The Impact of Trans-Regulation on the Evolutionary Rates of Metazoan Proteins

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ABSTRACT

Transcription factor (TF) and microRNA (miRNA) are two crucial trans-regulatory factors that coordinately control gene expression. Understanding the impacts of these two factors on the rate of protein sequence evolution is of great importance in evolutionary biology. While many biological factors associated with evolutionary rate variations have been studied, evolutionary analysis of simultaneously accounting for TF and miRNA regulations across metazoans is still uninvestigated. Here, we provide a series of statistical analyses to assess the influences of TF and miRNA regulations on evolutionary rates across metazoans (human, mouse and fruit fly). Our results reveal that the negative correlations between trans-regulation and evolutionary rates hold well across metazoans, but the strength of TF regulation as a rate indicator becomes weak when the other confounding factors that may affect evolutionary rates are controlled. We show that miRNA regulation tends to be a more essential indicator of evolutionary rates than TF regulation, and the combination of TF and miRNA regulations has a significant dependent effect on protein evolutionary rates. We also show that trans-regulation (especially miRNA regulation) is much more important in human/mouse than in fruit fly in determining protein evolutionary rates, suggesting a considerable variation in rate determinants between vertebrates and invertebrates.

INTRODUCTION

Gene expression is largely controlled by actions of various trans-regulatory factors. Undoubtedly, transcription factor (TF) and microRNA (miRNA) are the most conspicuous classes of trans-regulatory factors and are regarded as primary gene regulators in metazoans. TFs are proteins that facilitate or repress the transcription of their target genes through binding to specific DNA sequences, the so-called TF-binding sites (TFBSs), in the gene promoter regions (1). On the other hand, miRNAs are ~22 nucleotide noncoding RNAs, which target mRNAs and reduce stability and/or translation activity of mRNA to regulate gene expression at the posttranscriptional level (2). TFs and miRNAs may work together and form a complex regulatory network that generally consists of intricate feedback and feed-forward loops (3–5). The coordinated regulation of TFs and miRNAs may play important roles in a wider diversity of biological processes (6). A previous study reported that genes with more TFBSs tend to be targeted by miRNAs and have more miRNA-binding sites, suggesting a positive correlation between these two trans-regulatory factors (7). Although the mechanism of how miRNAs cooperate with TFs in the regulatory network remains largely unknown (8), accumulating evidence indicates its biological significance. Thus, it is of interest to investigate the relationship between these two trans-regulatory factors.

In terms of molecular evolution, it was shown that genes regulated by more different TFs (N_{TF}) tend to evolve more slowly in yeast (9,10). Similarly, genes targeted by more distinct miRNAs (N_{miR}) were suggested to experience more functional constraints and thereby evolve more slowly in human and mouse (11,12). These observations revealed that trans-regulation complexity is an important indicator of evolutionary rates, regardless of TF regulation at the transcriptional level or miRNA regulation at the posttranscriptional level. However, comparative studies of trans-regulatory factors have been hampered by the paucity or incompleteness of TF and miRNA information. To our knowledge, there is currently no systematic evolutionary analysis available that simultaneously accounts for these two trans-regulatory factors across metazoans. Whether the negative correlation between the number of trans-regulators that regulate a
gene (i.e. \(N_{TF}\) and \(N_{miR}\)) and evolutionary rates is maintained across metazoans, whether \(N_{TF}\) and \(N_{miR}\) have a dependent effect on evolutionary rates, and which of these two factors has a greater effect on metazoan protein evolution still await investigation.

In addition to \textit{trans}-regulation, many other biological factors associated with and potentially underlying evolutionary rates of proteins have been reported. These factors include protein connectivity in protein–protein interaction (PPI) networks \((9,10,13–19)\), expression level (or expression abundance) \((9,11,13,14,17–30)\), tissue specificity (or expression breadth) \((13,21,23,25,26,31–34)\), length of untranslated regions (UTRs) \((12,21,26)\), intron length \((13,21,26,35)\), intron number \((23,26)\), solvent accessibility \((36–39)\) and disorder content \((11,40–42)\). Some of these factors were also shown to be correlated with \(d_{dS}/d_{ds}\) values = 0 and \(d_{dS}/d_{ds}\) values \(\geq 2\) were not considered. Additionally, the human and mouse genes on chromosome \textit{Y} were excluded for reducing the possibility of irregular evolutionary rates in the short single-copy sex chromosome.

