected most organisms across all domains of life. This stress is associated with reactive oxygen species (ROS) that disrupt cellular redox state and covalently damage essential macromolecules (1-3). While endogenous ROS, including hydrogen peroxide and superoxide, arise as byproducts of oxygen metabolism (1), ROS levels can increase due to environmental stressors (1, 4). Prolonged oxidative stress induces a range of responses, including disease, autophagy, and cell death (5-8). To neutralize ROS, prokaryotes utilize numerous enzymes (9-13), and certain bacteria and archaea, such as haloarchaea, are known to be exceptionally resistant to oxidative stress (4, 14-17).

Archaea have attracted interest because of mounting evidence that they are ancestral to eukaryotes (18). This is reflected in the mosaic nature of archaeal cells with prokaryotic features and yet information processing machinery more closely related to that of eukaryotes (18-20). The study of archaea has led to the discovery of novel biological systems, such as unique lipids and protein modifications not found in other domains (21, 22). These findings shed light on the evolution of eukaryotes from a prokaryotic ancestor (23) and expand possibilities for biotechnology applications (24). However, many archaeal regulatory systems remain poorly characterized, and our knowledge of them lags behind that of bacterial and eukaryotic counterparts. For example, mechanisms of transcriptional regulation, especially in response to oxidative stress, have only been studied in a few archaeal species (25-27). In the model archaeon, *Haloferax volcanii*, a key transcriptional regulator, RosR, was shown to affect the expression of many genes in response to oxidative stress (26). However, while RosR is conserved among haloarchaea, its function varies among species (25). Gene regulation at the post-transcriptional level by small noncoding RNAs (sRNAs) is particularly critical to stress responses in many prokaryotic organisms (28-31), and has been linked to oxidative stress in several bacteria (32-34) and in the archaeon *H. volcanii* (27, 35). In *H. volcanii*, the most upregulated sRNA during oxidative stress (SHOxi) binds and destabilizes malic enzyme transcripts, leading to higher cell survival rates during oxidative stress (35).

While many studies have characterized mechanisms of oxidative stress response at the transcriptional, post-transcriptional, and post-translational levels, little is known about the impacts of oxidative stress at the translation level. Translational regulation has been shown to play a major role in various stress conditions in both bacteria and yeast (36-39). In yeast, the global translation landscape during oxidative stress has been explored using ribosome profiling (Ribo-seq), revealing the regulation of several individual genes and general shifts in translation patterns across all genes (40). Mechanisms of translational regulation by proteins and sRNAs during stress have also been reported in archaea. The archaeal protein IF6, a homolog to eukaryotic IF6, inhibits translation by binding to the large ribosomal subunit, preventing assembly of the full ribosome, and is overexpressed during thermal stress (41). In *Methanosarcina mazei*, sRNAs were shown to mask the ribosome binding site of target mRNAs to modulate translation in response to nitrogen starvation (42, 43). This mechanism bears resemblance to an oxidative stress-responsive sRNA in *E. coli* (44). Additionally, proteomic studies in *H. volcanii* have begun to elucidate the differences between transcription and

89 translation during stress responses (45, 46). However a comprehensive study of translational
90 regulation during oxidative stress response has thus far been lacking.
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In this work we present evidence of translational regulation during oxidative stress in *H.*
volcanii. This model archaeon is well-characterized at the genetic level (47-49) and a variety of
genetic and biochemical tools are available for its manipulation (50, 51). Recent advances in
translation research in *H. volcanii* (52, 53) have demonstrated that Ribo-seq enables the
detection of translational changes, providing a means to probe the impact of oxidative stress on
protein synthesis. In the present work, we combined RNA sequencing (RNA-seq) and ribosome
profiling (Ribo-seq) to determine the global translation landscape during oxidative stress
response. We identified genes that are differentially regulated at the translation level under
oxidative stress and, using an integrative approach, investigated the potential role of stress-
responsive ribosome-associated sRNAs and sRNA-encoded small proteins.
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Results

We investigated the global translation landscape in *H. volcanii* during oxidative stress by
performing RNA-seq and Ribo-seq *on H. volcanii* cultures with and without stress treatment.
Ribo-seq, a technique that captures ribosome occupancy across thousands of transcripts, can
be used as a proxy for translation (54). By comparing transcription levels from RNA-seq data to
ribosome occupancy from Ribo-seq data, we assessed differential expression, ribosome
occupancy, and translation efficiency, allowing us to identify genes regulated at the translation
level. Using this integrated approach, we also identified ribosome-associated sRNAs responsive
to oxidative stress.
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Hundreds of genes, including known oxidative stress-responsive genes, had differential
ribosome occupancy during oxidative stress.
Libraries for RNA-seq and Ribo-seq were prepared from four biological replicate cultures
treated with 2 mM hydrogen peroxide for one hour to induce oxidative stress, as previously
described (27, 35). Four replicates without stress treatment were used as controls. Sequenced
reads were aligned to the genome (49) and normalized expression values of transcripts per
million (TPM) were calculated (Table S1, Table S2). Using a minimum detection cutoff of 10 TPM
per gene, averaged across all biological replicates, we detected 84% of annotated genes in both
RNA-seq control and stress samples. For the Ribo-seq data, we detected 74% of annotated
genes in control samples and 80% in stress samples.
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We calculated differential expression between controls and oxidative stress treatments for the
RNA-seq and Ribo-seq datasets (Table S3). Genes with an adjusted p-value <0.05 and an
absolute $\log_2$ fold change >1 were considered differentially expressed during oxidative stress.
Lowly expressed genes with TPM <10 in both conditions were excluded from the analysis. We
found 559 genes with differential RNA expression during oxidative stress, in contrast to 966
genes with differential ribosome occupancy (Fig. 1A, B).
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To validate our experimental approach, we investigated the differential expression of five
previously known oxidative stress-responsive genes. These genes were for superoxide
dismutase (HVO_RS03960), catalase (HVO_RS13250), a universal stress protein
(HVO_RS06755), and a ssDNA binding replication protein (HVO_RS06110); the latter two were
both reported as upregulated proteins in *H. volcanii* under hypochlorite stress (46). All showed
significant upregulation in both RNA-seq and Ribo-seq datasets (Fig1A, B; Table S4), implying
our experimental approach recapitulated known aspects of oxidative stress response. We also
observed upregulation of a gene involved in metal homeostasis (HVO_RS07285; Fig1A, B; Table
S4) and downregulation of four others (HVO_RS00195-210; HVO_RS07290; Fig1A, B; Table S4),
consistent with previous findings (46).
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We then tested the hypothesis that genes with differential transcript expression would have
differential ribosome occupancy, as transcripts highly abundant during oxidative stress would
likely be bound by a higher number of ribosomes than transcripts with low abundance. By
comparing significant gene lists from RNA-seq and Ribo-seq data, we identified 320 genes with
both differential RNA expression and ribosome occupancy during stress. The remaining 646
genes changed only in ribosome occupancy during stress (67% of all genes with differential
ribosome occupancy; Fig. S1). Several genes had differential ribosome occupancy in accordance
with previously published proteomics data [HVO_RS02870-*msrA;* HVO_RS04695-cysteine
desulfurase; Table S3; (46)]. Overall, in both RNA-seq and Ribo-seq datasets, we detected the
majority of annotated genes and identified hundreds of genes with differential ribosome
occupancy during oxidative stress.
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Translation efficiency revealed global downregulation of translation during oxidative stress.
To increase the stringency of our analysis and identify genes that were regulated uniquely at
the translation level, we calculated translation efficiency (TE). This quantity is defined as the
ratio between the Ribo-seq fold change and the RNA-seq fold change and was used for
differential expression analysis (Table S3). TE values account for changes in transcript
availability and identify genes that change at the Ribo-seq and/or RNA-seq level while
eliminating those that change proportionally in both. We found 281 genes with significant
differential TE (Fig. 1C; adjusted p-value <0.05, absolute $\log_2$ fold change >1). When comparing
genes with differential TE to those with differential transcript expression and differential
ribosome occupancy, we found that 240 genes (85.4%) were regulated only at the level of
translation (Fig. S2). The remaining 41 genes were regulated at both the transcriptional and
translational levels, with 30 genes displaying opposing effects at each level (Table S3). The
majority (66.7%) of genes with opposing effects were upregulated at the transcriptional level
yet downregulated at the translational level. Of the 281 genes with differential TE, 29.9% were
upregulated and 70.1% were downregulated during oxidative stress (Table S5).
169
We investigated some basic properties of transcripts with differential TE to determine whether
they were distinct from the overall transcriptome. We found no differences in amino acid or
codon frequencies (Fig. S3) and no difference in the proportion of leaderless transcripts
compared to the whole transcriptome (Table S5), most likely because *H. volcanii* translation
initiation is not dependent on the presence of a 5'UTR (55). The average size for genes with

differential TE was slightly smaller, likely due to a narrower size range of significant genes
(Table S5).
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We next investigated whether genes with differential TE during oxidative stress exhibited
functional enrichments. Gene ontology (GO) analysis was performed using PANTHER generic
mapping (56, 57), with enrichment significance determined via Fisher's test and false discovery
rate (FDR correction). Additionally, KEGG pathway enrichment analysis was conducted using the
STRING database (58). Both PANTHER and STRING rely on homology-based functional
predictions. Approximately half of all annotated *H. volcanii* genes were assigned to functional
categories using PANTHER (Table S6). However, few significant functional enrichments were
observed among genes with differential TE, likely due to small sample size (Fig. 1D, Table S7).
Among genes with downregulated TE during oxidative stress, we observed significant
enrichment of translation-related functions (Fig. 1D). Specifically, GO enrichment analysis
revealed overrepresentation of ribosomal proteins (fold enrichment = 4.41, FDR = 0.0005) and
translation-associated proteins (fold enrichment = 3.39, FDR = 0.0008). Consistent with these
results, KEGG pathway analysis also identified significant enrichment of ribosomal proteins (FDR
= 0.00093). In addition, we observed differential TE for many genes associated with redox
homeostasis. Notably, downregulated genes showed enrichment of peroxidases (GO; fold
enrichment = 9.5, FDR = 0.0213) and tricarboxylic acid (TCA) cycle components (KEGG; FDR =
0.0242). In contrast, no statistically significant functional enrichment was detected among
genes with upregulated TE during oxidative stress (Fig. 1D).
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In addition to analyzing functional categories of genes with differential TE, we sought to identify
whether specific cellular pathways were subject to translational regulation during oxidative
stress. To do so, we used the STRING database to predict interaction networks for genes with
upregulated or downregulated TE. Few predicted interactions were identified among
upregulated genes (Fig. S4A). In contrast, genes with downregulated TE formed a larger,
interconnected network with many functional clusters (Fig. S4B). The two largest clusters were
composed of ribosome-associated genes, including numerous ribosomal proteins, and genes
involved in the TCA cycle. Additional smaller clusters, with four genes each, were related to
oxidative phosphorylation, pyrimidine biosynthesis, and putative translation initiation factors.
These interaction networks suggest that while global translation is broadly reduced under
oxidative stress, specific pathways are subject to targeted translational regulation, likely to
modulate metabolic activity and maintain cellular homeostasis.
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While the majority of genes with differential TE were regulated only at the translational level,
15% of genes with differential TE exhibited changes (absolute $\log_2$ fold change >1) at both the
transcriptional and translational levels. One such gene, HVO_RS04895, encoding a protein with
a transmembrane domain, showed increased ribosome occupancy and TE (Table S8). This gene
is known to be transcriptionally upregulated during oxidative stress via the transcriptional
regulator OxsR (59). We also identified two genes with a distinct regulation pattern
characterized by downregulated TE, coupled with increased RNA expression and ribosome
occupancy (Table S8). These genes encode KatG (HVO_RS13250), a catalase/peroxidase that
uses hydrogen peroxide as its substrate (60, 61), and DpsA (HVO_RS07285), a DNA

