Detecting selection using a single genome sequence of *M. tuberculosis* and *P. falciparum*

Joshua B. Plotkin¹, Jonathan Dushoff^{2,3} & Hunter B. Fraser⁴

- ¹Harvard Society of Fellows and Bauer Center for Genomics Research,
- 7 Divinity Avenue, Cambridge, Massachusetts 02138, USA
- ²Department of Ecology And Evolutionary Biology, Princeton University, Princeton, New Jersey 08540, USA
- ³Fogarty International Center, National Institutes of Health, Bethesda, Maryland 20892, USA
- ⁴Department of Molecular and Cell Biology, University of California, Berkeley, California 94720, USA

Selective pressures on proteins are usually measured by comparing nucleotide sequences¹. Here we introduce a method to detect selection on the basis of a single genome sequence. We catalogue the relative strength of selection on each gene in the entire genomes of Mycobacterium tuberculosis and Plasmodium falciparum. Our analysis confirms that most antigens are under strong selection for amino-acid substitutions, particularly the PE/PPE family² of putative surface proteins in M. tuberculosis and the EMP1 family³ of cytoadhering surface proteins in P. falciparum. We also identify many uncharacterized proteins that are under strong selection in each pathogen. We provide a genome-wide analysis of natural selection acting on different stages of an organism's life cycle: genes expressed in the ring stage⁴ of P. falciparum are under stronger positive selection than those expressed in other stages of the parasite's life cycle. Our method of estimating selective pressures requires far fewer data than comparative sequence analysis, and it measures selection across an entire genome; the method can readily be applied to a large range of sequenced organisms.

Historically, the study of natural selection has been pursued under a comparative paradigm⁵. Genes under selection are identified by comparing homologous nucleotide sequences sampled either from different individuals within a species (for example, nucleotide polymorphism studies) or from different species (for example, phylogenetic analysis). The widely used non-synonymous to synonymous substitution ratio (d*N*/d*S*) falls within this model⁶, as do all other existing methods for detecting natural selection on coding sequences^{7–9}. Within the comparative paradigm, it would be impossible to measure selective pressures on the basis of a genome sequence from a single individual.

Here we present a method for rapidly detecting differential selective pressures on genes by inspecting a single genome sequence for a footprint of non-synonymous substitutions. Our method rests on a simple observation: if a protein coding region of a nucleotide sequence has undergone an excess number of amino-acid substitutions, then the region will on average contain an overabundance of 'volatile' codons, compared with the genome as a whole. For each of the 61 sense codons, we define its volatility as the proportion of its point-mutation neighbours that encode different amino acids (see Fig. 1). The volatility of a codon will be used to quantify the chance that the most recent nucleotide mutation to that codon caused an amino-acid substitution.

Using the concept of codon volatility, we can scan an entire genome to find genes that show significantly more, or less, pressure for amino-acid substitutions than the genome as a whole. If a gene contains many residues under pressure for amino-acid replacements, then the resulting codons in that gene will on average exhibit elevated volatility, because its ancestor codons encoded different amino acids from those encoded by the current codons. Similarly, if

a gene is under strong purifying selection not to change its amino acids, then the resulting sequence will on average exhibit lower volatility¹⁰.

We assess the statistical significance of each gene's observed volatility by comparing it with a bootstrap distribution of alternative synonymous sequences, drawn according to the background codon usage in the genome (see Methods). This randomization procedure controls for the gene's length and amino-acid composition. As a result of this procedure we obtain a two-sided 'volatility *P* value' for each gene, indicating whether the gene is more, or less, volatile than the genome as a whole. A *P* value near zero indicates significantly elevated volatility, whereas a *P* value near one indicates significantly depressed volatility.

Our method of estimating selective pressures by using volatility does not assume a constant mutation rate across sites. If a particular gene experiences a higher nucleotide mutation rate, the gene's volatility will not be biased. Volatility simply measures the chance that the most recent accepted nucleotide mutation in the series of mutations that gave rise to the observed current codon caused a change in the amino acid that is currently encoded. The timing of the most recent accepted mutation can vary from site to site; nevertheless, regardless of its timing, the probability that a site's most recent substitution caused a non-synonymous change is greater (smaller) for a site under positive (negative) selection.