To address these issues, we widely collect TF- and miRNA-binding data from human \textit{(Homo sapiens)} mouse \textit{(Mus musculus)} and fruit fly \textit{(Drosophila melanogaster)} and then systematically examine the correlations between these two \textit{trans}-regulatory factors \((N_{TF}\) and \(N_{miR}\)) and evolutionary rates: nonsynonymous substitution rate \((\text{\textit{d}}_{\text{dS}}\)) synonymous substitution rate \((\text{\textit{d}}_{\text{ds}}\)) and \(d_{dS}/d_{ds}\) ratio. We show that genes regulated by more different TFs/miRNAs evolve more slowly is generally maintained in human, mouse and fruit fly. By controlling for the other confounding factors (i.e. protein connectivity, gene expression, gene compactness and protein structure), the partial correlations between \(N_{miR}\) and evolutionary rates still hold well, whereas the strength of \(N_{TF}\) as a rate indicator is greatly decreased in human/mouse and even disappears in fruit fly. We further find two trends: miRNA regulation tends to be much stronger than TF regulation in determining the rate of protein sequence evolution, and TF and miRNA regulations have a dependent effect on evolutionary rates, both of which are generally maintained across metazoans (human, mouse and fruit fly). We also observe that \textit{trans}-regulation seems to play a much greater role in human/mouse than in fruit fly in causing variation in protein evolutionary rates. This result reveals that the relative impact of \textit{trans}-regulation on the evolutionary rates appears to be different between vertebrates and invertebrates.

**MATERIALS AND METHODS**

**Data retrieval and extraction**

The protein-coding genes in human and mouse, orthology assignments and human–mouse and mouse–human evolutionary rates \((d_{dc}, d_{ds} \text{ and } d_{ds}/d_{dc})\) were downloaded from the Ensembl genome browser at http://www.ensembl.org/(release 69) \((45)\). For an alternatively spliced gene, only its longest isoform was selected. To avoid the confounding factor of gene duplication, only 1:1 orthologs between human and mouse genes were considered. Meanwhile, fruit fly protein-coding genes were downloaded from Flybase (release 4.3) \((46)\). Fruit fly genes with single-copy orthologs across five other \textit{Drosophila} species \((i.e. \text{\textit{D. melanogaster}}, \text{\textit{Drosophila simulans}}, \text{\textit{Drosophila yakuba}}, \text{\textit{Drosophila erecta}}, \text{\textit{Drosophila sechellia}} \text{and} \text{\textit{Drosophila ananassae}})\) and the evolutionary rates were obtained from Larracuente et al.’s study \((23)\). Here, \(d_{dS}\) values = 0 and \(d_{dS}/d_{ds}\) values \(\geq 2\) were not considered. Additionally, the human and mouse genes on chromosome \textit{Y} were excluded for reducing the possibility of irregular evolutionary rates in the short single-copy sex chromosome.

Chromatin immunoprecipitation (ChIP) data including 162 human TF ChIP-seq datasets and 59 mouse TF ChIP-chip and ChIP-seq datasets were downloaded from ENCODE project \((47)\) and hmChIP \((48)\), respectively. The promoter of each human gene was defined as the intergenic region of 8 kb upstream to 2 kb downstream of the gene start position \((4 \text{ kb upstream to } 1 \text{ kb downstream for each mouse gene})\). Also, we defined that a TF regulates a gene if at least one ChIP-seq peak of the TF lies within the promoter region of the gene. The nonredundant associations for 149 fruit fly TFs and their target genes were obtained from DroID \((51)\) which integrates TF-gene associations from modENCODE \((50)\) and REDfly \((51)\). For extraction of predicted human TFBS data, 843 human position frequency matrices were downloaded from TRANSFAC \textsuperscript{R} free trial \((52)\). The position weight matrix (PWM) of each position frequency matrix and the cutoffs were obtained by using PATSER \((53)\). This study considered the potential binding motifs whose \(P\)-values were smaller than or equal to the minimum of the default cutoff and \(10^{-2}\). We further considered the general-binding preference (GBP) score \((54)\) to obtain more reliable predictions. Only the binding sites with GBP scores \(>0.2\), as Ernst et al. \((54)\) suggested, were retained. A TF was defined to regulate a gene if at least one potential binding motif of the TF locates within the promoter region of the gene. Human, mouse and fruit fly miRNA target prediction data were downloaded from TargetScan release 6.2 \((55,56)\). For accuracy, this study considered all human, mouse and fruit fly miRNA families whose target sites were conserved. The site conservation is defined by conserved branch length as determined in TargetScan \((56)\). The used human, mouse and fruit fly genes and the related information are available at http://bits.iis.sinica.edu.tw/TransRegEvoRate/index.html.