starvation/stationary phase protection protein (62, 63). Previous proteomics studies reported
no significant change in KatG protein levels, while DpsA was upregulated during oxidative stress
(46). These findings suggest that transcriptional changes alone may not fully predict protein
abundance under stress conditions, and that translational regulation likely serves as an
additional rapid mechanism for fine-tuning protein levels during stress.
224
Many small noncoding RNAs had ribosome occupancy.
As expected, most ribosome footprints in our dataset corresponded to annotated coding
sequences. However, it was remarkable that several small noncoding RNAs (sRNAs), previously
identified by sRNA-seq (27), also exhibited ribosome occupancy. In total, 42 out of 56 sRNAs
detected in our RNA-seq dataset showed ribosome occupancy (TPM >10; Table S9), with 17 of
these sRNAs displaying differential ribosome occupancy or TE during oxidative stress (Table 3).
231
To investigate the coding potential of sRNAs with ribosome occupancy, we used several
computational approaches to identify putative small ORFs (smORFs; Fig. 2A). Public database
searches revealed nine annotated smORFs encoded by sRNAs (Fig. 2A). Of these, three have
been detected by mass spectrometry (MS) as reported in the Archaeal Proteome Project
database (64). Next, we used REPARATION (65), a tool designed to predict novel ORFs from
ribosome profiling data (53). Using our ribosome profiling dataset, REPARATION accurately
predicted 82% of all annotated proteins (Table S10), including 436 of 542 (80%) annotated
smORFs (≤100 amino acids). In addition, REPARATION predicted 194 novel genes (Table S11) of
which only seven encoded small proteins and one originated from a ribosome-associated sRNA
(Fig. 2A). While REPARATION predicted few smORFs within sRNAs, sequence-based tools such
as ORFfinder were overly permissive [Fig. 2A; (66)], often predicting ORFs in sRNAs even in the
absence of a stop codon within or around the sRNA sequence (Table S12).
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These conflicting computational predictions, combined with empirical evidence for coding
potential for only 10 out of 42 sRNAs with ribosome occupancy (Fig. 2A), prompted further
investigation of the nature of the ribosome occupancy on sRNAs. To distinguish between true
translation and non-canonical ribosome association, we examined the ribosome footprint
length distribution. Footprint length distributions have previously been used to infer translation
states at a genome-wide level (52), and we applied this approach to individual sRNAs to assess
their coding potential.
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Size distributions of ribosome footprints revealed distinct patterns for coding and noncoding
genes.
We analyzed ribosome footprint length distributions of coding genes, noncoding genes, and
sRNAs to assess the coding potential of ribosome-associated sRNAs. As expected, the
distribution of footprint lengths for coding genes - both at the level of individual genes - and
across the sum of all coding genes - was sharply enriched in footprints between 24 and 27
nucleotides (nt) in length (Fig. 2B). This was consistent with previous work identifying that the
characteristic footprint length for elongating ribosomes was 27 nt (52). In contrast, noncoding
genes, including rRNAs, SRP RNA, RNaseP RNA, and tRNAs, displayed distinct footprint length
distributions that were markedly different from those of coding genes (Fig. 2B).

To further explore sRNA coding potential, we performed clustering analysis based on the
footprint length distributions of coding genes, noncoding genes, and sRNAs of interest.
Clustering was optimized using the minimum number of clusters required to separate known
coding genes from rRNAs and tRNAs. When clustering sRNAs with annotated smORFs (Fig. S5A),
we observed that sRNAs with low total read counts did not consistently group with coding
genes (Fig. S5B), indicating that sufficient read count is necessary to accurately infer coding
potential. From this analysis, we determined that a minimum of 65 read counts across all
biological replicates was required for reliable classification.

Using this threshold value, we found that 12 sRNAs clustered with known coding genes based
on their footprint length distribution (Fig. 2B), seven of which corresponded to sRNAs with
annotated smORFs. The high proportion of sRNAs with annotated smORFs included in the
coding cluster supports the utility of footprint length distribution as a means of distinguishing
coding from noncoding sRNAs, providing sufficient read coverage is available. However, we also
identified 12 sRNAs ribosome-associated sRNAs that lacked both annotated smORFs and
footprint length distributions consistent with coding genes.

Discovery of small proteins encoded by sRNA transcripts.
To validate predictions of coding sRNAs and assess whether predicted small proteins encoded
by sRNAs could be detected, we used liquid chromatography tandem mass spectrometry (LC-
MS/MS). This analysis included three biological replicates with and without oxidative stress
treatment, the latter chosen to induce the expression of stress-responsive sRNAs. We
sequentially passed cell lysates through centrifugal filters with 100 kDa and 30 kDa molecular
cutoffs to deplete high molecular weight proteins (Fig. S6).

Our label-free quantitative differential expression analysis detected 2,095 proteins, filtered to
5% false discovery rate (FDR) and with at least two peptide spectrum matches (PSMs). This
dataset represented 53% of the total proteome of *H. volcanii*, with a median protein sequence
coverage of 59%, consistent with other high-quality MS datasets reported for this organism
(64). As previously reported (67), centrifugal filtering is an imperfect method to enrich for small
proteins, and indeed, the size distribution of the proteins we detected closely represented that
of the full proteome (Fig. 3A). Notably, we did not detect any protein smaller than 25 amino
acids, despite the existence of predicted smORFs as short as 10 amino acids (Fig. 3B).
Nevertheless, we detected 235 smORFs (Fig. 3B) ranging from 31 to 100 amino acids in length,
representing 40% of annotated smORFs (Table S13). Among these, seven smORFs were
encoded within putative sRNAs, including four previously annotated (Fig. 2A; Table 1). For five
out of these seven sRNA-encoded proteins, ribosome footprint length distributions clustered
with those of known coding genes (Fig. 2B) and two smORFs, sRNA_93 and sRNA_KL, were
highly conserved among haloarchaea. However, computational predictions, including sequence
and structural homology searches, did not reveal functional annotations for these smORFs.
Despite these findings, seven sRNAs with footprint length distributions consistent with coding
genes lacked detectable protein-level evidence in our MS dataset.

To further investigate sRNAs with ribosome occupancy, we selected a subset for validation by
Western blot analysis (Table 2). This set included one sRNA with read counts below the
minimum threshold for clustering (sRNA_38), one sRNA not present in the coding cluster
(sRNA_83), three sRNAs within the coding cluster but not detected by MS (sRNA_20, sRNA_61,
and SHOxi), and two smORFs detected by MS (sRNA_KL, sRNA_93). Each selected sRNA was
tagged with a 3xFLAG epitope immediately downstream of the putative start codon and cloned
into *H. volcanii* on an overexpression plasmid (Fig. 3C). To preserve native regulatory elements,
150 bp upstream and 50 bp downstream of each sRNA were included. For sRNA_20, which
contained multiple putative ORFs, two start codons were tagged, including one corresponding
to a previously annotated protein. Western blot analysis confirmed the expression of both MS-
detected smORFs (sRNA_KL, sRNA_93), while no signal was observed for any of the other
tagged sRNAs (Fig. 3D). Despite having both expression level and ribosome occupancy
exceeding that of sRNA_KL and sRNA_93 (Table 2), no signal was detected for SHOxi and
sRNA_61. This strongly suggests that SHOxi and sRNA_61 function as noncoding RNAs.
321
322 Taken together, our combined LC-MS/MS and Western blot analyses identified seven smORFs
323 encoded by sRNAs, including three previously unannotated smORFs. However, several sRNAs -
324 most notably sRNA_61 and SHOxi - exhibited high ribosome occupancy without detectable
325 protein products, highlighting the complexity of interpreting ribosome profiling data and
326 suggesting potential regulatory or ribosome-associated noncoding functions.
327
Ribosome-associated sRNAs may play regulatory roles during oxidative stress.
We then focused on 17 stress-responsive sRNAs that had differential ribosome occupancy or TE
under oxidative stress conditions (Fig. 4A, Table 3). Among these, five sRNAs had annotated
smORFs, while the remaining 12 showed no evidence of coding potential. To further assess
their coding potential, we applied the ribosome footprint length clustering analysis described
earlier, this time using Ribo-seq data from oxidative stress-treated samples. Of the 12
unannotated sRNAs (with no evidence of coding potential), one failed to meet the minimum
read count threshold and was excluded from the analysis. Among the remaining 11, three
clustered with known coding genes, whereas nine did not (Fig. 4B). Given their lack of coding-
like ribosome footprint distributions, we hypothesized that these nine stress-responsive sRNAs
with high ribosome occupancy may play a regulatory role during oxidative stress. To investigate
their potential functional roles, we used a suite of *in silico* approaches. Notably, two sRNAs
were excluded from this analysis: SHOxi, which has been previously characterized as a
regulatory RNA (35), and sRNA_41, which is annotated as encoding a small protein.
342
We first performed BLASTn to assess the conservation of these noncoding stress-responsive
sRNAs. Five had homology to one or more halophilic species. However, for two of these, the
majority of homologous hits overlapped with an upstream gene on the opposite strand,
complicating the interpretation. The remaining two sRNAs had no detectable homology to
sequences in other species. We selected three sRNAs - sRNA_58, sRNA_77, and sRNA_83 - for
further analysis based on their conservation in at least one other species and the absence of
overlap with annotated genes.
350

We performed a multiple sequence alignment and predicted consensus secondary structures
for sRNA_58, sRNA_77, and sRNA_83 using LocARNA (68), incorporating all homologous
sequences identified in our BLASTn search. Each sRNA exhibited strong secondary structure
potential and high sequence conservation across species (Fig. 5A; Fig. S7), suggesting functional
relevance. To explore their regulatory role, we predicted putative mRNA targets using IntaRNA
[Fig. 5B; Tables S14-16; (69)] and determined which of those predicted targets had differential
ribosome occupancy or TE under oxidative stress (Fig. 5C, Table 4). sRNA_58 had the fewest
high-confidence predicted targets (p <0.01), with only five out of 29 (17%) showing differential
ribosome occupancy or TE in response to oxidative stress. In contrast, sRNA_77 and sRNA_83
had a larger number of predicted high-confidence targets. Specifically, 13 out of 44 (30%)
putative mRNA targets for sRNA_83, and 15 out of 42 (36%) targets for sRNA_77 were
differentially translated in response to oxidative stress.
363
364   Collectively, of the eight sRNAs with differential ribosome occupancy or TE under oxidative
365   stress [excluding SHOxi, previously characterized (35)], five were conserved among halophilic
366   species. Two of these, sRNA_77 and sRNA_83, had numerous putative targets that exhibited
367   translational regulation during oxidative stress, suggesting they may play regulatory roles in the
368   stress response.
369

sRNA knockouts have a similar phenotype to wild-type during oxidative stress.
To explore the functional role of ribosome-associated sRNAs during oxidative stress, we
generated sRNA knockout strains for three sRNAs with a range of ribosome occupancy.
sRNA_24 represented low ribosome occupancy (TPM <10), sRNA_83 represented moderate
occupancy (50-100 TPM), and sRNA_20 represented high occupancy (>200 TPM). Knockouts
were generated as previously described (70) and whole genome sequencing confirmed the
complete deletion of the target sRNAs. Under oxidative stress conditions induced by H_2O_2
treatment, none of the knockout strains exhibited observable phenotypic differences compared
to the wild-type (WT) strain (Fig. S8A, B).
379

