

Figure S1. Association between mRNA and protein abundance.

(A) The plot shows a very strong correlation (Pearson correlation coefficient *r* = 0.7252) between the experimentally measured mRNA and protein abundances, where each point is a gene. Despite the evident association between mRNA and protein abundance, there are a few genes that diverge significantly from the fitted linear regression (highlighted in red). **(B)** Histogram of the standardized residuals for the linear regression between protein and mRNA abundances. The red dashed line indicates the 3σ sigma deviation from the expected mean of the normal distribution of residuals centered at zero (blue line). There were 13 genes with residuals variance greater than 3σ, which are the ones highlighted in red in panel (A). All of them show very high levels of mRNA when compared to the corresponding protein abundances. Among these genes, we found that many of these genes are post-transcriptionally regulated by complex mechanisms. In particular, we found genes that are *cis*-regulated by the formation of long-range mRNA secondary structures (*gnd*) or translation attenuators (*cspG* and *ugpB*) that inhibit translation initiation, as well as other genes (*dppA*, *ompC* and *gltI*) that are *trans*-regulated by small RNAs. Additionally, we found genes that, despite not having any post-transcriptionally regulation described, show a complex transcriptional regulatory architecture composed by many promoters, transcription start sites and transcription factor binding sites (*osmC*, *pykF*, *atpC*, *rbsB* and *rob*), as well as two other genes that were not well studied (*ybgF* and *yiaF*). These observations point out that some of these genes may have very complicated regulatory mechanisms that our model does not intend to cover and hence were removed from the final analyzed dataset.

Figure S2. Sequence features of the 16S:SD hybridization complex.

The figure depicts a detailed schematic of the sequence features considered for the 16S:SD hybridization complex. The feature referenced as "Exterior loop" shows a significant positive correlation with protein abundance when controlled for mRNA levels ($r = 0.1240$, P-value = 0.001). This means that the weaker the binding at the end of the 16S:SD complex, the higher the translation efficiency will be. We hypothesize that this weak binding may facilitate the consequent disruption of the initiation complex to start the elongation step. The double helix RNA structures were predicted using the UNAFold Software and in-house Perl scripts were developed to extract the multiple features from the predicted structure.

Figure S3. Partial least squares (PLS) regression model shows better accuracy than more complex models.

We compared the accuracy of the PLS model with that of the regular multiple regression (MR), as well as more complex models such as: neural networks (NN), support vector machines (SVM), and random forest (RF). By using the latter models, we expect to encapsulate a more complex behavior of our predictor variables, such as non-linearity and interaction between factors. These models were fitted using the data-mining package *rminer* developed for R. NN and SVM parameters were tuned to yield the best performing model, namely the number of neurons in the hidden layer and the Gaussian kernel parameter, respectively. The RF model was run using default parameters. We show that the PLS model employed in this study has higher accuracy than all the other models. This means that the assumed linear relationship between the predictors and the response variable protein abundance is acceptable and that considering non-linear behavior and interaction between these factors does not yield better results.

The figure depicts the correlation between each of the 108 features considered and protein abundance **(A)**, or protein abundance given the mRNA levels **(B)**. This analysis demonstrates that most of the factors are moderately correlated with absolute protein abundance and slightly less associated with protein levels given mRNA abundances.

Figure S5. Determinants of protein abundance and composite model search.

(A) More than 100 sequence features were integrated with mRNA levels to predict experimentally measured protein abundances. To select the best composite model, we employed a stepwise regression with backward selection to find the variables with the highest explanatory power (Materials and Methods). **(B)** The plot depicts the PLS model performance — both using the entire training set (gray) and the 10-fold CV procedure (black) as the number of components increases. A model composed by only 3 principal components (red asterisk), where each component is composed by 10 to 13 features, is enough to capture the maximum covariance between the 16 predictors and the response variable (protein abundance).

Figure S6. Expression profile by gene function.

(A) Boxplots depict predicted protein concentration by gene function (only functional classes with more than 20 genes were considered). Gene functions showing lower or higher median expression than all proteins are colored in blue and red, respectively. Grey dashed lines indicate the 95% confidence interval around the median abundance of all proteins. **(B)** There is a strong association between the median transcriptional and translational contribution for each functional category (*rho* = 0.81, P-value ≤ 0.001, *n* = 15). Solid lines represent median transcriptional and translational contributions across all proteins and gray shadow indicates the 95% confidence interval of these medians.

Functional groups: T—signal transduction mechanisms; H—coenzyme transport and metabolism; L—replication, recombination and repair; R—general function prediction only; P—inorganic ion transport and metabolism; M cell wall/membrane/envelope biogenesis; S—function unknown; I—lipid metabolism; K—transcription; E—amino acid transport and metabolism; C—energy production and conservation; G—carbohydrate transport and metabolism; O—posttranslational modifications, protein turnover and chaperones; F—nucleotide transport and metabolism; J—translation, ribosomal structure and biogenesis.

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Figure S7. Dependence between noise and mean abundance level, and calculation of noise differential metric.

(A) Noise (as measured by the coefficient of variation) initially decreases quickly with protein abundance and plateaus at higher levels. The median noise across the multiple genes was calculated using a sliding window of 30 data points and is shown in orange. Proteins with very low abundance (less than ~1 molecule per cell) were removed from the analysis due to their extreme noise profile. **(B)** The noise differential is the distance between the noise level of a given gene and the expected median noise level for genes with similar proteins abundance. The boxplot depicts the noise differential for all the genes in our dataset.

Table S1. Factors considered and their correlation with protein abundance.

Pearson correlation coefficients between the factors considered and protein abundance (PA) or PA given mRNA levels. F-test p-values were adjusted using false discovery rate (FDR) method to correct for multiple testing.