**Protein connectivity**

The connectivity of a protein was defined by the total number of distinct proteins interacting with the protein. The PPI datasets of human, mouse and fruit fly were downloaded from STRING 9.0 \((57)\), which retrieved known and predicted PPIs from literature.
Gene expression

Normalized expression datasets of 78 nonpathogenic human tissues and 77 nonpathogenic mouse tissues were downloaded from BioGPS (58), and a normalized expression dataset of 27 fruit fly nonpathogenic tissues was downloaded from FlyAtlas (59). If multiple probe sets refer to the same gene, the signals from different probe sets of the same gene were averaged. Here, expression was analyzed in terms of expression level and tissue specificity (\(\tau\)). The expression level of a gene was defined as the average signal intensity across all examined tissues. The tissue specificity of a gene is defined by

\[
\tau = \frac{\sum_{j=1}^{n} \left(1 - \frac{\log S(j)}{\log S_{\text{max}}} \right)}{n - 1}
\]

in which \(n\) denotes the number of the examined tissues, \(S(j)\) denotes the signal intensity and \(S_{\text{max}}\) denotes the highest signal across all examined tissues (60). A large \(\tau\) value represents high tissue specificity. Of note, to minimize potential noise that might be caused by low signal intensities, we set the signal to 100 if it is <100 (21,61,62).

Gene compactness and protein structural features

Gene compactness was measured by the intron number and the average lengths of UTRs and introns of a gene. Regarding protein structure, it was analyzed in terms of solvent accessibility and disorder content. The solvent accessibility of a protein was calculated by the maximum number of exposed residues that interact with solvent molecules over the length of the protein, in which the exposed residues were predicted by ACCPro release 4.1 with the default threshold of 25% (63). We only considered the proteins of lengths <8000 amino acids owing to the limitation of ACCPro. The disorder content of a protein, defined by the percentage of intrinsically disordered region, was estimated by the number of disordered residues over the length of the protein. The disordered residues were predicted by DISOPRED2 version 2.4 with the default 5% false-positive threshold (64). To ensure a lower standard error, we only considered the proteins of length longer than 100 amino acids.

Calculation of the relative contribution to variability explained

The relative contribution to variability explained (RCVE) is used to measure the relative importance of each tested factor, which is calculated as follows:

\[
\text{RCVE} = \frac{R_{\text{full}}^2 - R_{\text{reduced}}^2}{R_{\text{full}}^2}
\]

where \(R_{\text{full}}^2\) and \(R_{\text{reduced}}^2\) denote the \(R^2\) value of the full model (including all of the factors examined) and that of the reduced model (excluding the factor of interest), respectively. A larger RCVE indicates a more important contribution of the factor of interest to the regression model (65).