To identify putative regulatory targets for these sRNAs, we performed RNA-seq using three
biological replicates for each knockout strain and the WT strain exposed to oxidative stress,
along with non-stress WT controls, as previously described (35). The RNA-seq data were
analyzed, as described above, with significance cutoffs of adjusted p-value <0.05 and absolute
$\log_2$ fold change >1. No significantly differentially expressed genes were detected for sRNA_83
and sRNA_20 knockout strains when compared to the WT strain under oxidative stress (Fig.
S8C, D). However, we found 7 genes significantly upregulated for the sRNA_24 knockout strain
(Fig. S8E), which was further validated by qPCR (Fig. S8F). Three of these targets were members
of an operon involved in glycerol metabolism in *H. volcanii* [Table S17, (71)]. Remarkably,
genome analysis revealed that nine genes differentially regulated and with p-value <0.05 were
located immediately downstream of sRNA_24 locus (Fig. S8G, Table S17). None of these genes
were predicted as putative sRNA targets using IntaRNA, indicating a likely polar effect of the
sRNA gene deletion.
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Discussion

This study provides a comprehensive view of the translational landscape of the model archaeon *H. volcanii* during oxidative stress by integrating RNA-seq and Ribo-seq analyses. While previous studies in *H. volcanii* have reported changes in protein abundance under oxidative stress using MS (46), such approaches cannot distinguish between transcriptional and translational regulation. Furthermore, it is well established that transcript levels measured by RNA-seq often correlate only modestly - and with high variability - with protein level determined by MS (72, 73), highlighting the complexity of processes that govern protein synthesis. To better understand how gene expression is controlled at the level of translation, we used RNA-seq and Ribo-seq to examine both ribosome occupancy and TE across the transcriptome.

Our analysis revealed that hundreds of genes exhibited differential TE in *H. volcanii* during oxidative stress. Notably, we observed global downregulation of translation, particularly affecting ribosomal proteins, suggesting a substantial reduction in *de novo* protein synthesis under stress conditions. This translational repression is consistent with previous studies in *H. volcanii* and *E. coli* under oxidative stress (27, 74, 75), as well as in *Halobacterium* NRC-1 following UV irradiation (76), all of which reported downregulation of translation-related genes. This downregulation is thought to serve as a protective and energy-conserving strategy, redirecting cellular resources toward damage repair and stress defense while minimizing oxidative damage to the translation machinery (77). Similarly, in eukaryotic systems, stress-induced translation arrest is well documented and often involves the formation of stress granules containing translationally stalled complexes (40, 78, 79). Interestingly, a previous mass spectrometry study in *H. volcanii* reported upregulation of several translation-related proteins, including ribosomal proteins, in cells exposed to hypochlorite stress (46), highlighting potential discrepancies between transcriptional, translational, and proteomic responses. However, a study with *Halobacterium* NRC1 subjected to ionizing radiation (IR) addressed the sequential nature of the cell's transcriptional (RNA-seq) and translational (proteomic) responses (80). The study found a high level of correlation between mRNA and protein levels by temporally shifting the protein level changes by 20 to 30 min, demonstrating the importance of the time dimension.

In addition to translation-related genes, we observed downregulation of genes encoding peroxidases and components of the tricarboxylic acid (TCA) cycle - findings that are consistent with responses observed in *Deinococcus radiodurans* and *Halobacterium* NRC-1 following IR (80-82). Because IR generates massive oxidative stress, suppression of general metabolism and redox-active pathways may help cells limit further damage and maintain homeostasis. Taken together, the divergence between RNA-seq, Ribo-seq, and MS datasets suggests that multiple layers of regulation are employed to control gene expression during oxidative stress. Such complex gene regulation has been documented in both eukaryotes and bacteria. For example, cold shock protein in mammals (83), quorum sensing signals in *Agrobacterium tumefaciens* (84, 85), and the tryptophan operon in *E. coli* (86, 87) are all regulated at both the transcriptional and translational levels. Similarly, in *H. volcanii*, the integration of transcriptional and translational control likely enables a rapid and precise response to oxidative stress, allowing

437 selective synthesis of essential proteins while conserving energy by broadly reducing
438 translation.
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Remarkably, we found that many sRNAs previously classified as noncoding (27) exhibited high
ribosome occupancy, suggesting that ribosome association may not be limited to actively
translated transcripts. Leveraging our Ribo-seq data, we analyzed ribosome footprint length
distribution and found that several of these sRNAs had footprint length distributions similar to
those of coding genes. A subset of these sRNAs were found to encode annotated smORFs, and
using MS, we identified seven small proteins encoded by sRNAs. Unfortunately, sequence or
structural homology searches did not provide insights into the potential functions of these
sRNA-encoded proteins. One exception is the small protein encoded in sRNA_KL, which has
previously been detected by both Ribo-seq and MS (53). This small protein contains a zinc
finger domain, and a deletion mutant showed increased growth on glycerol (88). It is important
to note that the ability to encode small proteins does not exclude these sRNAs from having
post-transcriptional regulatory roles. In bacteria, dual function sRNAs that both encode proteins
and act as regulatory sRNAs are well documented (89-91). Similar dual-function sRNAs have
been proposed in archaea, particularly under nitrogen starvation conditions (92). These findings
suggest that, as in other organisms (89, 93), *H. volcanii* may also use dual-function sRNAs,
especially in response to oxidative stress.
456
Ribo-seq is potentially a more sensitive method than MS for detecting smORFs (53, 92).
However, there is enduring concern that it may overestimate the number of translated sRNAs
(94, 95), making MS-based proteomics an important complementary approach to provide direct
protein-level evidence. In addition, analyzing ribosome footprint length distribution offers
another strategy to assess the coding potential of sRNAs. As discussed above, this analysis
successfully distinguished most coding genes and sRNAs with annotated smORFs from
noncoding genes. Nonetheless, this method was not accurate for all coding genes and requires
high read counts to reliably separate coding and noncoding transcripts.
465
We also identified several sRNAs with high ribosome occupancy that had no evidence of coding
potential. These sRNAs did not yield detectable protein even when putative ORFs were
individually tagged and probed by Western blotting. In contrast, smORFs detected by LC-MS
were also confirmed by Western blot, despite having lower ribosome occupancy. This
discrepancy may reflect the limitations in detecting low-abundance small proteins by MS or
Western blotting. For lowly expressed sRNAs, overexpression with an inducible promoter, as
previously shown (53), may be necessary for detection. Alternatively, sRNAs with high ribosome
occupancy and no evidence of coding potential may be functionally associated with ribosomes,
possibly directly interacting with them. Their association is unlikely to be an artefact of the
ribosome profiling protocol; although RNAs with secondary structure are generally resistant to
nuclease digestion, the small size of these sRNAs would prevent their co-sedimentation with
monosomes in a sucrose gradient. This suggests a specific association with ribosomes or
ribosome-bound mRNAs. Prior studies have reported the presence of sRNAs associated with
ribosomes in *H. volcanii* under stress conditions (96, 97). Sequencing and northern blotting of
sRNAs that co-purify with ribosomes identified a tRNA-derived fragment that binds the small

ribosome subunit, inhibiting peptide bond formation (96), as well as an intergenic sRNA that
interacts with the large subunit to regulate the translation of a specific mRNA (97).
483
Several ribosome-associated sRNAs lacking coding potential were also responsive to oxidative
stress, suggesting potential regulatory functions. These included SHOxi, which binds to and
destabilizes malic enzyme transcripts, enhancing cell survival during oxidative stress (35), thus
arguing against this sRNA being a nonfunctional *de novo* gene intermediate. Importantly, our
RNA-seq and Ribo-seq experiments were performed with four biological replicates each, and
the ribosome-associated sRNAs discussed here consistently showed high ribosome
occupancies. Deletion of three such sRNAs did not result in a growth phenotype under oxidative
stress and caused little to no change in the expression level of other genes. This suggests that
these sRNAs may not modulate transcript stability directly, unlike some well-characterized
sRNAs in both bacteria (32, 98, 99) and archaea (100, 101). For example, in *H. volcanii*, SHOxi
destabilized its mRNA target through complementary base pairing (35). However, as observed
in bacterial systems (102, 103), deletion of a single sRNA may be insufficient to observe its
regulatory function. Targeted knockout of multiple stress-responsive, ribosome-associated
sRNAs may therefore be necessary to fully elucidate their role during oxidative stress. Taken
together, our findings suggest that several oxidative stress-associated sRNAs in *H. volcanii* are
closely associated with ribosomes but do not affect mRNA stability. We hypothesize they
regulate translation directly through interaction with the ribosome or ribosome-bound mRNAs.
501
Using RNA-seq and Ribo-seq in a model archaeon, we demonstrated global and targeted
translation regulation in response to oxidative stress. We also identified a class of untranslated,
ribosome-associated sRNAs likely involved in translational regulation under oxidative stress.
While the precise mechanisms of action remain to be elucidated, this study highlights the
complexity of translational regulation in archaea and underscore the multifaceted architecture
of stress-responsive regulatory networks.
508

Materials and Methods

Cell culturing and oxidative stress treatment
Haloferax volcanii DS2 strain H98 (70) was grown in liquid Hv-YPC (70) supplemented with 40
mg/mL thymidine at 42°C, with shaking, to OD >0.5. Cultures were diluted into fresh media to
an OD of 0.01 and grown to OD 0.4-0.6. For oxidative stress treatment, cultures were incubated
with 2mM H_2O_2 for one hour at 42°C with shaking, as previously described (27).
Ribosome profiling
Ribo-seq was performed as previously described (52, 104). In brief, cultures were flash frozen in
liquid nitrogen and lysed by cryogenic mill, using 55 g of frozen culture and 100 µg/mL of
anisomycin. Ribosomes were collected by ultracentrifugation on a 1 M sucrose cushion using a
Ti45 rotor at 185,511x*g* (40,000 rpm) for three hours at 4°C. Polysomes were digested using
MNase and separated using a 10-50% sucrose gradient (Fig. S9A). RNA from monosome
fractions was isolated with Trizol LS reagent, followed by size selection (Fig. S9B), and
generation of libraries for high-throughput sequencing (Fig. S9C, D). Libraries were sequenced
by Novogene (150 bp, paired-end reads, NovaSeq).

RNA-seq

RNA-seq libraries were prepared using 20 mL of culture pelleted by centrifugation. RNA extraction was performed as previously described (27) using a Quick-RNA Miniprep kit (Zymo). rRNA was depleted using 2.5 µg of DNase-treated RNA and the Ribo-Zero rRNA removal kit for bacteria (Illumina). The SMARTer Stranded RNA-Seq kit (Takara Bio) was used to prepare the libraries with 100 ng RNA, dual-index primers, and 12 PCR cycles. Libraries were sequenced by Novogene (150 bp, paired-end reads, NovaSeq). For knockout strains, RNA was prepared as described above, using 3 replicates per strain. All strains were treated with H_2O_2, with 3 replicates of untreated WT as controls. Library preparation and sequencing were performed by SeqCenter in Pittsburgh, PA (150 bp, paired-end reads, NovaSeq X plus) using Illumina's Stranded Total RNA Prep Ligation with Ribo-Zero Plus kit and custom probes.

