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

Emma Dallon[a], Haley M. Moran[b], Sadhana R. Chidambaran[a], Arman Kian[a], Betty Y.H. Huang[a],
Stephen D. Fried[b,c], Jocelyne DiRuggiero[a,d*]

[a] Department of Biology, Johns Hopkins University, Baltimore, Maryland, USA

[b] Department of Chemistry, Johns Hopkins University, Baltimore, Maryland, USA

[c] T. C. Jenkins Department of Biophysics, Johns Hopkins University, Baltimore, Maryland, USA

[d] Department of Earth and Planetary Sciences, Johns Hopkins University, Baltimore, Maryland,
USA

Corresponding author: Jocelyne DiRuggiero

Email: jdiruggiero@jhu.edu

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 observed upregulated TE for several transporters and membrane-bound proteases, highlighting the importance of membrane dynamics during oxidative stress. We additionally 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 originating from 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. In combination with the evidence of regulation at the translation level during oxidative stress, this demonstrates the complexity of gene regulation in response to stress.

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, revealed novel biological systems, and increased possible applications for biotechnology and bioremediation. Many archaeal systems, however, have yet to be fully characterized. Using *Haloferax volcanii* as a model, we investigated the global translation landscape during oxidative stress and revealed the presence of several noncoding ribosome-associated sRNAs that likely play a role in translational regulation. This work expands our knowledge of translational regulation in archaea and underscores the complexity of gene regulation during stress response.

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). Prokaryotes utilize numerous enzymes that neutralize ROS (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. Mechanisms of transcriptional regulation, especially in response to oxidative stress, have been studied in few archaeal species (25-27). 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). Post-transcriptional regulation by small noncoding RNAs (sRNAs) is 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* (37). In *H. volcanii*, the most upregulated sRNA during oxidative stress (SHOxi) binds to and destabilizes malic enzyme transcripts, leading to higher cell survival rates during oxidative stress (35). Post-translational regulation has been investigated with eukaryotic-like protein modifications in archaea, such as sampylation (22). Many proteins associated with the oxidative stress response are targeted by sampylation, suggesting it may play a role in its regulation (36).

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 (37-40). 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 (41). Mechanisms of translational regulation by proteins and sRNAs during stress have 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 (42). In *Methanosarcina mazei*, sRNAs were shown to mask the ribosome binding site of target mRNAs to modulate translation in response to nitrogen starvation (43, 44). This mechanism bears resemblance to an oxidative

88 stress-responsive sRNA in *E. coli* (45). Additionally, proteomic studies in *H. volcanii* have begun
89 to elucidate the differences between transcription and translation during stress responses (46,
90 47). However a comprehensive study of translational regulation during oxidative stress
91 response has thus far been lacking.
92
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 (48-50) and a range of
genetic and biochemical tools are available (51, 52). Recent advances in studying translation in
H. volcanii (53, 54) have demonstrated that Ribo-seq can be used to detect translational
changes, providing a way to probe the effects of oxidative stress on translation. In the present
study, we used RNA-seq and Ribo-seq to determine the global translation landscape during
oxidative stress response. We identified genes that were regulated at the translation level
during oxidative stress and investigated the potential role of ribosome-associated sRNAs in
translation regulation during stress response.
102