RESULTS AND DISCUSSION

miRNA regulation is much more important than TF regulation in determining the evolutionary rates of metazoans

Previous studies have shown that the number of regulatory TFs that regulate a gene (\(N_{\text{TF}}\)) is negatively correlated with \(d_N/d_s\) in a yeast transcriptional regulatory network (9,10), leading to that genes with more regulatory TFs tend to evolve more slowly. We are then interested to know whether the trend is maintained in multicellular organisms. We first extract experimentally determined TFBS data (i.e. TF ChIP-binding datasets) from human, mouse and fruit fly (`Materials and Methods’ section; Table 1) and estimate the Spearman’s rank correlation (\(\rho\)) between \(N_{\text{TF}}\) and evolutionary rates (i.e. \(d_N, d_s\) and \(d_{\text{cis}}/d_{\text{trans}}\)). In general, we find that evolutionary rates are negatively correlated with \(N_{\text{TF}}\) in the three species examined (Table 2). In terms of miRNA regulation, we extract human, mouse and fruit fly miRNA target data (Table 1) and also show negative correlations between \(N_{\text{mir}}\) and evolutionary rates in the three species examined (Table 2). These observations reveal a common trend that genes regulated by more TFs or miRNAs evolve more slowly at both the protein and RNA levels in metazoans.

The above results, however, should be treated carefully because many confounding factors that may affect evolutionary rates of protein-coding genes have not been controlled. As stated above (see ‘Introduction’ section), the confounding factors include protein connectivity, gene expression [expression level and tissue specificity (or expression breadth)], gene compactness (UTR length, intron length and intron number), protein structure (solvent accessibility and disorder content) and so on. Some of these confounding factors have also been reported to be correlated with \(N_{\text{TF}}\) or \(N_{\text{mir}}\). For example, \(N_{\text{TF}}\) was shown to be positively correlated with mRNA expression (9) and UTR length (44). Meanwhile, \(N_{\text{mir}}\) was shown to be positively correlated with protein connectivity (11,43), expression breadth (43), 3’UTR length (12) and disorder content (11). Thus, we reevaluate the correlations between \(\text{trans-regulation (} N_{\text{TF}} \text{ and } N_{\text{mir}}\text{)}\) and evolutionary rates by using partial correlation analyses (66) to simultaneously control for these confounding factors. As shown in Table 2, \(N_{\text{TF}}\) is still negatively correlated with evolutionary rates in human and mouse after controlling for \(N_{\text{mir}}\) and the other eight potential confounding factors. However, the partial correlations between \(N_{\text{TF}}\) and evolutionary rates are substantially reduced in human/mouse and even disappear in fruit fly (Table 2). This result suggests that the evolutionary effect of \(N_{\text{TF}}\) is considerably affected by these confounding factors. On the other hand, the negative correlations between \(N_{\text{mir}}\) and evolutionary rates remains strong in all three species examined after controlling for \(N_{\text{TF}}\) and the other confounding factors (Table 2). These observations reveal that \(N_{\text{TF}}\) and \(N_{\text{mir}}\) tend to have different effects on evolutionary rates. We find that the partial correlation between \(N_{\text{mir}}\) and evolutionary rates is remarkably stronger than that between \(N_{\text{TF}}\) and evolutionary rates.
when the other confounding factors are controlled, suggesting that \( N_{\text{miR}} \) is much more important than \( N_{\text{TF}} \) in affecting \( d_N, d_S \) and \( d_{N/S} \) (Table 2). This trend is maintained across metazoans.

### Dependent effects of TF and miRNA regulations on protein evolutionary rates in metazoans

It is known that TF and miRNA would cooperate with each other in gene regulation (3–5). In addition, genes with more TFBSs have a higher probability to be targeted by miRNAs and tend to have more miRNA-binding sites in human (7). Also, highly connected TFs in human regulatory network tend to regulate more miRNAs and tend to have more miRNA-

### Table 1. The numbers of TFs and miRNAs used in this study

| Species       | TF Data source | Number of TFs | miRNA Data source | Number of miRNAs |
|---------------|----------------|---------------|-------------------|-----------------|
| Human         | ENCODE (hg19)  | 162           | TargetScanHuman (release 6.2) | 1267            |
| Mouse         | hmChIP (mm8)   | 59            | TargetScanMouse (release 6.2)  | 663             |
| Fruit fly     | DroID (May 2011) | 149         | TargetScanFly (release 6.2)    | 121             |