Analysis of sequencing data

Demultiplexed reads provided by Novogene and SeqCenter were analyzed using only forward reads for Ribo-seq libraries and both reads for RNA-seq libraries. For full analysis details, see Table S18. Adapters were trimmed using Trim Galore [(105), https://github.com/FelixKrueger/TrimGalore] and reads were aligned to rRNA genes using Bowtie (106). Unaligned reads (those not aligning to rRNA) were written to a new file and used for genome alignment, which was performed using Bowtie and the *H. volcanii* DS2 genome assembly ASM2568v1 from NCBI (49). Samtools (107) was used to generate bam and sorted bam files. Coverage and depth were calculated using samtools and bedtools. Average depth per chromosome was calculated using a custom Python script. TPM were calculated using StringTie (108), with a provided reference annotation file (gff from NCBI Refseq assembly GCF_000025685.1 downloaded March 2023 with added entries for sRNAs). Read counts were calculated using featureCounts (109). See Tables S19, S20, and S21 for statistical summaries of all analyses.

Differential expression and TE analysis

Differential expression was determined using DESeq2 (110). For RNA-seq and Ribo-seq data, the variable of interest was experimental condition. For TE, the ratio between Ribo-seq and RNA-seq was used, in addition to two variables of interest: sample (RNA-seq or Ribo-seq) and experimental condition. For full details, see Table S18.

Characterization of significant genes

The number of leaderless genes was determined using published data that characterized 1851 annotated genes as leadered or leaderless (111). 68% of genes with differential TE were uncharacterized and therefore not considered in calculations for the percent of leaderless genes. Custom Python scripts were used to calculate percent of leaderless genes, codon frequencies, and amino acid frequencies. Heatmaps were generated using R. The STRING database [web version 12.0; (58)] was used to predict interactions and to determine KEGG enrichments with default settings and MCL clustering. Gene interaction predictions are based on evidence including genomic proximity, experimental data and co-expression of homologs, association in curated databases, and text mining of abstracts from published literature. 84% of genes with differential TE were successfully mapped to the STRING database. The PANTHER database (web version 19.0) was used to generate a generic mapping file (57, 112) for the *H. volcanii* DS2 protein fasta file downloaded from NCBI. Overrepresentation tests were conducted using Fisher's test and FDR correction.

smORF prediction
For ORF prediction using the web version of Open Reading Frame Finder [ORFfinder, NCBI;
(66)], a minimal length of 30 nt and alternative initiation codons were allowed. For ORF
prediction using Ribo-seq data, an adapted version of REPARATION (65), using blast instead of
USEARCH (https://github.com/RickGelhausen/REPARATION_blast) was used. For option details,
see Table S18. A custom python script compared and combined predictions with and without
Shine-Dalgarno. Predicted genes were visualized using IGV, and a manual scan was conducted
to compare overlap between replicates for control or oxidative stress treatment. Predicted
genes were required to be present in at least 3 biological replicates. Novel gene lists for control
and stress samples were then combined.
Footprint distribution clustering
Lengths of reads aligning to individual genes were obtained using a custom Bash script,
followed by analysis using R to generate heatmaps. Clustering was performed using the
pheatmap (https://github.com/raivokolde/pheatmap) package with default settings and the
minimum number of clusters required to separate rRNA from known coding genes in control
samples.
Mass spectrometry sample preparation
Samples for mass spectrometry were prepared using 600 mL cultures from three replicates; half
of the culture was used for control samples and the other half was treated with H_2O_2. Cells
were pelleted by centrifugation then resuspended in 8 mL lysis buffer (2 M NaCl, 8 M urea, 0.1
M Tris-Cl, 10 mM DTT) and flash frozen. Resuspension was ground in a cryogenic mill (SPEX
6870) with a 1 minute pre-cool, then 8 cycles of alternating 1 minute of run time and 1 minute
of cool time, at a rate of 8 cycles/second. The thawed lysate was spun twice at 15000 x*g* for 15
minutes at 4°C. Lysis buffer was added to a volume of 10 mL, then filtered through a 0.2-micron
syringe filter and brought to a final volume of 12 mL with lysis buffer. Size selection was
performed by centrifugation in 100K MWCO filters (Pall) at 5000 x*g* for 2 hours at room
temperature, then centrifugation in 30K MWCO filters (Pall) at 5000 x*g* for 45 minutes at room
temperature. Iodoacetamide was added to a final concentration of 54 mM and incubated for 45
minutes in the dark at room temperature, followed by addition of 11.1% of volume of
trichloroacetic acid. Samples were flash frozen, then incubated at 4°C overnight. Samples were
centrifuged at 20000 x*g* for 30 minutes at 4°C and supernatant was removed. Pellets were
washed twice with acetone, air-dried for 10 minutes, then resuspended in 50 µL of 8 M urea in
phosphate-buffered saline (PBS), pH 7.4 and quantified using the Qubit Protein Assay kit. 30 µg
of total protein in 200 µL of 2 M urea in PBS, pH 7.4 were digested with trypsin and prepared
for MS as previously described (113).
Mass spectrometry acquisition
Chromatographic separation of protein digests was carried out as previously described (114),
injecting 1 µg of protein per sample.
Mass spectrometry data analysis
The Proteome Discoverer (PD) Software Suite v2.4, Minora Algorithm (ThermoFisher) was used
to process mass spectra and perform Label Free Quantification (LFQ), comparing control and
stress samples with default settings for all analysis nodes except where specified. Data were
searched against the *H. volcanii* DS2 proteome fasta file from Uniprot (entry UP000008243,
organism ID 309800; downloaded January 2023). The reference fasta file was appended with

additional sequences for putative smORFs. For peptide identification, the Proteome Discoverer
Sequest HT node was selected for a tryptic search allowing up to 2 missed cleavages. A
precursor mass tolerance of 10 ppm was used for the MS1 level, and a fragment ion tolerance
of 0.02 was set at the MS2 level. Methionine oxidation and N-terminus acetylation were
allowed as dynamic modifications, with carbamidomethylation on cysteines defined as a static
modification. Protein abundance ratio data were exported using a three-level hierarchy
(protein > peptide group > consensus features). A minimum of 2 PSMs and maximum FDR of 5%
were required to determine detection of novel small proteins. See Table S22 for statistical
summaries.

Generating tagged sRNAs
sRNA regions (including at minimum 150 bp upstream and 50 bp downstream) were amplified
from genomic DNA and cloned into pTA1300 using *Kas*I and *Bam*HI. Ligation products were
transformed into DH5α competent cells (NEB), followed by plasmid extraction (QIAprep spin
miniprep kit) and verification by Sanger sequencing (GENEWIZ, Azenta). A 3xFLAG tag was
added after the predicted start codon using Q5 site-directed mutagenesis (NEB). Purified
plasmids were transformed into *H. volcanii* as previously described (115), using the lab strain
H98.

Western blots
25 mL of culture were pelleted by centrifugation at 10,000 x*g* for 6 minutes at 4°C. Pellets were
resuspended in 1 mL lysis buffer (50 mM Tris-HCl pH 7.5, 2 M urea, 0.2% SDS, 0.1 mg/mL EDTA-
free protease inhibitor cocktail (Roche)) and lysed with sterile glass beads (116). Protein
concentration was quantified using the Qubit Protein Assay kit. Proteins (10-100 μg total) were
separated on a 4-15% stain free acrylamide gel (BioRad), transferred to a nitrocellulose
membrane, and incubated with anti-Flag monoclonal antibodies conjugated with alkaline
phosphatase (1:10,000 dilution; Sigma cat no. A9469), as previously described (116). The
antibody:protein complexes were visualized using 0.25 mM CDP-Star Substrate (Tropix) with 1x
Nitro-Block-II Enhancer (Invitrogen) and the BioRad ChemiDoc Imager.

sRNA in silico tools
Web versions of nucleotide BLAST (117), IntaRNA (69, 118), and LocARNA (68) were used with
default settings.

Generating knockouts
Knockout strains were generated using the established protocol for *H. volcanii* (70)*.* For
sRNA_83, a knockout plasmid was constructed by amplifying upstream and downstream
flanking regions from genomic DNA and cloning into pTA131 using *Hind*III, *Xba*I, and *Eco*RI.
Knockout plasmids for sRNA_20 and sRNA_24 were generated by Azenta, with upstream and
downstream flanking regions cloned into pTA131 using *Hind*III and *Xba*I. Knockout plasmids
were transformed into *H. volcanii* (115), strain H98, followed by selection for pop-in (uracil
selection) and pop-out (5-FOA selection). Whole genome sequencing of successful pop-outs
was performed by Plasmidsaurus using Oxford Nanopore Technology with custom analysis. For
ΔsRNA_83 and ΔsRNA_24, no additional mutations were identified. For ΔsRNA_20, two
additional point mutations were detected (C->G at position 50,650 in HVO_RS02135; A->G at
position 1,284,523 in HVO_RS11505).

Knockout phenotyping

To assess survival during acute oxidative stress, 3 replicates of WT and mutant strains were grown as described above in a total volume of 20 mL. 50 µL of culture were plated, and remaining culture was treated with H_2O_2. Cultures were plated on YPC with thymidine and incubated at 42°C for 4 days. Colonies were counted and used to calculate CFUs/mL and percent survival. To assess survival during chronic oxidative stress, 3 replicates of WT and mutant strains were grown as described above. Cultures were diluted into fresh media to an OD of 0.02 and treated with various H_2O_2 concentrations. Cultures were transferred to 100-well plates (250 µL/well) and grown in a Bioscreen C Pro for 42 hours at 42°C with shaking (normal speed, max amplitude, orbital). Absorbance measurements were taken every six hours. Data were plotted using R.

qPCR

Samples for qPCR were prepared using 40 mL cultures from 3 replicates; half used for control samples and half treated with H_2O_2. Cells were harvested and RNA was extracted as described for RNA-seq library preparation. Conversion to cDNA was performed using a Superscript RT III kit (Invitrogen) with random hexamers. qPCR was conducted in 48-well plates with PowerUp™ SYBR™ Green Master Mix (Applied Biosystems, A25742) using the StepOne™ Real-Time PCR System with standard conditions and annealing temperature of 60°C (for primers, see Table S23). Fold change was determined by the Livak method (119).

Data availability

RNA-seq reads, ribosome profiling reads, and annotation files are available on NCBI GEO: GSE293312 (RNA-seq) and GSE293326 (Ribo-seq). The mass spectrometry proteomics data have been deposited to the ProteomeXchange Consortium via the PRIDE (120) partner repository with the dataset identifier PXD062323 and 10.6019/PXD062323. Data analysis scripts are available on GitHub: https://github.com/diruggiero-lab/sRNAs.

Acknowledgements

We thank Dr. Cesar Perez-Fernandez, Dr. Diego Gelsinger, and Frank Liu for experimental advice and helpful discussions. We thank Matthew F. Isada for extensive manuscript editing and helpful discussions. This work was supported by US National Science Foundation grants MCB-2034271 and MCB-57951. We would also like to thank the NSF Division of Molecular and Cellular Biology for a CAREER grant (Grant No. 2045844) and NIH/NIGMS for a New Innovator Award (No. DP2-GM140926) both to SDF. SDF further acknowledges support from the Camille & Henry Dreyfus Foundation and the Sloan Foundation. HMM is thankful for the Chemistry-Biology Interface Program training grant (Grant No. NIH-T32GM080189-13).