Using the method of codon volatility, we have estimated selective pressures across the complete genomes of M. tuberculosis strain CDC1551 (4,099 unambiguous coding sequences) and of P. falciparum strain Pf3D7 (5,440 unambiguous coding sequences). Table 1 summarizes the volatility P values for the most volatile genes in each genome. The P values for all genes are reported in the Supplementary tables. Each pathogen exhibits a substantial proportion of genes that show signs of much stronger pressure for amino-acid substitutions than the genome as a whole (Fig. 2). We also find a substantial proportion of genes that show much stronger purifying selection than the genome as a whole (Fig. 2). For both pathogens, the genes with extreme volatility are distributed throughout the genome.

The PE and PPE gene families of *M. tuberculosis*, which are putatively expressed on the extracellular surface and exhibit extensive non-synonymous variability², have been identified as potential antigens for the host immune response^{11–13}. The PE family (81 genes) and the PPE family (57 genes) both exhibit significantly greater volatility than the other genes in the *M. tuberculosis* genome $(P_{\rm w}=6\times10^{-8}\ {\rm for\ PE}\ {\rm and\ }P_{\rm w}=3\times10^{-22}\ {\rm for\ PPE};$ Wilcoxon

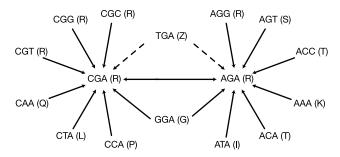


Figure 1 Two examples of calculating codon volatility. The volatility of each codon depends only on the structure the genetic code. The codon CGA, encoding arginine, has eight potential ancestor codons; that is, non-stop codons that differ from CGA by one point mutation. Four of the potential ancestor codons of CGA encode an amino acid different from arginine. Thus the volatility of CGA equals 4/8. The codon AGA also encodes arginine but has a volatility of 6/8. There are 22 codons that have at least one synonym with a different volatility. We use volatility to quantify the chance that the most recent accepted mutation to a site caused an amino-acid change. Letters in parentheses are one-letter amino-acid codes.

test). In fact, the PE and PPE genes are ten times more frequent among the 100 most volatile M. tuberculosis genes than they are in the genome as a whole. The elevated volatility of these genes indicates increased pressure for amino-acid substitutions, presumably because of diversifying selection mediated by interactions with the host immune system^{12,13}. These results, based on a single genome sequence, agree with an extensive study in which the authors compared the genomes of two fully sequenced M. tuberculosis strains². In that study, the authors found the PE/PPE gene families to have the highest non-synonymous to synonymous substitution ratio (dN/dS) among all families with a significantly elevated substitution rate².

A recent, genome-wide mutagenesis study of M. tuberculosis identified 614 genes essential for optimal growth of the bacterium¹⁴. These genes are highly conserved among related organisms and are presumably under stronger purifying selection than the remaining non-essential genes¹⁴. The 614 essential genes are significantly less volatile than the non-essential genes $(P_{\rm w}=4\times10^{-6})$, confirming that the volatility method correctly detects purifying selection. Those genes of M. tuberculosis that are both essential and exhibit low volatility are excellent candidates for drug targets, because their disruption is lethal and their sequences are more stable than those of other genes.

Although the genetic, cellular, life-history and population structures of the eukaryote P. falciparum are more complicated than those of the bacterium M. tuberculosis, an analysis by codon volatility produces a similarly detailed and biologically reasonable picture of differential selection across the *P. falciparum* genome. The 49 P. falciparum genes denoted as antigens—including asparaginerich antigens, liver-stage antigens, octapeptide-repeat antigens and erythrocyte membrane-associated antigens—exhibit significantly elevated volatility compared with the other genes in the genome $(P_{\rm w} = 0.00013)$. In particular, the liver-stage antigens exhibit extremely significant elevated volatility (Table 1), in agreement with a comparative study that implicated liver-stage antigen for strong selection on the basis of its dN/dS ratio and a McDonald–Kreitman test¹⁵. These results confirm the ability of our method to detect those genes whose biology and sequence variation indicate strong diversifying selection.