### Table 2. Spearman’s rank coefficient of correlation (\( \rho \)) between evolutionary rates (\( d_N, d_S \) and \( d_{N/S} \)) and experimentally determined \( N_{\text{TF}} \) (or \( N_{\text{miR}} \)) before and after controlling for \( N_{\text{miR}} \) (or experimentally determined \( N_{\text{TF}} \)) and the other eight confounding factors: protein connectivity, expression level, tissue specificity (\( r \)), UTR length, intron length, intron number, solvent accessibility and disorder content

| Indicator and species | Before control | After control |
|-----------------------|---------------|--------------|
|                       | \( d_N \)     | \( d_S \)     | \( d_{N/S} \) |
| Human                 | \(-0.1852^{***}\) | \(-0.1641^{***}\) | \(-0.1388^{***}\) |
| Mouse                 | \(-0.1499^{***}\) | \(-0.1087^{***}\) | \(-0.1213^{***}\) |
| Fruit fly             | \(-0.0759^{***}\) | \(-0.1081^{***}\) | \(-0.0460 \) |
| Mouse                 | \(-0.3760^{***}\) | \(-0.2941^{***}\) | \(-0.3216^{***}\) |
| Fruit fly             | \(-0.3165^{***}\) | \(-0.2710^{***}\) | \(-0.2369^{***}\) |
| Fruit fly             | \(-0.1172^{***}\) | \(-0.2027^{***}\) | \(-0.0406 \) |
|                       | \(-0.1999^{***}\) | \(-0.1076^{***}\) | \(-0.0763^{***}\) |
|                       | \(-0.0832^{***}\) | \(-0.0501^{***}\) | \(-0.0683^{***}\) |
|                       | 0.0006         | 0.0092        | 0.0049             |

\*The analysis was based on 6870 human genes and their mouse orthologs.
\*\*The analysis was based on 4903 mouse genes and their human orthologs.
\*\*\*The analysis was based on 1768 fruit fly genes. The \( d_N, d_S \) and \( d_{N/S} \) values were estimated in single-copy orthologs within the six Drosophila group species (23).

Significance: * \( P < 0.05 \), ** \( P < 0.01 \), and *** \( P < 0.001 \).

Trans-regulation is much more important in mammals than in fruit fly in determining protein evolutionary rates

We have shown that trans-regulation (\( N_{\text{TF}} \) and \( N_{\text{miR}} \)) is an important indicator of evolutionary rates in metazoans (Table 2). Considering the other biological factors...
genes). Significance: ***

Factors (6870 human genes, 4903 mouse genes and 1768 fruit fly genes with TFBSs, miRNA targets and the other eight confounding factors (6870 human genes, 4903 mouse genes and 1768 fruit fly genes). Significance: ***P < 0.001.

Figure 1. Pearson’s coefficient of correlations (r) between N_{TF} and N_{miR} in human, mouse and fruit fly. The analyses were based on genes with TFBSs, miRNA targets and the other eight confounding factors (6870 human genes, 4903 mouse genes and 1768 fruit fly genes). Significance: ***P < 0.001.

associated with evolutionary rates of proteins [protein connectivity, gene expression (expression level and tissue specificity), gene compactness (UTR length, intron length and intron number) and protein structure (solvent accessibility and disorder content)], we then ask which biological factor(s) is/are the dominant determinant(s) of evolutionary rates. To this end, we measure the relative effect of each individual factor in determining the evolutionary rates by calculating the RCVE (see ‘Materials and Methods’ section). As shown in Figure 3 and Supplementary Figure S1A, the most dominant determinants of d_{s} and d_{s}/d_{N} common to human and mouse are trans-regulation (N_{TF} and N_{miR}) and protein structure (solvent accessibility and disorder content), whereas only protein structure is shown as a dominant determinant in fruit fly. Regarding d_{s}, trans-regulation also exhibits influential determinants in human and mouse; however, the trend is not observed in fruit fly (Supplementary Figure S1B). Our results suggest that the effect of trans-regulation (especially miRNA regulation) on protein evolutionary rates is much stronger in mammals than in insects, in consistent with our above finding that the correlations between trans-regulation and evolutionary rates are relatively less significant in fruit fly than in human/mouse (Table 2). The results reveal that trans-regulation seems to be much more important in human/mouse than in fly in determining the rate of protein sequence evolution.