E.D.: Conceptualization, Methodology, Investigation – RNA-seq, Ribo-seq, mass spectrometry sample preparation, Western blots, knockout phenotyping, Formal analysis – analysis of sequencing data, footprint distribution analysis, Visualization, Writing – original draft, Writing – review & editing; H.M.M: Investigation – mass spectrometry sample preparation, mass spectrometry data acquisition, Formal analysis – mass spectrometry data analysis, Writing – review & editing; S.R.C: Formal analysis – DESeq2 analysis for all datasets; A.K.: Investigation – construction of tagged sRNA constructs and sRNA knockout strains, qPCR analysis; B.Y.H.H.:

698 Investigation – construction of tagged sRNA constructs; S.D.F.: Methodology, Writing – review
699 & editing; J.D.: Conceptualization, Methodology, Funding acquisition, Writing – review &
700 editing, Supervision. All authors read and approved the final manuscript.
701

References

1. Cabiscol Catalā E, Tamarit Sumalla, J, Ros Salvador, J. 2000. Oxidative stress in bacteria and
protein damage by reactive oxygen species. Int Microbiol 3:3-8.

2. Seixas AF, Quendera, AP, Sousa, JP, Silva, AFQ, Arraiano, CM, Andrade, JM. 2022. Bacterial
response to oxidative stress and RNA oxidation. Front Genet 12: 821535.

3. Ezraty B, Gennaris, A, Barras, F, Collet, J. 2017. Oxidative stress, protein damage and repair in
bacteria. Nat Rev Microbiol 15:385–396.

4. Maezato Y, Blum, P. 2012. Survival of the fittest: Overcoming oxidative stress at the extremes
of acid, heat and metal. Life 2:242.

5. Farrugia G, Balzan, R. 2012. Oxidative stress and programmed cell death in yeast. Front Oncol
2:64.

6. Jelic MD, Mandic, AD, Maricic, SM, Srdjenovic, BU. 2021. Oxidative stress and its role in
cancer. J Cancer Res Ther 17:22–28.

7. Teleanu DM, Niculescu, A, Lungu, II, Radu, CI, Vladâcenco, O, Roza, E, Costăchescu, B,
Grumezescu, AM, Teleanu, RI. 2022. An overview of oxidative stress, neuroinflammation, and
neurodegenerative diseases. Int J Mol Sci 23:5938.

8. Steven S, Frenis, K, Oelze, M, Kalinovic, S, Kuntic, M, Bayo Jimenez, MT, Vujacic-Mirski, K,
Helmstädter, J, Kröller-Schön, S, Münzel, T, Daiber, A. 2019. Vascular inflammation and
oxidative stress: Major triggers for cardiovascular disease. Oxid Med Cell Longev 2019:7092151.

9. Johnson LA, Hug, LA. 2019. Distribution of reactive oxygen species defense mechanisms
across domain bacteria. Free Radic Biol Med 140:93–102.

10. Sato Y, Kameya, M, Fushinobu, S, Wakagi, T, Arai, H, Ishii, M, Igarashi, Y. 2012. A novel
enzymatic system against oxidative stress in the thermophilic hydrogen-oxidizing bacterium
Hydrogenobacter thermophilus. Plos One 7:e34825.

11. Cannio R, D'angelo, A, Rossi, M, Bartolucci, S. 2000. A superoxide dismutase from the
archaeon *Sulfolobus solfataricus* is an extracellular enzyme and prevents the deactivation by
superoxide of cell-bound proteins. Eur J Biochem 267:235–243.

12. Takao M, Oikawa, A, Yasui, A. 1990. Characterization of a superoxide dismutase gene from
the archaebacterium *Methanobacterium thermoautotrophicum*. Arch Biochem Biophys
283:210–216.

13. Jeon S, Ishikawa, K. 2002. Identification and characterization of thioredoxin and thioredoxin
reductase from *Aeropyrum pernix* K1. Eur J Biochem 269:5423–5430.

14. Dea S, Miroslav, R. 2011. Oxidative stress resistance in *Deinococcus radiodurans*. Microbiol
Mol Biol Rev 75:133–191.

15. Matarredona L, Camacho, M, Zafrilla, B, Bravo-Barrales, G, Esclapez, J, Bonete, M. 2021. The
survival of *Haloferax mediterranei* under stressful conditions. Microorganisms 9:336.

16. Robinson CK, Webb, K, Kaur, A, Jaruga, P, Dizdaroglu, M, Baliga, NS, Place, A, DiRuggiero, J.
2011. A major role for nonenzymatic antioxidant processes in the radioresistance of
Halobacterium salinarum. J Bacteriol 193:1653–1662.

17. Webb KM, Yu, J, Robinson, CK, Noboru, T, Lee, YC, DiRuggiero, J. 2013. Effects of
intracellular Mn on the radiation resistance of the halophilic archaeon *Halobacterium*
salinarum. Extremophiles 17:485–497.

18. Eme L, Spang, A, Lombard, J, Stairs, CW, Ettema, TJG. 2017. Archaea and the origin of
eukaryotes. Nat Rev Microbio 15:711–723.

19. Phung DK, Etienne, C, Batista, M, Langendijk-Genevaux, P, Moalic, Y, Laurent, S, Liuu, S,
Morales, V, Jebbar, M, Fichant, G, Bouvier, M, Flament, D, Clouet-d'Orval, B. 2020. RNA
processing machineries in archaea: The 5'-3' exoribonuclease aRNase J of the β-CASP family is
engaged specifically with the helicase ASH-Ski2 and the 3'-5' exoribonucleolytic RNA exosome
machinery. Nucleic Acids Res 48:3832–3847.

20. Brochier-Armanet C, Forterre, P, Gribaldo, S. 2011. Phylogeny and evolution of the archaea:
One hundred genomes later. Curr Opin Microbiol 14:274–281.

21. Řezanka T, Kyselová, L, Murphy, DJ. 2023. Archaeal lipids. Prog Lipid Res 91:101237.

22. Humbard MA, Miranda, HV, Lim, J, Krause, DJ, Pritz, JR, Zhou, G, Chen, S, Wells, L, Maupin-
Furlow, JA. 2010. Ubiquitin-like small archaeal modifier proteins (SAMPs) in *Haloferax volcanii*.
Nature 463:54–60.

23. Nunoura T, Takaki, Y, Kakuta, J, Nishi, S, Sugahara, J, Kazama, H, Chee, G, Hattori, M, Kanai,
A, Atomi, H, Takai, K, Takami, H. 2010. Insights into the evolution of archaea and eukaryotic
protein modifier systems revealed by the genome of a novel archaeal group. Nucleic Acids Res
39:3204–3223.

24. Haque RU, Paradisi, F, Allers, T. 2020. *Haloferax volcanii* for biotechnology applications:
Challenges, current state and perspectives. Appl Microbiol Biotechnol 104:1371–1382.

25. Pastor MM, Darnell, CL, Vreugdenhil, A, Schmid, AK. 2024. Rapid rewiring of an archaeal
transcription factor function via flexible cis-trans interactions. bioRxiv 2024.11.20.624553.

26. Sharma K, Gillum, N, Boyd, JL, Schmid, A. 2012. The RosR transcription factor is required for
gene expression dynamics in response to extreme oxidative stress in a hypersaline-adapted
archaeon. BMC Genomics 13:351–351.

27. Gelsinger DR, DiRuggiero, J. 2018. Transcriptional landscape and regulatory roles of small
noncoding RNAs in the oxidative stress response of the haloarchaeon *Haloferax volcanii*. J
Bacteriol 200:e00779–17.

28. Lease RA, Smith, D, McDonough, K, Belfort, M. 2004. The small noncoding DsrA RNA is an
acid resistance regulator in *Escherichia coli*. J Bacteriol 186:6179–6185.

29. Majdalani N, Chen, S, Murrow, J, St John, K, Gottesman, S. 2001. Regulation of RpoS by a
novel small RNA: The characterization of RprA. Mol Microbiol 39:1382–1394.

30. Massé E, Gottesman, S. 2002. A small RNA regulates the expression of genes involved in
iron metabolism in *Escherichia coli*. Proc Nat Acad Sci U S A 99:4620–4625.

31. Delihas N, Forst, S. 2001. MicF: An antisense RNA gene involved in response of E*scherichia
coli* to global stress factors11Edited by D. draper. J Mol Biol 313:1–12.

32. Lalaouna D, Baude, J, Wu, Z, Tomasini, A, Chicher, J, Marzi, S, Vandenesch, F, Romby, P,
Caldelari, I, Moreau, K. 2019. RsaC sRNA modulates the oxidative stress response of
Staphylococcus aureus during manganese starvation. Nucleic Acids Res 47:9871–9887.

33. Altuvia S, Weinstein-Fischer, D, Zhang, A, Postow, L, Storz, G. 1997. A small, stable RNA
induced by oxidative stress: Role as a pleiotropic regulator and antimutator. Cell 90:43–53.

34. Chen Y, Xue, D, Sun, W, Han, J, Li, J, Gao, R, Zhou, Z, Zhang, W, Chen, M, Lin, M, Wang, J,
Zuo, K. 2019. sRNA OsiA stabilizes catalase mRNA during oxidative stress response of
Deincoccus radiodurans R1. Microorganisms 7:422.

35. Gelsinger DR, Reddy, R, Whittington, K, Debic, S, DiRuggiero, J. 2021. Post-transcriptional
regulation of redox homeostasis by the small RNA SHOxi in haloarchaea. RNA Biol 18:1867–
1881.

36. Halbeisen RE, Gerber, AP. 2009. Stress-dependent coordination of transcriptome and
translatome in yeast. PLOS Biology 7:e1000105.

37. Picard F, Loubière, P, Girbal, L, Cocaign-Bousquet, M. 2013. The significance of translation
regulation in the stress response. BMC Genomics 14:588.

38. Kuhn KM, DeRisi, JL, Brown, PO, Sarnow, P. 2001. Global and specific translational
regulation in the genomic response of *Saccharomyces cerevisiae* to a rapid transfer from a
fermentable to a nonfermentable carbon source. Mol Cell Biol 21:916–927.

39. Melamed D, Pnueli, L, Arava, Y. 2008. Yeast translational response to high salinity: Global
analysis reveals regulation at multiple levels. RNA 14:1337–1351.

40. Gerashchenko MV, Lobanov, AV, Gladyshev, VN. 2012. Genome-wide ribosome profiling
reveals complex translational regulation in response to oxidative stress. Proc Natl Acad Sci U S A
109:17394–17399.

41. Benelli D, Marzi, S, Mancone, C, Alonzi, T, la Teana, A, Londei, P. 2008. Function and
ribosomal localization of aIF6, a translational regulator shared by archaea and eukarya. Nucleic
Acids Res 37:256–267.

42. Jäger D, Pernitzsch, SR, Richter, AS, Backofen, R, Sharma, CM, Schmitz, RA. 2012. An
archaeal sRNA targeting cis - and trans -encoded mRNAs via two distinct domains. Nucleic Acids
Res 40:10964–10979.

43. Prasse D, Ehlers, C, Backofen, R, Schmitz, RA. 2013. Regulatory RNAs in archaea: First target
identification in methanoarchaea. Biochem Soc Trans 41:344–349.

44. Altuvia S, Zhang, A, Argaman, L, Tiwari, A, Storz, G. 1998. The *Escherichia coli* OxyS
regulatory RNA represses *fhlA* translation by blocking ribosome binding. Embo J 17:6069–6075;
6075.

45. Jevtić Ž, Stoll, B, Pfeiffer, F, Sharma, K, Urlaub, H, Marchfelder, A, Lenz, C. 2019. The
response of *Haloferax volcanii* to salt and temperature stress: A proteome study by label-free
mass spectrometry. Proteomics 19:1800491.