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 (55). 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 during 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 (35, 56). Four replicates without stress treatment were used as controls. Sequenced
reads were aligned to the genome (50) 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.
122
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). We next investigated the differential
expression of five previously known oxidative stress-responsive genes. These genes included
superoxide dismutase, catalase, 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 (47). All showed significant upregulation in both RNA-
seq and Ribo-seq datasets (Fig1A, B; Table S4), implying our experimental approach
recapitulates 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 (47).
138
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; (47)). 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. Of genes with differential ribosome occupancy, only one
third (33%) also had differential transcript expression, while two thirds (67%) only had changes
in ribosome occupancy.
152
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 identifies genes that change only at the Ribo-seq or RNA-seq level, eliminating
those that change proportionally in both. 281 genes were found to have 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 the majority were indeed changing primarily at the level of
translation (Fig. 1D).
164
We investigated some basic properties of transcripts with differential TE to determine whether
they were distinct from the overall transcriptome. Several characteristics were explored,
including gene size, presence of 5' UTR, and amino acid frequency. The average and range of
sizes for genes with differential expression and differential ribosome occupancy were similar to
that of all mRNAs. Genes with differential TE had a slightly smaller average size, likely due to a
narrower size range of significant genes (Table S5). We observed no differences in amino acid
or codon frequencies for genes with differential TE (Fig. S2), suggesting the effect is not
governed by tRNA levels (57, 58). We also investigated the proportion of leaderless transcripts
in genes with differential TE because 72% of transcripts in *H. volcanii* lack a 5' UTR (59). We
observed no difference in the proportion of leaderless transcripts compared to the whole

transcriptome (Table S5) and found that, like the majority of the *H. volcanii* transcriptome, most
genes with differential TE lack a 5' UTR.

We then investigated whether there were functional enrichments in genes with differential TE
during oxidative stress. We performed a gene ontology analysis using PANTHER generic
mapping (60, 61), with enrichment determined using Fisher's test and FDR correction, and
KEGG pathway enrichment analysis using the STRING database (62), both of which rely on
homology-based predictions. Approximately half of all annotated genes for *H. volcanii* were
assigned to functional categories using PANTHER (Fig. 1E), yet very few significant functional
enrichments were found among genes with differential TE. Among genes with downregulated
TE during oxidative stress, we found enrichment of genes related to translation, with ribosomal
proteins and translation proteins having GO fold enrichments of 4.41 (FDR = 0.0005) and 3.39
(FDR = 0.0008), respectively, detected by GO enrichment tests. Enrichment of ribosomal
proteins was also found by KEGG analysis (FDR = 0.00093). We observed differential TE for
many genes related to redox homeostasis. Among downregulated genes, this included an
enrichment of peroxidases (GO; fold enrichment = 9.5, FDR = 0.0213) and genes involved in the
TCA cycle (KEGG; FDR = 0.0242). When analyzing genes with upregulated TE during oxidative
stress we found no statistical overrepresentation of any functional categories. The most
upregulated TE (HVO_RS20570; TE fold change of 2.79; Table S6) was for small protein of 51
amino acids classified by NCBI as a rubrerythrin-like domain-containing protein. We also
observed some interesting trends with functional categories, including an increase, albeit not
statistically significant, in transporters and protein modifying enzymes (Fig. 1E). Of particular
interest were two genes that encode membrane-bound proteases Sec11a (HVO_RS17270;
Table S6) and RhoI (HVO_RS11815; Table S6). Sec11a is one of two known Type I signal
peptidases in *H. volcanii*. Direct substrates for each are unknown (63, 64) and, in contrast to
Sec11a, the expression and translation of its counterpart (HVO_RS04715) was unaffected by
stress conditions. RhoI is one of two known rhomboid proteases in *H. volcanii.* While its
substrates are unknown, rhomboid proteases are well-conserved across domains and have
been found to play roles in a wide variety of cellular processes (65, 66), including glycosylation
of the S-layer in *H. volcanii* (67, 68). The increased translation of these genes may indicate the
importance of membrane dynamics during oxidative stress response.

In addition to investigating functional categories of genes with differential TE, we sought to
identify whether specific pathways were susceptible to translational regulation during oxidative
stress. To do so, we used the STRING database to predict interactions between genes with
upregulated or downregulated TE. We observed few predicted interactions among upregulated
genes (Fig. S3). In contrast, genes with downregulated TE formed a larger network containing
many functional clusters (Fig. 1F). The two largest clusters consisted of ribosome related genes,
including many ribosomal proteins, and genes related to the TCA cycle. The next largest
clusters, with 4 genes each, were classified as related to oxidative phosphorylation, pyrimidine
biosynthesis, and putative translation initiation factors. These interaction networks suggest
that, while translation is generally downregulated, specific pathways undergo targeted
translational regulation to modulate metabolic activity within cells.