The P. falciparum gene families named rifin, stevor and var are all

Table 1 Ten genes in the *P. falciparum* and *M. tuberculosis* genomes that show the strongest signs of positive selection

Locus	Description	P value
P. falciparum		
PF10_0314	Asparagine-rich antigen	$< 10^{-6}$
PF11_0111	Asparagine-rich antigen	<10 ⁻⁶
PF10_0356	Liver-stage antigen	$< 10^{-6}$
PFB0915w	Liver-stage antigen 3	<10 ⁻⁶
PFD1175w	Trophozoite antigen	$< 10^{-6}$
MAL6P1.191	Protein kinase	$< 10^{-6}$
MAL6P1.131	SET-domain protein	<10 ⁻⁶
PFI1280c	Protein kinase	$< 10^{-6}$
PFL0465ci	Zinc-finger transcription factor	<10 ⁻⁶
PF11_0213	Hypothetical protein	<10 ⁻⁶
M. tuberculosis		
MT0318	PPE family protein	$< 10^{-6}$
MT3106	PPE family protein	<10 ⁻⁶
MT0607	PE PGRS family protein	<10 ⁻⁶
MT2561	PE_PGRS family protein	$< 10^{-6}$
MT3612.1	PE_PGRS family protein	<10 ⁻⁶
MT3615.3	PE_PGRS family protein	$<10^{-6}$
MT0291.4	Hypothetical protein	$<10^{-6}$
MT3449	PE_PGRS family protein	10^{-6}
MT1689	PE_PGRS family protein	2×10^{-6}
MT3101	PPE family protein	7×10^{-6}

The P value for each gene indicates whether it exhibits significantly greater volatility than the genome as a whole. Complete lists of volatility P values for all genes are given in Supplementary tables

thought to alter the parasite's antigenic surface proteins ¹⁶. Although the roles of rifin and stevor are not understood, var-encoded proteins mediate adherence to host endothelial receptors, resulting in the sequestration of infected red cells ¹⁷. Expression of var and cytoadherence are associated with disease severity and induction of protective antibodies ³. The rifin or stevor families are not significantly over-represented among genes with high volatility. But the 71 var-encoded erythrocytic membrane proteins (EMP1) are significantly more volatile than other genes ($P_{\rm w}=6\times10^{-10}$). The elevated volatility of EMP1 genes reflects positive selection that is presumably driven by the known interactions between these proteins, which are expressed on the surface of infected red blood cells ¹⁸, and the immune system of the host.

Despite the fact that EMP1 genes as a whole exhibit significantly elevated volatility, they constitute a heterogeneous family. A recent study has classified the EMP1 genes into biologically significant groupings: three major groups (called A, B and C) and two separate smaller groups (called A/B and B/C)¹⁹. None of the 30 most volatile EMP1 genes belong to the A or A/B groups. This segregation of genes is statistically significant ($P < 5 \times 10^{-6}$). We therefore propose that the A and A/B groups may experience less interaction with the human immune system than other EMP1 genes. Consistent with this hypothesis is the observation that recombinant CIDR domains from genes in group A do not bind to CD36, the major endothelial receptor for infected erythrocytes, whereas CIDR domains from groups B and C do bind CD36 (ref. 20).

Our estimates of the selective pressures across the *P. falciparum* genome will be useful for understanding host–pathogen interactions and for developing appropriately targeted vaccines²¹. The

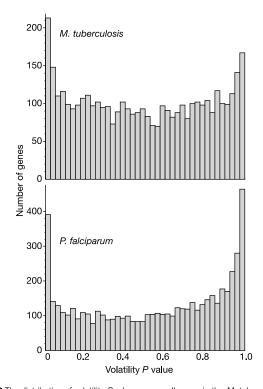


Figure 2 The distribution of volatility P values across all genes in the M. tuberculosis and P. falciparum genomes. In the absence of differential evolutionary pressures between genes—and, in particular under completely neutral evolution—the distribution of P values would be uniform. Instead, each genome shows a characteristic U-shaped distribution, with a significant (Kolmogorov–Smirnov, $P < 10^{-6}$) excess number of genes with low or high P values. The non-random tails of these distributions indicate a large number of genes under greater pressure for amino-acid substitutions than the genome as a whole, and a large number of genes under greater pressure against amino-acid substitutions.