46. McMillan LJ, Hwang, S, Farah, RE, Koh, J, Chen, S, Maupin-Furlow, JA. 2018. Multiplex
quantitative SILAC for analysis of archaeal proteomes: A case study of oxidative stress
responses. Environ Microbiol 20:385–401.

47. Soborowski AL, Hackley, RK, Hwang, S, Zhou, G, Dulmage, K, Schönheit, P, Daniels, C, Bisson-
Filho, AW, Marchfelder, A, Maupin-Furlow, JA, Allers, T, Schmid, AK. 2024. Genomic re-
sequencing reveals mutational divergence across genetically engineered strains of model
archaea. bioRxiv 2024.08.08.607208.

48. Hawkins M, Malla, S, Blythe, MJ, Nieduszynski, CA, Allers, T. 2013. Accelerated growth in the
absence of DNA replication origins. Nature 503:544–547.

49. Hartman AL, Norais, C, Badger, JH, Delmas, S, Haldenby, S, Madupu, R, Robinson, J, Khouri,
H, Ren, Q, Lowe, TM, Maupin-Furlow, J, Pohlschroder, M, Daniels, C, Pfeiffer, F, Allers, T, Eisen,
JA. 2010. The complete genome sequence of *Haloferax volcanii* DS2, a model archaeon. PLoS
One 5:e9605.

50. Pohlschroder M, Schulze, S. 2019. *Haloferax volcanii*. Trends Microbiol 27:86–87.

51. Pérez-Arnaiz P, Dattani, A, Smith, V, Allers, T. 2020. *Haloferax volcanii*-a model archaeon for
studying DNA replication and repair. Open Biol 10:200293.

52. Gelsinger DR, Dallon, E, Reddy, R, Mohammad, F, Buskirk, AR, DiRuggiero, J. 2020. Ribosome
profiling in archaea reveals leaderless translation, novel translational initiation sites, and
ribosome pausing at single codon resolution. Nucleic Acids Res 48:5201–5216.

53. Hadjeras L, Bartel, J, Maier, L, Maaß, S, Vogel, V, Svensson, SL, Eggenhofer, F, Gelhausen, R,
Müller, T, Alkhnbashi, OS, Backofen, R, Becher, D, Sharma, CM, Marchfelder, A. 2023. Revealing
the small proteome of *Haloferax volcanii* by combining ribosome profiling and small-protein
optimized mass spectrometry. Microlife 4:uqad001.

54. Ingolia I, Ghaemmaghami, G, Newman, N, Weissman, W. 2009. Genome-wide analysis *in
vivo* of translation with nucleotide resolution using ribosome profiling. Science 324:218–223.

55. Kramer P, Gäbel, K, Pfeiffer, F, Soppa, J. 2014. *Haloferax volcanii*, a prokaryotic species that
does not use the Shine Dalgarno mechanism for translation initiation at 5'-UTRs. PloS One
9:e94979.

56. Mi H, Muruganujan, A, Casagrande, JT, Thomas, PD. 2013. Large-scale gene function
analysis with the PANTHER classification system. Nat Protoc 8:1551–1566.

57. Mi H, Muruganujan, A, Huang, X, Ebert, D, Mills, C, Guo, X, Thomas, PD. 2019. Protocol
update for large-scale genome and gene function analysis with the PANTHER classification
system (v.14.0). Nat Protoc 14:703–721.

58. Szklarczyk D, Kirsch, R, Koutrouli, M, Nastou, K, Mehryary, F, Hachilif, R, Gable, AL, Fang, T,
Doncheva, NT, Pyysalo, S, Bork, P, Jensen, LJ, von Mering, C. 2023. The STRING database in
2023: Protein-protein association networks and functional enrichment analyses for any
sequenced genome of interest. Nucleic Acids Res 51:D638–D646.

59. Mondragon P, Hwang, S, Kasirajan, L, Oyetoro, R, Nasthas, A, Winters, E, Couto-Rodriguez,
RL, Schmid, A, Maupin-Furlow, JA. 2022. TrmB family transcription factor as a thiol-based
regulator of oxidative stress response. mBio 13:e0063322–22.

60. Llorca MG, Martínez-Espinosa, RM. 2022. Assessment of *Haloferax mediterranei* genome in
search of copper-molecular machinery with potential applications for bioremediation. Front
Microbiol 13:895296.

61. Liao Y, Williams, TJ, Ye, J, Charlesworth, J, Burns, BP, Poljak, A, Raftery, MJ, Cavicchioli, R.
2016. Morphological and proteomic analysis of biofilms from the antarctic archaeon,
Halorubrum lacusprofundi. Sci Rep 6:37454.

62. Reindel S, Anemüller, S, Sawaryn, A, Matzanke, BF. 2002. The DpsA-homologue of the
archaeon *Halobacterium salinarum* is a ferritin. Biochim Biophys Acta 1598:140–146.

63. Zeth K, Offermann, S, Essen, L, Oesterhelt, D. 2004. Iron-oxo clusters biomineralizing on
protein surfaces: Structural analysis of *Halobacterium salinarum* DpsA in its low- and high-iron
states. Proc Natl Acad Sci U S A 101:13780–13785.

64. Schulze S, Adams, Z, Cerletti, M, De Castro, R, Ferreira-Cerca, S, Fufezan, C, Giménez, MI,
Hippler, M, Jevtic, Z, Knüppel, R, Legerme, G, Lenz, C, Marchfelder, A, Maupin-Furlow, J, Paggi,
RA, Pfeiffer, F, Poetsch, A, Urlaub, H, Pohlschroder, M. 2020. The archaeal proteome project
advances knowledge about archaeal cell biology through comprehensive proteomics. Nat
Commun 11:3145.

65. Ndah E, Jonckheere, V, Giess, A, Valen, E, Menschaert, G, Van Damme, P. 2017.
REPARATION: Ribosome profiling assisted (re-)annotation of bacterial genomes. Nucleic Acids
Res 45:e168.

66. Sayers EW, Barrett, T, Benson, DA, Bolton, E, Bryant, SH, Canese, K, Chetvernin, V, Church,
DM, DiCuccio, M, Federhen, S, Feolo, M, Fingerman, IM, Geer, LY, Helmberg, W, Kapustin, Y,
Landsman, D, Lipman, DJ, Lu, Z, Madden, TL, Madej, T, Maglott, DR, Marchler-Bauer, A, Miller,
V, Mizrachi, I, Ostell, J, Panchenko, A, Phan, L, Pruitt, KD, Schuler, GD, Sequeira, E, Sherry, ST,
Shumway, M, Sirotkin, K, Slotta, D, Souvorov, A, Starchenko, G, Tatusova, TA, Wagner, L, Wang,
Y, Wilbur, WJ, Yaschenko, E, Ye, J. 2011. Database resources of the national center for
biotechnology information. Nucleic Acids Res 39:38.

67. Chen Y, Cao, X, Loh, KH, Slavoff, SA. 2023. Chemical labeling and proteomics for
characterization of unannotated small and alternative open reading frame-encoded
polypeptides. Biochem Soc Trans 51:1071–1082.

68. Will S, Joshi, T, Hofacker, IL, Stadler, PF, Backofen, R. 2012. LocARNA-P: Accurate boundary
prediction and improved detection of structural RNAs. RNA 18:900–914.

69. Wright PR, Georg, J, Mann, M, Sorescu, DA, Richter, AS, Lott, S, Kleinkauf, R, Hess, WR,
Backofen, R. 2014. CopraRNA and IntaRNA: Predicting small RNA targets, networks and
interaction domains. Nucleic Acids Res 42:119.

70. Allers T, Hien-Ping N, Mevarech M, Lloyd RG. 2004. Development of additional selectable
markers for the halophilic archaeon *Haloferax volcanii* based on the *leuB* and *trpA* genes. Appl
Environ Microbiol 70:943–953.

71. Rawls KS, Martin JH, Maupin-Furlow JA. 2011. Activity and transcriptional regulation of
bacterial protein-like glycerol-3-phosphate dehydrogenase of the haloarchaea in *Haloferax*
volcanii. J Bacteriol 193:4469–4476.

72. Wang X, Liu, Q, Zhang, B. 2014. Leveraging the complementary nature of RNA-seq and
shotgun proteomics data. Proteomics 14:2676–2687.

73. de Sousa Abreu R, Penalva, LO, Marcotte, EM, Vogel, C. 2009. Global signatures of protein
and mRNA expression levels. Mol Biosyst 5:1512–1526.

74. Zhong J, Xiao, C, Gu, W, Du, G, Sun, X, He, Q, Zhang, G. 2015. Transfer RNAs mediate the
rapid adaptation of *Escherichia coli* to oxidative stress. PLOS Genetics 11:e1005302.

75. Zhu M, Dai, X. 2019. Maintenance of translational elongation rate underlies the survival of
Escherichia coli during oxidative stress. Nucleic Acids Res 47:7592–7604.

76. Baliga NS, Bjork, SJ, Bonneau, R, Pan, M, Iloanusi, C, Kottemann, MCH, Hood, L, DiRuggiero,
J. 2004. Systems level insights into the stress response to UV radiation in the halophilic
archaeon *Halobacterium* NRC-1. Genome Res 14:1025–1035.

77. Warner JR. 1999. The economics of ribosome biosynthesis in yeast. Trends Biochem Sci
24:437–440.

78. Bąkowska-Żywicka K, Kasprzyk, M, Twardowski, T. 2016. tRNA-derived short RNAs bind to
Saccharomyces cerevisiae ribosomes in a stress-dependent manner and inhibit protein
synthesis in vitro. FEMS Yeast Res 16:fow077.

79. Holcik M, Sonenberg, N. 2005. Translational control in stress and apoptosis. Nat Rev Mol
Cell Biol 6:318–327.

80. Whitehead K, Kish, A, Pan, M, Kaur, A, Reiss, DJ, King, N, Hohmann, L, DiRuggiero, J, Baliga,
NS. 2006. An integrated systems approach for understanding cellular responses to gamma
radiation. Molecular Systems Biology 2:47.

81. Ghosal D, Omelchenko, MV, Gaidamakova, EK, Matrosova, VY, Vasilenko, A, Venkateswaran,
A, Zhai, M, Kostandarithes, HM, Brim, H, Makarova, KS. 2005. How radiation kills cells: Survival
of *Deinococcus radiodurans* and *Shewanella oneidensis* under oxidative stress. FEMS Microbiol
Rev 29:361–375.

82. Liu Y, Zhou, J, Omelchenko, MV, Beliaev, AS, Venkateswaran, A, Stair, J, Wu, L, Thompson,
DK, Xu, D, Rogozin, IB. 2003. Transcriptome dynamics of *Deinococcus radiodurans* recovering
from ionizing radiation. Proc Natl Acad Sci U S A 100:4191–4196.

83. Al-Fageeh MB, Smales, CM. 2009. Cold-inducible RNA binding protein (CIRP) expression is
modulated by alternative mRNAs. RNA 15:1164–1176.

84. Costa ED, Chai, Y, Winans, SC. 2012. The quorum-sensing protein TraR of *Agrobacterium*
tumefaciens is susceptible to intrinsic and TraM-mediated proteolytic instability. Mol Microbiol
84:807–815.

85. Dessaux Y, Faure, D. 2018. Quorum sensing and quorum quenching in *Agrobacterium*: A
"go/no go system"? Genes (Basel) 9:210.

86. Turnbough CLJ. 2019. Regulation of bacterial gene expression by transcription attenuation.
Microbiol Mol Biol Rev 83:e00019–19.