While the majority of genes with differential TE were regulated only at the translational level,
we observed that 5% of genes with differential TE were regulated (absolute $\log_2$ fold change >1)
at both the transcriptional and translational levels. HVO_RS04895, upregulated for ribosome
occupancy and TE (Table S6), encodes a protein with a transmembrane domain, and is known
to be upregulated at the transcriptional level during oxidative stress by transcriptional regulator
OxsR (69). We additionally observed two genes with a unique regulation pattern of
downregulated TE and upregulation of both RNA expression and ribosome occupancy (Table
S6). These two genes encode KatG (HVO_RS13250), a catalase/peroxidase that uses hydrogen
peroxide as its substrate (70, 71), and DpsA (HVO_RS07285), a DNA starvation/stationary phase
protection protein (72, 73). Previously published proteomics data showed no change in protein
levels for KatG, and upregulation for DpsA (47). The regulation patterns we observed with Ribo-
seq suggested that, in some cases, transcriptional regulation may give an incomplete picture of
protein expression during oxidative stress, and translational regulation may act as an additional
modulator to quickly titrate protein levels during stress response. In our characterization of
genes with differential TE during oxidative stress, we observed no distinct chemical or physical
properties to distinguish genes that undergo translational regulation. We found that many
ribosome and translation-associated genes have decreased translation, suggesting a global
downregulation of translation in response to stress. We also observed differential translation of
genes related to redox homeostasis and membrane dynamics, with many transporters and
membrane-bound proteases upregulated during oxidative stress. Several genes with differential
translation were regulated at both the transcriptional and translational levels, highlighting the
likelihood that multiple levels of gene regulation are necessary to modulate protein expression
in response to stress.
242
Many small noncoding RNAs had ribosome occupancy.
As expected, most ribosome footprints in our analysis corresponded to coding genes. However,
it was remarkable to find that several small noncoding RNAs (sRNAs), as previously identified
using sRNA-seq (56), had ribosome occupancy. In total, we found that 42 out of 56 sRNAs
detected in our RNA-seq dataset had ribosome occupancy (TPM >10; Table S7), of which 17
sRNAs exhibited differential ribosome occupancy or differential TE during oxidative stress. We
used several computational approaches to determine whether sRNAs with ribosome occupancy
encoded putative small proteins (smORFs; Fig. 2A). By searching public databases, we found
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 (74). Next, we
used REPARATION (75) a program that predicts novel ORFs, including smORFs, from ribosome
profiling data (54). We found that 82% of all proteins in the annotated proteome were
accurately predicted by REPARATION using our ribosome profiling data (Table S8); this included
436 of 542 (80%) annotated smORFs (less than or equal to 100 amino acids). In addition,
REPARATION predicted 194 novel genes (Table S9); only seven of these were small proteins and
one was a ribosome-associated sRNA (Fig. 2A). While REPARATION indicated a lack of smORFs
encoded by sRNAs, software that predicted ORFs based on sequence alone was overly
permissive. ORFfinder (Fig. 2A; (76)) predicted ORFs in sRNAs sequences even when no stop
codon was contained within or around the sRNA sequence (Table S10). With conflicting
predictions from our computational analyses, and evidence of coding potential for only 10 out