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largest proportion of the highly volatile P. falciparum genes, however, are of unknown function (see Supplementary tables). This indicates the importance of further, targeted research on the biology of P. falciparum, particularly on genes under positive selection. We note that the P. falciparum genome also contains many genes, including some surface proteins, that exhibit strong signs (volatility P > 0.999) of purifying selection; some of these proteins might be attractive candidates for drug targets.

The identification of selective pressures across an entire genome also allows us to study the interplay between evolution and an organism's natural history, ecology or molecular processes. In Fig. 3 we compare volatility with gene expression data across the stages of *P. falciparum*'s 48-hour intraerythrocytic development cycle⁴, and find a highly significant correlation between stage-specific gene expression and volatility: genes expressed in the ring stage show signs of positive selection relative to the rest of the genome, whereas genes expressed in the trophozoite and schizont stages show relatively more purifying selection (Fig. 3). These results shed light on the strength of immune pressure across the parasite's life cycle.

When sufficient data are available, comparative sequence analysis is also a powerful method for estimating selective pressures. The most widely used measure, dN/dS, quantifies the ratio of non-synonymous to synonymous substitution rates^{6,22,23}. Such techniques are usually applied to a small number of genes with orthologues in a large number of related species; power to detect selection is reduced when analysing fewer than six orthologous sequences²⁴. At the genome-wide scale, comparative techniques are limited by the inability to find orthologues for all, or even most, genes in the genome being studied. (Fewer than half of the *P. falciparum* genes have identifiable orthologues for its closest fully sequenced relative, *P. yoelii yoelii*.)

We have seen that dN/dS and volatility detect elevated positive

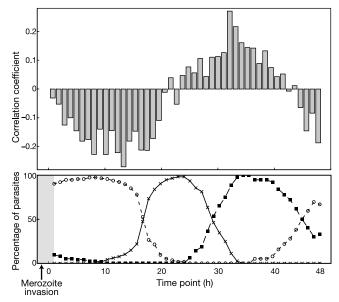


Figure 3 The relationship between volatility and gene expression across the intraerythrocytic development cycle of P. falciparum. The lower panel shows the percentage of ring-stage (circles), trophozoite-stage (crosses) and schizont-stage (squares) parasites at each time point for which relative mRNA expression levels of 4,488 ORFs were measured⁴. The upper graph shows the Spearman correlation coefficient between gene expression level, Cy5/Cy3, and volatility P value among the genes of high (P < 0.001) and low (P > 0.999) volatility. Genes expressed during the ring stage are significantly correlated with high volatility, whereas trophozoite- and schizont-expressed genes generally exhibit low volatility. Of the 46 time points, 21 have significantly positive or negative correlations (P < 0.05 each).

selection in the same gene families of M. $tuberculosis^2$. For the purpose of a gene-by-gene comparison, we have analysed the genomes of three organisms related to M. tuberculosis strain CDC1551: M tuberculosis strain H37Rv, M. bovis and M. leprae. The set of M. tuberculosis genes with identifiable orthologues is significantly biased towards lower volatility ($P_{\rm w}=10^{-6}$). Among the identifiable orthologues in pairwise genome comparisons, we find highly significant correlations between volatility P values and dN ($P=5\times10^{-9}$; see Supplementary Methods). Therefore, even though analysis by codon volatility requires far fewer data than comparative techniques, it can produce a more complete, genomewide account of selective pressures that is consistent with comparative techniques. Moreover, our method does not rely on some of the strongest assumptions inherent in comparative analyses (see Supplementary Methods).

Our method is not free of assumptions, however. In its simplest form, analysis by differential codon volatility rests on two underlying assumptions: (1) nucleotide mutations are unbiased and (2) the *a priori* probability of a codon's occurrence does not vary across the genome. The first assumption can easily be relaxed. When differential nucleotide mutation rates have been measured, such as a transition/transversion bias, these rates can be incorporated into the definition of codon volatility (see Methods).