The above results thus suggest that the relative impacts of trans-regulation on evolutionary rates are different between vertebrates and invertebrates. In view of the relationship between regulatory complexity and organismal complexity, there are two possible reasons. First, for TF regulations, previous studies have indicated that organismal complexity might arise from progressively more elaborate gene regulation and the number of TFs per gene is positively correlated with the size of the genome (68–70). Second, in terms of miRNAs, a recent study showed an exponential correlation between the 3′UTR length and morphological complexity (71). The median 3′UTR length is much longer in human than in fruit fly, leading to the conclusion that human genes generally have longer potential miRNA-targeted regions and more complex miRNA regulations (71). Several studies also demonstrated that miRNAs regulate 20–30% of vertebrate genes (72–75) but only 15% of Drosophila genes (75). These notions imply that regulatory complexity might increase with the increase of organismal complexity and trans-regulations tend to play a much greater role in mammals than in insects, leading to a higher correlation between trans-regulation and evolutionary rates in mammals.

Potential caveats

Although the trends that miRNA regulation is much stronger than TF regulation in determining the rate of protein sequence evolution, and TF and miRNA regulations have a dependent effect on evolutionary rates generally hold in metazoans (human, mouse and fruit fly), the limited experimental data (i.e. ChIP-supported TFs and TFBSs) probably cause bias in our results. To address this possibility, we retrieve 843 TRANSFAC human TFs with known PWMs, filter out potentially false-positive TFBSs using the GBP scores (see ‘Materials and Methods’ section) and then conduct the same analyses. Obviously, the number of the TRANSFAC human TFs is much larger than that of the ChIP-supported TFs used above (843 versus 162; Table 1). On the basis of TRANSFAC-based N_{TF} (or predicted N_{TF}), we find that the abovementioned trends still hold well (Table 3, Supplementary Figures S2A and S3A and Supplementary Table S1). Although highly accurate TFBS predictions (which are currently more comprehensive than experimental data) remain challenging (76–78), the predicted TFBS data used here were generated by integrating multiple evidence sources (including sequence conservation, cis-feature, transcriptional information, epigenetic information, and so on) with motif information (54), which were shown to be highly predictive of true locations of TF binding (54,79–81). It is worthwhile to apply our evolutionary analyses to other species (or newly generated data) as the dramatic increase of publicly available trans-regulation data. Because the probability of observing the same trends from two biased datasets appears to be small, our results are likely unbiased.

Moreover, because rodents have a faster molecular clock than primates (82,83), it is possible to yield different tendencies between comparison of human–mouse orthologs and that of two species with similar molecular clocks. We therefore ask whether our results may be biased toward different molecular clocks. To address this question, we conduct the same statistical analyses for mouse–rat orthologs, which have similar molecular clocks, and show the same tendencies as above (Table 4, Supplementary Figures S2B and S3B and Supplementary Table S1). These results indicate that these observed trends are not affected by species selection or different molecular clocks. Therefore, our results can be regarded, in a broad view, as exploring the impacts of trans-regulation on evolutionary rates.
Concluding remarks

This study analyzes the impacts of two trans-regulatory factors ($N_{TF}$ and $N_{miR}$) on the evolutionary rates in the metazoan protein-coding genes. Our results indicate that (i) both $N_{TF}$ and $N_{miR}$ are negatively correlated with evolutionary rates ($d_N$, $d_S$ and $d_N/d_S$) in metazoans, but the strength of $N_{TF}$ becomes weak in human/mouse and even disappears in fruit fly if the other confounding factors are controlled for; (ii) evolutionary rates tend to more strongly correlated with $N_{miR}$ than with $N_{TF}$; (iii) genes simultaneously regulated by TFs and miRNAs are subject to stronger selection pressure than those regulated by only TFs or miRNAs, and the stepwise multiple regression analysis also reveals that the coefficients of the $N_{TF}$–$N_{miR}$ interaction term ($\beta_{1,2}$) significantly deviate from zero, both of which suggest the dependence between $N_{TF}$ and $N_{miR}$ in affecting $d_N/d_S$; and (iv) compared with other biological factors, trans-regulation exhibits an influential impact on evolutionary rates.
Figure 3. The RCVE of the ten factors: $N_{TF}$, $N_{miR}$, protein connectivity (PPI), expression level (ExpLvl), tissue specificity ($r$), UTR length (UTRLeng), intron length (InLeng), intron number (InNum), solvent accessibility (SolAcc) and disorder content (DisCont) on $d_{N}/d_{S}$ in human, mouse and fruit fly. The analyses were based on 6870 human genes, 4903 mouse genes and 1768 fruit fly genes.
Table 3. Spearman’s rank coefficient of correlation (\( \rho \)) between human–mouse evolutionary rates (\( d_s \) and \( d_{\text{N/C0}} \)) and predicted \( N_{\text{TF}} \) (or \( N_{\text{miR}} \)) before and after controlling for \( N_{\text{miR}} \) (or predicted \( N_{\text{TF}} \)) and the other eight confounding factors: protein connectivity, expression level, tissue specificity (\( \tau \)), UTR length, intron length, intron number, solvent accessibility and disorder content in human