of 42 sRNAs with ribosome occupancy (Fig. 2A), we sought to further explore the nature of the
ribosome occupancy on sRNAs using ribosome footprint length distribution.
265
Size distributions of ribosome footprints revealed distinct patterns for coding and noncoding
genes.
Ribosome footprint length distributions of coding genes, noncoding genes, and sRNAs were
used to explore the coding potential of ribosome-associated sRNAs. The distribution of
footprint lengths for coding genes (both for single genes and the sum of all coding genes)
showed that most footprints were between 24 and 27 nucleotides (nt) in length (Fig. 2B). This
was supported by previous work reporting that the footprint length for elongating ribosomes
was 27 nt (53). In contrast, we found that the distribution for noncoding genes, such as rRNAs,
SRP RNA, RNaseP RNA, and tRNAs, had a footprint pattern distinct from that of coding genes
(Fig. 2B). We performed clustering analysis on the footprint length distributions of coding and
noncoding genes, and sRNAs of interest, using the minimum number of clusters to separate
known coding genes from rRNAs and tRNAs. When performing clustering using only sRNAs with
annotated smORFs (Fig. S4A), we observed that those with low total read counts (Fig. S4B) did
not cluster with coding genes, thus suggesting that a minimum of 65 read counts across all
biological replicates was required to distinguish sRNAs with coding potential. Using this
threshold value, we found that 12 sRNAs clustered with known coding genes (Fig. 2B), seven of
which were sRNAs with annotated smORFs. The high proportion of sRNAs with annotated
smORFs included in the coding cluster suggests that this method may distinguish coding genes
from known noncoding genes when high enough read counts are available. However, 12 sRNAs
with ribosome occupancy remained that had neither an annotated smORF nor a distribution
similar to coding genes.
287
Discovery of small proteins encoded by sRNA transcripts.
Using another approach, we performed liquid chromatography tandem mass spectrometry
analysis (LC-MS/MS) to validate predictions of coding sRNAs and determine whether small
proteins encoded by sRNAs could be detected. In this experiment we used three biological
replicates with and without oxidative stress treatment; the stress treatment was essential to
ensure expression of stress-responsive sRNAs. To deplete high molecular weight proteins, we
sequentially processed the cell lysates through two sizes of centrifugal filters, first a 100 kDa
filter and then a 30 kDa filter, (Fig. S5). Our label-free quantitation differential expression
analysis detected 2,095 proteins filtered to an FDR of 5% and at least two peptide spectrum
matches (PSMs), accounting for 53% of the total proteome of *H. volcanii*. The median protein
sequence coverage of 59% was similar to other high-quality MS datasets reported for *H.*
volcanii (74). Previous studies (77) have demonstrated that centrifugal filtering is an imperfect
means to enrich for small proteins, and indeed the sizes of the proteins we detected were
roughly representative of the total proteome (Fig. 3A). Moreover, we did not detect any protein
smaller than 25 amino acids, even though smORFs are predicted to encode proteins as short as
10 amino acids (Fig. 3B). Nevertheless, we detected a total of 235 smORFs (Fig. 3B) ranging
from 31-100 amino acids, accounting for 40% of annotated smORFs (Table S11). Seven of these
smORFs were encoded in putative sRNAs, including four with prior annotations (Fig. 2A; Table
S12), and five out of the seven sRNA-encoded detected proteins had their ribosome footprint