The second assumption of our method holds approximately for most organisms, provided that the genome does not contain large variation in GC content. Although *M. tuberculosis* has different G and C contents on the leading and lagging replication strands²⁵, our results remain unchanged if we analyse the genes on these two strands separately. The marked GC variation caused by isochores in mouse and human²⁶ can be addressed by a separate analysis of volatility for those genes in each distinct region of GC content. Any other source of selection on synonymous codons that varies from gene to gene and that correlates with volatility will introduce some error into our estimates of relative selective pressures.

Genomic analysis by codon volatility has several important limitations. The foremost is that volatility P values are intrinsically relative. We cannot conclude that any gene is under positive selection in an absolute sense; rather, we can only conclude that some genes are under more positive, or less negative, selection than others. Moreover, codon volatility only detects selection on point mutations. Our method does not produce estimates of effective population sizes, divergence times, substitution rates or other evolutionary parameters that can be fitted through comparative analysis.

Finally, it is important to note that our method measures selective pressures in a fundamentally different way from comparative sequence analysis. Whereas comparative techniques consider sequence changes that have occurred since the divergence of the species being studied, volatility is based on the most recent substitution at each codon position in a single sequence. As a result, our method is preferentially sensitive to recent selective pressure, and it might even reflect selection on different timescales for different genes within the same genome; these timescales might be shorter or longer than those of comparative methods, depending on the species being compared and the orthologues that can be identified. Thus, the method of differential codon volatility complements comparative techniques. For a large range of fully sequenced organisms, a combination of volatility and comparative techniques will help to explain patterns of genome-wide evolution over a broad range of timescales.

Methods

Computing volatility P values

We define the volatility of codon c by the equation

$$\nu(c) = \frac{1}{\text{no. of neighbours}} \sum_{\text{neighbours } c_i} D[\text{acid}(c), \text{ acid}(c_i)]$$
 (1)

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where we sum over those non-stop codons c_i that can mutate into c by a single point mutation. We use the simplest possible measure D: the Hamming metric, which equals zero if two amino acids are identical, and one otherwise. Equation (1) is similar to a measure recently used to analyse influenza virus genes²⁷. Here, however, we disallow stop codons as potential ancestor codons.

Given a gene G, we define $\nu(G)$ as the summed volatility of the codons in the coding region of the gene G. To calculate the volatility P value of G, we compare the observed volatility $\nu(G)$ with a bootstrap distribution of 10^6 synonymous versions of the gene G. In each randomization trial, we construct a nucleotide sequence G' that has the same translation as G but whose codons are drawn randomly according to the relative frequencies of synonymous codons in the genome as a whole. The P value for gene G is given by the proportion of the randomization trials in which $\nu(G')$ exceeds or equals $\nu(G)$. Because there were no ties in our randomization trials, 1-P is a P value that tests whether a gene is significantly less volatile than the genome as a whole. Software and a web implementation to perform this calculation are freely available (http://www.cgr.harvard.edu/volatility).

Our method of computing P values controls for both the length and amino-acid composition of each gene. If a gene contains many amino acids that can be encoded only by highly volatile codons (such as methionine), this feature will not bias the P value. The randomization procedure also controls for the nucleotide composition of the genome as well as any other source of genome-wide codon bias.

Equation (1) defines codon volatility under the assumption of equal mutation rates from each of the potential ancestor codons. When differential nucleotide mutation rates are known (for example, a transition/transversion bias), these rates can be incorporated into the definition of volatility by weighting the ancestor codons appropriately:

$$\nu(c) = \sum_{\text{neighbours } c_i} \frac{r_i}{\sum r_j} D[\text{acid}(c), \text{ acid}(c_i)]$$
 (2)

where r_i is the rate of mutation from codon c_i to codon c. Under a standard transition/ transversion bias model, for example, r_i will equal either κ or 1 depending upon whether codons c_i and c differ by a transition or a transversion ²⁸. More detailed nucleotide mutation biases, including time-irreversible rates such as those measured for $Drosophila^{29}$, can likewise be incorporated. The genomes of some mammals also exhibit strong dinucleotide mutational biases, particularly on CpG³⁰. Such biases can also be incorporated into the definition of volatility by considering the flanking nucleotides of each codon when calculating the rates r_i .