87. Xiu Z, Chang, Z, Zeng, A. 2002. Nonlinear dynamics of regulation of bacterial trp operon:
Model analysis of integrated effects of repression, feedback inhibition, and attenuation.
Biotechnol Prog 18:686–693.

88. Nagel C, Machulla, A, Zahn, S, Soppa, J. 2019. Several one-domain zinc finger μ-proteins of
Haloferax volcanii are important for stress adaptation, biofilm formation, and swarming. Genes
10:361.

89. Aoyama JJ, Raina, M, Zhong, A, Storz, G. 2022. Dual-function spot 42 RNA encodes a 15–
amino acid protein that regulates the CRP transcription factor. Proc Natl Acad Sci U S A
119:e2119866119.

90. Raina M, King, A, Bianco, C, Vanderpool, CK. 2018. Dual-function RNAs. Microbiol Spectr
6:10.1128/microbiolspec.rwr–2018.

91. Lloyd CR, Park, S, Fei, J, Vanderpool, CK. 2017. The small protein SgrT controls transport
activity of the glucose-specific phosphotransferase system. J Bacteriol 199:e00869–16.

92. Tufail MA, Jordan, B, Hadjeras, L, Gelhausen, R, Cassidy, L, Habenicht, T, Gutt, M, Hellwig, L,
Backofen, R, Tholey, A, Sharma, CM, Schmitz, RA. 2024. Uncovering the small proteome of
Methanosarcina mazei using ribo-seq and peptidomics under different nitrogen conditions. Nat
Commun 15:8659.

93. Raina M, Aoyama, JJ, Bhatt, S, Paul, BJ, Zhang, A, Updegrove, TB, Miranda-Ríos, J, Storz, G.
2022. Dual-function AzuCR RNA modulates carbon metabolism. Proc Natl Acad Sci U S A
119:e2117930119.

94. Guttman M, Russell, P, Ingolia, NT, Weissman, JS, Lander, ES. 2013. Ribosome profiling
provides evidence that large noncoding RNAs do not encode proteins. Cell 154:240–251.

95. Gelhausen R, Müller, T, Svensson, SL, Alkhnbashi, OS, Sharma, CM, Eggenhofer, F, Backofen,
R. 2022. RiboReport - benchmarking tools for ribosome profiling-based identification of open
reading frames in bacteria. Brief Bioinform 23:bbab549.

96. Gebetsberger J, Zywicki, M, Künzi, A, Polacek, N. 2012. tRNA-derived fragments target the
ribosome and function as regulatory non-coding RNA in *Haloferax volcanii*. Archaea
2012:260909.

97. Wyss L, Waser, M, Gebetsberger, J, Zywicki, M, Polacek, N. 2018. mRNA-specific translation
regulation by a ribosome-associated ncRNA in *Haloferax volcanii*. Sci Rep 8:12502.

98. Collins JA, Irnov, I, Baker, S, Winkler, WC. 2007. Mechanism of mRNA destabilization by the
glmS ribozyme. Genes Dev 21:3356–3368.

99. Desnoyers G, Morissette, A, Prévost, K, Massé, E. 2009. Small RNA-induced differential
degradation of the polycistronic mRNA iscRSUA. Embo J 28:1551–1561.

100. Märtens B, Manoharadas, S, Hasenöhrl, D, Manica, A, Bläsi, U. 2013. Antisense regulation
by transposon-derived RNAs in the hyperthermophilic archaeon *Sulfolobus solfataricus*. EMBO
Rep 14:527–533; 533.

101. Bernick DL, Dennis, PP, Höchsmann, M, Lowe, TM. 2012. Discovery of *Pyrobaculum* small
RNA families with atypical pseudouridine guide RNA features. RNA 18:402–411.

102. Goldberger O, Livny, J, Bhattacharyya, R, Amster-Choder, O. 2021. Wisdom of the crowds:
A suggested polygenic plan for small-RNA-mediated regulation in bacteria. iScience 24:103096.

103. Westermann AJ. 2018. Regulatory RNAs in virulence and host-microbe interactions.
Regulating with RNA in Bacteria and Archaea 6:305–337.

104. Gelsinger, DR, Dallon, E, DiRuggiero, J. 2022. Conversion of Ribosome-Protected mRNA to
DNA and Deep Sequencing for Ribosome Profiling in *Haloferax volcanii*, p. 223–242. *In* S.
Ferreira-Cerca (ed.), Archaea: Methods and Protocols. Springer US, New York, NY.
https://doi.org/10.1007/978-1-0716-2445-6_14.

105. Martin M. 2011. Cutadapt removes adapter sequences from high-throughput sequencing
reads. EMBnet.Journal 17:10-12.

106. Langmead B, Trapnell, C, Pop, M, Salzberg, SL. 2009. Ultrafast and memory-efficient
alignment of short DNA sequences to the human genome. Genome Biol 10:R25.

107. Li H, Handsaker, B, Wysoker, A, Fennell, T, Ruan, J, Homer, N, Marth, G, Abecasis, G,
Durbin, R, 1000 Genome Project Data Processing Subgroup. 2009. The sequence
alignment/map format and SAMtools. Bioinformatics 25:2078–2079.

108. Pertea M, Pertea, GM, Antonescu, CM, Chang, T, Mendell, JT, Salzberg, SL. 2015. StringTie
enables improved reconstruction of a transcriptome from RNA-seq reads. Nat Biotechnol
33:290–295.

109. Liao Y, Smyth, GK, Shi, W. 2014. featureCounts: An efficient general purpose program for
assigning sequence reads to genomic features. Bioinformatics 30:923–930.

110. Love MI, Huber, W, Anders, S. 2014. Moderated estimation of fold change and dispersion
for RNA-seq data with DESeq2. Genome Biol 15:550.

111. Babski J, Haas, KA, Näther-Schindler, D, Pfeiffer, F, Förstner, KU, Hammelmann, M, Hilker,
R, Becker, A, Sharma, CM, Marchfelder, A, Soppa, Jö. 2016. Genome-wide identification of
transcriptional start sites in the haloarchaeon *Haloferax volcanii* based on differential RNA-seq
(dRNA-seq). BMC Genomics 17:629.

112. Thomas PD, Ebert, D, Muruganujan, A, Mushayahama, T, Albou, L, Mi, H. 2022. PANTHER:
Making genome-scale phylogenetics accessible to all. Protein Sci 31:8–22.

113. Moran HM, Manriquez-Sandoval, E, Sharma, P, Fried, SD, Gillilan, RE. 2024. Proteome-wide
assessment of protein structural perturbations under high pressure. PRX Life 2:033011.

114. To P, Whitehead, B, Tarbox, HE, Fried, SD. 2021. Nonrefoldability is pervasive across the E.
coli proteome. J Am Chem Soc 143:11435–11448.

115. Dyall-Smith, M. 2009. The Halohandbook – Protocols for haloarchaeal genetics. Available
at https://haloarchaea.com/wp-content/uploads/2025/02/Halohandbook_2009_REV_v2.pdf.

116. Fu X, Adams, Z, Maupin-Furlow, J. 2019. Assays for ubiquitin-like protein ligation and
proteasome function in archaea. Methods Enzymol 619:161–178.

117. Altschul SF, Gish, W, Miller, W, Myers, EW, Lipman, DJ. 1990. Basic local alignment search
tool. J Mol Biol 215:403–410.

118. Mann M, Wright, PR, Backofen, R. 2017. IntaRNA 2.0: Enhanced and customizable
prediction of RNA–RNA interactions. Nucleic Acids Res 45:W435–W439.

119. Livak KJ, Schmittgen, TD. 2001. Analysis of relative gene expression data using real-time
quantitative PCR and the 2(-delta delta C(T)) method. Methods 25:402–408.

120. Perez-Riverol Y, Bandla, C, Kundu, DJ, Kamatchinathan, S, Bai, J, Hewapathirana, S, John,
NS, Prakash, A, Walzer, M, Wang, S, Vizcaíno, JA. 2024. The PRIDE database at 20 years: 2025
update. Nucleic Acids Res 53:D543–D553.

Tables

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1019   **Table 1.** Annotated and novel small proteins encoded by sRNAs and detected by MS.

	Gene name	Genome location	Size (aa)	Start codon	Stop codon	RNA-seq TPMs		Ribo-seq TPMs	
						Control	Stress	Control	Stress
novel	sRNA_7	pHV3	31	CTG	TAG*	4.44	6.42	2.04	2.94
	sRNA_23	pHV4	70	CTG	TGA	11.55	17.46	5.86	12.98
	sRNA_80	chr	40	ATG	TAG	45.64	26.89	36.47	38.61
annotated	sRNA_JD	chr	56	ATG	TAA	203.29	307.16	163.10	497.56
	sRNA_KL	chr	57	ATG	TAA*	131.68	138.46	1207.81	405.01
	sRNA_81	chr	58	CTG	TAA	35.83	20.57	30.80	25.79
	sRNA_93	pHV1	116	ATG	TAG	262.20	276.16	627.41	421.53

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1021   Asterisks indicate sRNAs with stop codons outside of the annotated gene region.

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1024   **Table 2.** sRNAs tagged for Western blotting.

	Gene name	Genome location	sRNA length (nt)	smORF size (aa)	Stop codon	RNA-seq TPMs		Ribo-seq TPMs	
						Control	Stress	Control	Stress
MS-detected	sRNA_KL	chr	175	57	yes	131.68	138.46	1207.81	405.01
	sRNA_93	pHV1	507	116	yes	262.20	276.16	627.41	421.53
Putative smORFs	sRNA_38	pHV4	56	16	yes	18.19	40.62	40.61	120.04
	sRNA_83	chr	182	55	yes	288.90	270.63	22.64	81.98
	sRNA_20_ORF2	pHV4	189	21	yes	40.77	89.47	68.98	542.12
	sRNA_20_ORF4	pHV4	189	34	yes	40.77	89.47	68.98	542.12
High ribosome occupancy	sRNA_61	chr	111	32	no	4565.10	2281.40	1850.99	3381.31
	SHOxi	pHV3	254	73	no	346.33	1767.52	219.35	2034.76

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1026   sRNAs with "no" in the stop codon column had no stop codon contained in the predicted sRNA region as

1027   determined by ORFfinder.

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1037 **Table 3.** sRNAs with differential ribosome occupancy or translational efficiency during oxidative
1038 stress.