length distribution cluster with known coding genes (Fig. 2B). There still remained, however,
seven sRNAs with ribosome occupancy in the coding cluster for which we were unable to detect
evidence at the protein level.
310
To further investigate sRNAs with ribosome occupancy, we selected several of them for
western blot analysis. These included one sRNA with read counts below the minimum threshold
for clustering (sRNA_38), one sRNA not contained in the coding cluster (sRNA_83), 3 sRNAs
contained in the coding cluster that were not detected by MS (sRNA_20, sRNA_61, and SHOxi),
and two of the MS-detected smORFs (sRNA_KL, sRNA_93). The selected sRNAs were tagged
with a 3xFLAG tag after the putative start codon and cloned into *H. volcanii* on an
overexpression plasmid (Fig. 3C; Table S13). 150 bp upstream and 50 bp downstream of the
sRNAs were included to capture native promoters. sRNA_20 had multiple putative ORFs, so we
tagged two start codons (including one corresponding to a prior annotation). Both MS-detected
smORFs (sRNA_KL, sRNA_93) were detected by our western blot analysis, but we did not detect
any other tagged sRNAs (Fig. 3D). Despite having both expression level and ribosome occupancy
exceeding that of sRNA_KL and sRNA_93 (Table S13), no signal was detected for SHOxi and
sRNA_61, indicating they are most likely noncoding. From the analyses above, we detected
seven smORFs encoded by sRNAs using LC-MS/MS, including three novel smORFs not previously
annotated. However, some sRNAs, such as sRNA_61 and SHOxi, had no coding potential, were
not detected by MS or western blotting, but yet demonstrated high ribosome occupancy,
exceeding that of many coding regions.
328
Ribosome-associated sRNAs may play regulatory roles during oxidative stress.
We were particularly interested in 17 stress-responsive sRNAs that had differential ribosome
occupancy or TE in stress-treated samples (Fig. 4A). Five of these had an annotated smORFs and
12 had no evidence of coding potential. We repeated the ribosome footprint length clustering
analysis described above for Ribo-seq data from oxidative stress samples. We found that of the
12 sRNAs with no evidence of coding potential (unannotated), one did not meet the read count
threshold and was removed from the analysis, three clustered with coding genes, and nine did
not (Fig. 4B). We hypothesized that these nine stress-responsive sRNAs with high ribosome
occupancy may play a regulatory role during oxidative stress and sought to explore their
functional roles using a suite of *in silico* methods. We note that SHOxi has been previously
characterized (35) and sRNA_41 is annotated as encoding an smORF, thus neither were
included in this analysis.
341
We first determined whether these sRNAs were conserved by performing a blastn search. Five
had homology with one or more halophilic species, two of which had the majority of hits in a
region that overlapped with an upstream gene on the opposite strand. The remaining two had
no homology with any other species. We selected the three sRNAs (sRNA_58, sRNA_77, and
sRNA_83) with homology to at least one other species and that did not overlap with any genes
to further investigate their role in *H. volcanii* oxidative stress response. We performed a
multiple sequence alignment and predicted the consensus structures for sRNA_58, sRNA_77,
and sRNA_83 using LocARNA (78) and all hits from our previous blastn search as input. Each
sRNA showed a high potential for secondary structure and high conservation between species

(Fig. 5A; Fig. S6). We also predicted putative mRNA targets using IntaRNA (Fig. 5B; Tables S14-
16; 79) and determined which of those predicted targets had differential ribosome occupancy
or TE during oxidative stress. sRNA_58 had the fewest high confidence (p <0.01) predicted
targets, and only five out of 29 (17%) of those predicted targets had differential ribosome
occupancy or TE in response to oxidative stress. In contrast, sRNA_77 and sRNA_83 had many
targets predicted with high confidence and 14 out of 44 (32%) putative mRNA targets for
sRNA_83, and 19 out of 42 (45%) putative mRNA targets for sRNA_77 were differentially
translated in response to oxidative stress. Overall, eight sRNAs with differential ribosome
occupancy or TE during oxidative stress did not have coding potential, one of which was
previously characterized (35). Five were found to be conserved among halophilic species and
two had many putative mRNA targets that were differentially regulated at the translation level
during oxidative stress.
363
sRNA knockouts have similar phenotype to WT during oxidative stress.
To explore the functional role of ribosome-associated sRNAs during oxidative stress, we
generated sRNA knockouts. Three sRNAs with a range of ribosome occupancy were selected.
sRNA_24 represented the lowest range (TPM <10), with sRNA_83 and sRNA_20 representing
mid-range (50-100 TPM) and high ribosome occupancy (>200 TPM), respectively. Knockouts
were generated as previously described (80), followed by whole genome sequencing to verify
complete deletion of sRNAs. We did not observe any phenotypic differences from the WT
during oxidative stress for our sRNA knockouts, when using H_2O_2 as treatment (Fig. S7A, B).
372
In an attempt to identify experimentally putative targets for these sRNAs, we performed RNA-
seq with three biological replicates each of WT and the sRNA knockout strains exposed to
oxidative stress and WT without stress as a control, 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 genes were significantly upregulated or downregulated for
sRNA_83 and sRNA_20 knockout strains when compared to the WT strain under oxidative
stress (Fig. S7C, D). We found 7 genes significantly upregulated for the sRNA_24 knockout strain
when compared to the WT (Fig. S7E). qPCR further validated these results (Fig. S7F). We also
found that in the presence of sRNA_24 (WT strain) and oxidative stress treatment, 6 of the
genes described above had upregulated expression compared to untreated controls, and one
was downregulated for both ribosome occupancy and TE (Table S17). For all 7 significant
targets, the fold change increased substantially in the absence of sRNA_24, suggesting that this
sRNA may play a role in downregulating expression of these genes. Additionally, we observed
that the upregulated 9 genes with p-value < 0.05 in the sRNA_24 knockout strain were located
directly downstream of sRNA_24 in the genome of *H. volcanii* (Fig. S7G), and three of these
targets were members of an operon involved in glycerol metabolism in *H. volcanii* (Table S18,
81).
390