In the present study, we did not assume a transition/transversion bias because the strength of this bias is unknown for *M. tuberculosis*. Nevertheless, assuming that transitional mutations are twice as likely as transversional mutations does not significantly alter our results. (The volatility *P* values under $\kappa=1$ versus $\kappa=2$ are highly correlated; r=0.94.) For *P. falciparum*, evidence suggests there is little or no bias towards transitions¹⁵.

Statistical methods

We have used the Wilcoxon test to compare the volatility P values within a group of genes (for example, the PPE genes) against the P values for the rest of genes in a genome. We denote the two-tailed significance of the Wilcoxon test by P_w . The PE, PPE and essential M. tuberculosis genes i4 have median volatility P values of 0.06, 0.15 and 0.59, respectively. The EMP1 genes of P. falciparum have a median volatility P value of 0.17.

See also Supplementary Methods.

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Correspondence and requests for materials should be addressed to J.B.P. (jplotkin@fas.harvard.edu).

Regulation of ethylene gas biosynthesis by the *Arabidopsis* ETO1 protein

Kevin L.-C. Wang 1,2* , Hitoshi Yoshida $^{2\star}\dagger$, Claire Lurin $^{2\star}\dagger$ & Joseph R. Ecker 1,2

¹Plant Biology Laboratory, The Salk Institute for Biological Studies, La Jolla, California 92037, USA

²Plant Science Institute, Department of Biology, University of Pennsylvania, Philadelphia, Pennsylvania 19104-6018, USA

* These authors contributed equally to this work

† Present addresses: Department of Rice Research, National Agricultural Research Center, Jo-etsu, Niigata 943-0193, Japan (H.Y.); INRA-URGV, 2 rue Gaston Cremieux, CP 5708, 91057 Evry cedex, France (C.L.)

Ethylene gas is used as a hormone by plants, in which it acts as a critical growth regulator. Its synthesis is also rapidly evoked in response to a variety of biotic and abiotic stresses^{1,2}. The *Arabidopsis* ethylene-overproducer mutants *eto2* and *eto3* have previously been identified as having mutations in two genes, *ACS5* and *ACS9*, respectively; these encode isozymes of 1-aminocyclopropane-1-carboxylic acid synthase (ACS), which catalyse the rate-limiting step in ethylene biosynthesis^{3,4}. Here we report that another ethylene-overproducer mutation, *eto1*, is in a gene that negatively regulates ACS activity and ethylene production. The ETO1 protein directly interacts with and inhibits the enzyme activity of full-length ACS5 but not of a truncated form of the enzyme, resulting in a marked accumulation of ACS5 protein and ethylene. Overexpression of ETO1 inhibited induction of ethyl-

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Supplementary Methods

Volatility versus comparative sequence analysis

For comparison with volatility, we have analyzed the complete genomes of three organisms related to M. tuberculosis strain CDC1551: M. tuberculosis strain H37Rv, M. bovis, and M. leprae. We have compared volatility p-values in M. tuberculosis against dN. For large-scale pairwise analysis, dN is often a more stable indicator of recent amino acid changes than dN/dS, because dS can be strongly influenced by selection on synonymous sites due to codon bias^{1, 2}. We identified putative orthologs using the method of reciprocal smallest distances, which is more reliable than reciprocal best BLAST hits³. Of the 4099 CDC1551 genes, 3502 orthologs were identified in H37Rv, 3479 orthologs in M. bovis, and 1354 orthologs in M. leprae.