Name	RNA-seq fold change	RNA-seq p-value	Ribo-seq fold change	Ribo-seq p-value	TE fold change	TE p-value	RNA-seq control	RNA-seq stress	Ribo-seq control	Ribo-seq stress	coding cluster control	coding cluster stress	annotated protein	ArcPP detection	MS detected
sRNA_20	1.21	0.00	2.63	0.00	1.41	0.04	40.22	88.01	68.74	537.73	yes	yes	yes	no	no
sRNA_34	-0.44	0.22	-1.12	0.00	-0.70	0.26	19.44	15.34	12.93	7.52	yes	no	no	NA	no
sRNA_41	-0.93	0.00	-1.18	0.00	-0.27	0.66	46.64	24.21	11.62	6.65	no	no	yes	yes	no
sRNA_49	2.23	0.00	1.74	0.00	-0.50	0.57	37.41	195.67	127.06	525.30	no	no	no	NA	no
sRNA_58	0.40	0.37	1.23	0.01	0.81	0.39	21.45	34.76	41.31	135.96	no	no	no	NA	no
sRNA_60	-0.12	0.94	1.72	0.00	1.82	0.28	2491.07	1996.40	382.05	568.67	NA	no	no	NA	no
sRNA_61	-0.90	0.04	0.59	0.10	1.48	0.04	4496.30	2243.82	1843.17	3350.74	yes	yes	no	NA	no
sRNA_62	2.24	0.00	3.15	0.00	0.89	0.42	17.24	79.53	4.06	45.72	no	yes	no	NA	no
sRNA_71	-0.31	0.38	1.35	0.05	1.63	0.04	76.87	105.29	8.57	27.23	NA	NA	no	NA	no
sRNA_77	0.90	0.04	2.57	0.00	1.66	0.10	23.84	43.05	3.76	13.07	NA	no	no	NA	no
sRNA_83	0.06	0.89	1.59	0.00	1.52	0.03	284.91	266.25	22.57	81.26	no	no	no	NA	no
sRNA_95	1.14	0.00	1.61	0.00	0.46	0.56	21.16	45.04	9.43	33.82	no	no	no	NA	no
sRNA_96	1.65	0.00	1.59	0.00	-0.08	0.92	51.26	140.20	5.59	19.10	yes	yes	no	NA	no
sRNA_CD	0.95	0.01	1.50	0.00	0.53	0.44	83.53	141.43	168.64	569.29	no	yes	yes	yes	no
sRNA_JD	0.68	0.20	1.33	0.01	0.64	0.57	200.14	301.88	162.34	493.83	yes	yes	yes	yes	yes
sRNA_KL	0.16	0.57	-1.93	0.00	-2.12	0.00	129.94	136.19	1203.27	401.61	yes	yes	yes	yes	yes
sRNA_SHOxi	2.46	0.00	2.89	0.00	0.42	0.72	341.52	1738.88	218.70	2017.74	yes	no	no	NA	no

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1040 Fold change refers to log$_2$ fold change, and p-value refers to the adjusted p-value.
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1042 **Table 4.** Putative mRNA targets with differential ribosome occupancy or TE during oxidative stress.

	Target Name	Function	RNA-seq Fold Change	RNA-seq p-value	Ribo-seq Fold Change	Ribo-seq p-value	TE Fold Change	TE p-value	RNA-seq Control	RNA-seq Stress	Ribo-seq Control	Ribo-seq Stress
sRNA_58	HVO_RS04540	hypothetical protein	-1.21	0.00	-1.21	0.00	-0.02	0.98	326.20	169.80	370.97	208.87
	HVO_RS13165	ABC transporter permease	-1.64	0.00	-1.27	0.00	0.36	0.51	640.15	188.77	85.81	45.53
	HVO_RS17485	D-2-hydroxyacid dehydrogenase	-1.01	0.00	-1.60	0.00	-0.61	0.07	27.50	47.10	58.33	27.88
	HVO_RS17805	hypothetical protein	1.00	0.00	1.46	0.00	0.45	0.45	54.93	91.69	36.61	98.47
	HVO_RS19470	hypothetical protein	1.33	0.01	-0.65	0.05	-2.01	0.01	7.57	15.74	55.04	44.71
sRNA_77	HVO_RS05320	YccF domain-containing protein	1.01	0.00	1.37	0.00	0.34	0.62	26.87	53.00	37.93	121.84
	HVO_RS06805	co-chaperone YbbN	0.62	0.06	-0.66	0.03	-1.30	0.01	1088.48	1614.45	2937.95	2326.41
	HVO_RS07705	hypothetical protein	-0.52	0.09	0.80	0.07	1.31	0.04	51.84	33.24	11.22	23.01
	HVO_RS08415	amidohydrolase family protein	-0.88	0.00	-1.87	0.00	-1.01	0.03	82.41	82.17	87.53	55.80
	HVO_RS09105	2Fe-2S domain-containing protein	-0.24	0.31	-1.24	0.00	-1.01	0.05	67.63	53.64	76.35	40.75
	HVO_RS11380	hypothetical protein	1.06	0.00	2.71	0.00	1.63	0.04	21.14	49.53	68.11	579.99
	HVO_RS11455	BMP family protein	-0.72	0.00	-1.78	0.00	-1.08	0.05	1322.62	720.75	1618.05	586.70
	HVO_RS13145	hypothetical protein	0.93	0.00	1.06	0.00	0.11	0.86	193.21	286.04	47.28	123.46
	HVO_RS14580	dehydrorhamnose epimerase family protein	-0.76	0.03	-1.88	0.00	-1.14	0.07	1726.87	885.36	986.87	329.83
	HVO_RS15315	hypothetical protein	-0.73	0.00	0.74	0.03	1.46	0.00	133.96	75.10	13.40	25.06
	HVO_RS17930	30S ribosomal protein S28e	-1.01	0.00	-1.63	0.00	-0.63	0.13	8234.66	3814.46	1902.49	770.44
	HVO_RS18350	hypothetical protein	1.10	0.00	1.19	0.02	0.07	0.94	19.56	38.77	6.65	17.79
	HVO_RS18595	GNAT family N-acetyltransferase	0.27	0.39	1.05	0.00	0.76	0.12	30.92	27.85	9.31	23.79
	HVO_RS18740	hypothetical protein	0.16	0.66	1.18	0.00	0.99	0.08	68.49	68.32	17.95	42.57
	HVO_RS20570	rubrerythrin-like domain-containing protein	0.97	0.00	3.78	0.00	2.79	0.00	50.42	49.15	17.52	161.98
sRNA_83	HVO_RS00230	methyltransferase	-1.08	0.00	-1.08	0.00	-0.01	0.98	219.52	94.40	163.37	97.06
	HVO_RS00700	ABC transporter substrate-binding protein	-2.13	0.00	-2.70	0.00	-0.59	0.42	190.15	38.32	819.59	157.72
	HVO_RS01670	racemase enzyme family protein	1.66	0.00	1.20	0.01	-0.47	0.60	4.57	12.69	6.18	18.40
	HVO_RS03935	ring-cleaving dioxygenase	0.98	0.00	1.44	0.00	0.44	0.36	36.14	63.65	24.10	83.36
	HVO_RS04155	hypothetical protein	0.96	0.08	2.51	0.00	1.55	0.09	36.47	27.77	18.03	36.31
	HVO_RS04735	hypothetical protein	-0.12	0.72	1.10	0.00	1.21	0.01	50.36	45.95	18.86	51.67
	HVO_RS05345	thermosome subunit alpha	-1.06	0.00	-1.58	0.00	-0.53	0.37	4645.21	2047.07	6582.65	2681.76
	HVO_RS08545	SPFH domain-containing protein	0.46	0.04	1.25	0.00	0.77	0.10	295.03	436.26	65.36	202.53
	HVO_RS08645	NAD(P)-dependent dehydrogenase	-0.74	0.00	-1.63	0.00	-0.91	0.01	143.06	78.46	197.19	80.87
	HVO_RS13905	serine--tRNA ligase	-0.51	0.02	-1.27	0.00	-0.77	0.07	384.53	246.71	547.21	295.37
	HVO_RS13930	SIMPL domain-containing protein	0.99	0.00	1.69	0.00	0.68	0.17	65.12	120.33	24.14	91.85
	HVO_RS17570	HpcH/HpaI aldolase/citrate lyase family protein	0.96	0.01	1.87	0.00	0.89	0.38	133.65	232.04	49.88	213.11
	HVO_RS19230	ABC transporter ATP-binding protein	-1.35	0.00	-1.65	0.00	-0.32	0.55	38.24	18.34	66.16	27.28

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1044 Fold change refers to log$_2$ fold change, and p-value refers to the adjusted p-value.

Figures

Figure 1. Comparison of genes with differential transcription, ribosome occupancy, and translation during oxidative stress. Volcano plots of $\log_2$ fold changes and corresponding $-\log_{10}$ p-values of transcript abundances (A), ribosome occupancies (B), and translation efficiency (C) comparing stress vs no stress conditions. Red, green, and blue colored points highlight transcripts with differential expression (adjusted p-value <0.05 and absolute $\log_2$ fold change >1). Fold change and p-values were calculated using DESeq2. Labeled black points indicate genes previously shown to be involved in oxidative stress response. All other genes are shown in gray. D. Functional categories (protein class) of genes with differential TE during oxidative stress. Functions of significant genes were categorized using PANTHER generic mapping based on homology. Enrichment of functional categories in upregulated (TE up) or downregulated (TE down) genes compared to all annotated genes was calculated using the total number of PANTHER hits for each group (2061 for all annotated genes, 99 for TE down, and 42 for TE up). Asterisks indicate significant categories (translation) or categories that contain significantly enriched subcategories (ribosomal proteins; peroxidases).

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Figure 2. Ribosome footprint length distributions and sRNAs with ribosome occupancy. A.
Schematic of analyses to assess the coding potential for sRNAs with ribosome occupancy,
starting with the isolation of monosome fractions during ribosome profiling. B. Clustered
heatmap of ribosome footprint length distributions for sRNAs, coding genes, and noncoding
genes with ribosome occupancy under control conditions. Darker colors indicate higher read
percentage. Known coding genes are shown in blue, known noncoding genes in orange, and
sRNAs in black. sRNAs with annotated proteins are underlined. sRNAs for which peptides have
been detected by MS are marked with an asterisk. Percentages for 'All CDS' were calculated
using sum read counts of all coding genes.

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Figure 3. Discovery of novel small proteins encoded in sRNAs. A. Overlapping histogram of

protein length (aa) for the *H. volcanii* annotated proteome (gray) and proteins detected by MS

(overlaid in green). B. Overlapping histogram of protein length (aa) for putative peptides

(predicted using NCBI ORF finder) encoded by sRNAs (gray) and small proteins detected by MS

(overlaid in green). Detection cutoff of 30aa is indicated by red dashed line. C. Cloning strategy

for tagging sRNAs for Western blot analysis. FLAG indicates the location of the 3xFLAG-tag. D.

Western blot of tagged sRNAs. + indicates samples treated with hydrogen peroxide and -

indicates control samples.

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Figure 4. Ribosome footprint length distributions and stress-responsive sRNAs with ribosome occupancy. A. Schematic of analyses to assess the coding potential for sRNAs with ribosome occupancy, starting with the isolation of monosome fractions on a sucrose gradient using samples treated with oxidative stress. B. Clustered heatmaps of ribosome footprint length distributions for sRNAs, coding genes, and noncoding genes with ribosome occupancy under oxidative stress. Darker colors indicate higher read percentage. Known coding genes are shown in blue, known noncoding genes in orange, and sRNAs in black. sRNAs with annotated proteins are underlined. sRNAs for which peptides have been detected by MS are marked with an asterisk. Percentages for 'All CDS' were calculated using sum read counts of all coding genes.

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Figure 5. Characterization of stress-responsive sRNAs with ribosome occupancy. A. Consensus
RNA structural predictions for sRNAs with no evidence of coding potential were generated
using LocARNA. Colored bases indicate sequence and structural conservation of compatible

base pairs within the predicted structure (see Fig. S7). Colors correspond to number (red: 1,

yellow: 2, green: 3) of base pair types (C-G, G-C, A-U, U-A, G-U, or U-G) with red being the most

highly conserved and green the least conserved. Color saturation decreases with the number of

incompatible base pairs. B. IntaRNA was used to predict putative mRNA targets (Tables S14-16).

Blue lines indicate putative binding regions along the sRNA. Curves depict coverage of putative

binding regions along the sRNA. C. Bar chart of predicted mRNA targets ($p < 0.01$) with

differential ribosome occupancy or TE during oxidative stress (purple). The number of predicted

targets that are unaffected by oxidative stress are shown in gray.

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