Discussion

In this work, we investigated the global translation landscape of the model archaeon *H. volcanii*
during oxidative stress. While previous studies in *H. volcanii* have revealed changes in protein
levels during oxidative stress using MS (47), this method does not distinguish between

transcriptional and translational regulation. It is also known that transcript data from RNA-seq
and protein data from MS have modest and highly variable correlation rates (82, 83), leading to
questions regarding the processes that govern translation regulation. Using RNA-seq and Ribo-
seq, we examined ribosome occupancy and TE to better understand regulation at the level of
translation.
400
Our analysis revealed that hundreds of genes had differential TE in *H. volcanii* during oxidative
stress. We observed global downregulation of translation and ribosomal proteins, suggesting a
major slowdown of *de novo* protein biogenesis during oxidative stress. While previous studies
in eukaryotes have found arrest of translation during stress (41, 84, 85), including sequestration
of translationally inactive complexes within stress granules (86, 87), archaeal studies diverge. In
H. volcanii, downregulation of ribosomal proteins has been shown at the level of transcription
(56), while MS data showed upregulation of translation proteins, including ribosomal proteins,
during oxidative stress (47). However, our interaction networks analysis using the STRING
database further supported the downregulation of translation and ribosomal genes, with many
ribosomal proteins included in the largest cluster, suggesting that in addition to transcriptional
regulation, numerous genes were also regulated at the translation level. Among genes with
upregulated translation during oxidative stress, we found many transporters, in accordance
with data previously acquired from MS (47). In contrast, at the transcriptional level,
transporters have been shown to be an enriched category in downregulated genes during
oxidative stress (56). The differences found in RNA-seq, Ribo-seq, and MS data imply that
multiple levels of regulation might be used to modulate protein expression during stress
response. Complex gene regulation has been characterized in both eukaryotes and bacteria,
including examples such as combined transcription and translation regulation of a cold shock
protein in mammals (88), quorum sensing signals in *Agrobacterium tumefaciens* (89, 90), and
attenuation of the tryptophan operon in *E. coli* (91, 92). Indeed, the interplay of transcriptional
and translational regulation to modulate protein expression might enable a fast response to
changing environmental conditions.
423
Remarkably, we found that many sRNAs previously determined to be noncoding (56) had high
ribosome occupancy, suggesting that association with ribosomes was not limited to active
translation. We found that among these sRNAs, some encoded annotated smORFs, some had
footprint distributions matching that of coding genes, and we detected seven small proteins
encoded by sRNAs using MS. It is important to note, however, that encoding small proteins
does not preclude these sRNAs from playing regulatory roles post-transcriptionally. In bacteria,
the presence of dual function sRNAs that encode proteins in addition to performing regulatory
functions has been well established (93-95). Archaea have also been proposed to utilize dual
function sRNAs, particularly under nitrogen starvation (96). This suggests that, as in other
organisms (93, 97), *H. volcanii* may utilize dual function sRNAs during oxidative stress response.
434
Many sRNAs had no evidence of coding potential, even when individually tagged and probed,
while smORFs detected by LC-MS were also detected by tagging and western blot. Several of
the sRNAs for which no proteins were detected had higher ribosome occupancy than sRNAs
with smORFs detected by MS and western blotting. While Ribo-seq is potentially the most