The difficulty in finding orthologs is a systematic limitation of all comparative methods. Moreover, often the genes of greatest interest – *i.e.* those under selection for amino acid change – will diverge more quickly, further reducing the chance of identifying orthologs. Indeed, we note that the set of M. tuberculosis genes with identifiable orthologs in M. leprae is significantly less volatile than the genes without orthologs ($p_w = 10^{-6}$). For example, only six of the 57 PPE genes in M. tuberculosis have identifiable orthologs in M. leprae. (P. falciparum and its closest fully sequenced relative, P. yoelii yoelii, have only 2432 identifiable orthologs, none of which includes var, rifin, or stevor.)

We aligned the protein sequences of putative orthologs using the package ClustalW⁴. After alignment, we estimated dN using the maximum likelihood package PAML⁵. Maximum likelihood estimation assumes that substitutions follow a time-homogeneous Markov process, and that substitution rates vary across sites according to a fixed distribution⁵. We note that the method of differential codon volatility makes neither of these assumptions.

We have already seen that dN values and volatility p-values detect positive selection in the same gene families of M. $tuberculosis^6$. On a gene-by-gene basis, we find a highly significant, but weak, correlation between volatility and dN (CDC1551 volatility p-values versus dN to H37Rv,

Spearman r = -0.16, $p = 5 \cdot 10^{-9}$; versus dN to M. bovis, r = -0.14, $p = 2 \cdot 10^{-6}$; versus dN to M. leprae, r = -0.12, $p = 2 \cdot 10^{-5}$) for those genes that show at least one amino acid difference between species. These correlations demonstrate that differential codon volatility is consistent with comparative methods. It may not be reasonable to expect stronger correlations, considering the multitude of assumptions made in each stage of the genome-wide comparisons, and the lack of accuracy when comparing only two sequences. When extensive comparitive data are available, there is a stronger correlation between volatility and dN or dN/dS: the volatility p-values for 3031 S. cerevisiae genes with identified orthologs in S. bayanus, S. paradoxus, and S. mikatae exhibit a Spearman correlation of r = -0.38 ($p = 10^{-124}$) compared against dN/dS estimated using all four yeast species (J.B.P. & H.B.F., manuscript in preparation).

Calculation of volatility p-values

We define the volatility of a gene G as the summed volatility of its codons. In order to compute the volatility p-value for gene G, we employ a statistical test that evaluates whether or not $\nu(G)$ is significantly elevated or depressed compared to the rest of the genome, controlling for the length and amino acid composition of G. In the main text, we describe a randomization procedure to compute the volatility p-value of each gene. We supplement that procedure here by describing a more direct calculation of the volatility p-value, based upon a normal approximation, which agrees with the randomization procedure used in the main text.

We index the 61 sense (i.e. non-stop) codons in an arbitrary order i = 1...61. We use the notation aa(i) to denote the amino acid encoded by codon i. Let N_i denote the number of occurrences of codon i in the entire genome. Let M_a and m_a denote the number of occurrences of amino acid a in the entire genome and in the gene G, respectively. For each amino acid, a, we define its expected volatility and its variance in volatility, given the codon usage in the entire genome, by the equations:

$$E[\nu(a)] = \sum_{\text{aa}(i)=a} \nu(i) N_i / M_{\text{aa}(i)}$$

 $V[\nu(a)] = \sum_{\text{aa}(i)=a} \nu(i)^2 N_i / M_{\text{aa}(i)} - E[\nu(a)]^2$

Similarly, we define the expected volatility of gene G and its variance by the equations:

$$E[\nu(G)] = \sum_{a=1}^{20} m_a E[\nu(a)]$$

 $V[\nu(G)] = \sum_{a=1}^{20} m_a V[\nu(a)]$

We calculate the volatility p-value for G by comparing the gene's observed volatility to its expected volatility, given the amino acid content of the gene and the codon usage in the entire genome. Since genes typically contain at least 30 amino acids, we use a normal approximation to calculate the volatility p-value:

$$p = \frac{1}{2} \left(1 + \operatorname{Erf} \left(\frac{E[\nu(G)] - \nu(G)}{\sqrt{2V[\nu(G)]}} \right) \right)$$

where Erf denotes the error function,

$$\operatorname{Erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt.$$

Volatility p-values calculated using this normal approximation are virtually identical to p-values calculated via the randomization procedure ($r^2 > 0.99$ for each genome).

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