sensitive method for detecting smORFs (54, 96), there is enduring concern it may over-
represent the number of sRNAs being translated (98, 99), as we have observed here, making
MS proteomics an important filter to provide direct protein-level evidence. We additionally
utilized the distributions of ribosome footprint lengths to investigate coding potential of sRNAs
with ribosome occupancy. Using this analysis, we observed that the majority of coding genes
and sRNAs with annotated smORFs clustered together. We were further able to separate the
majority of known noncoding genes from known coding genes, thus suggesting that this
method can be used to provide an additional layer of information to increase confidence that
an sRNA has coding potential. However, this method requires a minimal read counts to
discriminate coding and noncoding genes. Similarly, it is possible that low abundance may limit
detection of small proteins by MS or western blotting. For lowly expressed sRNAs,
overexpression with an inducible promoter may be required for detection, as was found
previously (54). For sRNAs with higher expression, however, the lack of protein detection
despite high ribosome occupancy implies other mechanisms for the association of these sRNAs
with the ribosome.
454
Our data suggest that these sRNAs with no evidence of coding potential are closely associated
to ribosomes and may interact directly with ribosomes. While it is known that RNAs with
secondary structure are resistant to digestion, the inherently small size of these sRNAs would
preclude them from separating with monosomes in a sucrose gradient, thus suggesting that
they are specifically associated either with ribosomes or mRNAs bound to ribosomes. Prior
studies have reported the presence of sRNAs associated with ribosomes in *H. volcanii*,
particularly under stress conditions (100, 101). Sequencing and northern blotting of sRNAs that
co-purify with ribosomes identified a tRNA-derived fragment that bound the ribosome small
subunit, inhibiting peptide bond formation (100), and an intergenic sRNA that interacted with
the large subunit and targeted the translation of a specific mRNA (101).
465
The deletion of three ribosome-associated sRNA did not result in a growth phenotype during
oxidative stress and showed little to no change in the expression level of other genes. This
suggests that these sRNAs may not directly modulate transcript stability as some sRNAs in both
bacteria (32, 102, 103) and archaea (104, 105). In *H. volcanii*, for example, SHOxi destabilized its
mRNA target by complementary base pairing (35). Alternatively, the deletions of single sRNAs
may be insufficient to observe the effects of these sRNAs, as has been observed in bacteria
(106, 107). Knocking out multiple stress-responsive ribosome-associated sRNAs could further
elucidate their role during oxidative stress. Taken together, the data suggest that several
stress-associated sRNAs in *H. volcanii* are closely associated with ribosomes but are not directly
impacting mRNA stability.
476
Using RNA-seq and Ribo-seq in a model archaeon, we demonstrated global and targeted
regulation at the translation level during oxidative stress. We additionally revealed the
presence of several untranslated ribosome-associated sRNAs in *H. volcanii* that likely play a role
in translational regulation during oxidative stress. While the mechanisms of action of these
sRNA remain to be fully explored, this study highlights the use of multiple levels of gene

regulation to modulate protein expression in response to stress and provides the groundwork
to understand the complexities of oxidative stress response at the translation level.
484

Materials and Methods

Cell culturing and oxidative stress treatment

Haloferax volcanii DS2 strain H98 (80) was grown in liquid Hv-YPC (80) 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 (56).

Ribosome profiling

Ribo-seq was performed as previously described (53, 108). 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. S8A). RNA from monosome
fractions was isolated with Trizol LS reagent, followed by size selection (Fig. S8B), and
generation of libraries for high-throughput sequencing (Fig. S8C, 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 (56) 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 S19. Adapters were trimmed using Trim Galore (109,
https://github.com/FelixKrueger/TrimGalore) and reads were aligned to rRNA genes using
Bowtie (110). 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 (50). Samtools (111) 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
(112), with a provided reference annotation file (gff from NCBI Refseq assembly

525 GCF_000025685.1 downloaded March 2023 with added entries for sRNAs). Read counts were
526 calculated using featureCounts (113). See Tables S20, S21, and S22 for statistical summaries of
527 all analyses.
528
529 **Differential expression and TE analysis**
530 Differential expression was determined using DESeq2 (114). For RNA-seq and Ribo-seq data, the
531 variable of interest was experimental condition. For TE, the ratio between Ribo-seq and RNA-
532 seq was used, in addition to two variables of interest: sample (RNA-seq or Ribo-seq) and
533 experimental condition. For full details, see Table S19.
534
Characterization of significant genes
The number of leaderless genes was determined using published data that characterized 1851
annotated genes as leadered or leaderless (59). 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; 62) was used to determine KEGG enrichments with default settings
and MCL clustering. 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 (61, 115) for the *H. volcanii* DS2 protein fasta file downloaded from NCBI.
Overrepresentation tests were conducted using Fisher's test and FDR correction.
546
smORF prediction
For ORF prediction using the web version of Open Reading Frame Finder (ORFfinder, NCBI; 76),
a minimal length of 30nt and alternative initiation codons were allowed. For ORF prediction
using Ribo-seq data, an adapted version of REPARATION (75), 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.
557
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.
564
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 xg 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 xg for 2 hours at room
temperature, then centrifugation in 30K MWCO filters (Pall) at 5000 xg 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 xg 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 (116).
584
585 **Mass spectrometry acquisition**
586 Chromatographic separation of protein digests was carried out as previously described (117),
587 injecting 1 µg of protein per sample.
588
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 S23 for statistical
summaries.
604
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 (118), using the lab strain
H98.

Western blots

614
25 mL of culture were pelleted by centrifugation at 10,000 xg 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 (119). 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 (119). 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 (120), IntaRNA (79, 121), and LocARNA (78) were used with
default settings.

Generating knockouts
Knockout strains were generated using the established protocol for *H. volcanii* (80). 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* (118), 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

S24). Fold change was determined by the Livak method (122).

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 (123) partner repository

with the dataset identifier PXD062323 and 10.6019/PXD062323. Data analysis scripts are

available on GitHub: https://github.com/diruggiero-lab/sRNAs.

Reviewers' access to the manuscript data in public databases:

GEO accession GSE293312 (RNA-seq):

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%7C638794044694533383%7CUnknown%7CTWFpbGZsb3d8eyJFbXB0eU1hcGkiOnRydWUsIlYiO

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Password: 0vtHi3HDave2

Project accession: PXD062323

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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 TE (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. Scatterplot comparing $\log_2$ fold change for transcript abundances and ribosome occupancies. Genes with significant p-value (<0.05) in RNA-seq or Ribo-seq data are shown in gray, while those with a significant p-value in both are shown in purple. Genes with differential TE are shown in red. All

other genes (non-significant) are shown in black. Dark gray boxes encompass genes that are
predicted to change at the translation level only. E. 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 was calculated
for genes in each category using the total number of PANTHER hits (2061 for the full proteome,
99 for TE down, and 42 for TE up). Asterisks indicate significant categories (translation) or
categories that contain significantly enriched subcategories (ribosomal proteins; peroxidases).
F. STRING network depicting predicted interactions for genes with downregulated TE during
oxidative stress. Nodes depict individual genes, with predicted interaction as edges. Edge
thickness indicates increasing interaction confidence, where thinner edges have a confidence
score of at least 0.7 and thicker edges have a confidence score of at least 0.9. Dotted lines
indicate edges between clusters. Genes with no predicted interactions are not shown. Node
color indicates functional clusters.

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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.

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Figure 3. Discovery of novel small proteins encoded in sRNAs. A. Histogram of protein length
(aa) for the *H. volcanii* annotated proteome (gray) and proteins detected by MS (green). B.
Histogram of protein length (aa) for putative peptides (predicted using NCBI ORF finder)
encoded by sRNAs (gray) and small proteins detected by MS (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.

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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. Colors correspond to number of base pair types (red: 1, yellow: 2, green: 3) 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 S13-15). Blue lines indicate putative binding regions along the sRNA. Curves depict coverage of putative binding regions along the sRNA.