| Indicator                               | Before control | After control |
|-----------------------------------------|----------------|---------------|
|                                         | \( d_s \)       | \( d_{\text{N/C0}} \) | \( d_{\text{N/C0}}/d_s \) | \( d_s \)       | \( d_{\text{N/C0}} \) | \( d_{\text{N/C0}}/d_s \) |
| Evolutionary rate versus \( N_{\text{TF}} \) | -0.1494***     | -0.2075***    | -0.0831***     | -0.0792***     | -0.1520***     | -0.0258*          |
| Evolutionary rate versus \( N_{\text{miR}} \) | -0.3424***     | -0.2912***    | -0.2567***     | -0.3221***     | -0.2027***     | -0.2610***        |

The analysis was based on 6653 human genes and their mouse orthologs. Significance: *\( P < 0.05 \) and ***\( P < 0.001 \).

Table 4. Spearman’s rank coefficient of correlation (\( \rho \)) between mouse–rat evolutionary rates (\( d_s \) and \( d_{\text{N/C0}} \)) and experimentally-determined \( N_{\text{TF}} \) (or \( N_{\text{miR}} \)) before and after controlling for \( N_{\text{miR}} \) (or experimentally-determined \( N_{\text{TF}} \)) and the other eight confounding factors: protein connectivity, expression level, tissue specificity (\( \tau \)), UTR length, intron length, intron number, solvent accessibility and disorder content in mouse

| Indicator                               | Before control | After control |
|-----------------------------------------|----------------|---------------|
|                                         | \( d_s \)       | \( d_{\text{N/C0}} \) | \( d_{\text{N/C0}}/d_s \) | \( d_s \)       | \( d_{\text{N/C0}} \) | \( d_{\text{N/C0}}/d_s \) |
| Evolutionary rate versus \( N_{\text{TF}} \) | -0.1116***     | -0.0640***    | -0.1018***     | -0.0629***     | -0.0223         | -0.0629***        |
| Evolutionary rate versus \( N_{\text{miR}} \) | -0.2246***     | -0.1339***    | -0.2000***     | -0.2219***     | -0.1359***      | -0.1986***        |

The analysis was based on 4620 mouse genes and their rat orthologs. Significance: ***\( P < 0.001 \).

determinants in determining \( d_s \) and \( d_{\text{N/C0}} \) in vertebrates, whereas the effect of \( \text{trans} \)-regulation on protein evolutionary rates is relatively weaker in invertebrates. The first and fourth trends show a great variation in rate determinants between vertebrates and invertebrates, also echoing the previous notion that the rules governing evolutionary rates may not be the same for all species (21). Because the currently available \( \text{trans} \)-regulatory data may only partially represent the reality, we compare the impacts of TFs and miRNAs across species and evaluated the impacts of them by controlling for potential confounding factors. It is found that the second and third trends hold well in diverse species including vertebrates and invertebrate. We therefore suggest that these two observations should be generally maintained in metazoans, although the roles of various rate determinants might be different between species (21) (also see the first and fourth trends). In addition, our result shows remarkable dependent effects of TF and miRNA regulations on protein evolutionary rates. We thus demonstrate the intricate relationships between gene regulations and the actions of natural selection in metazoan protein evolution.

SUPPLEMENTARY DATA
Supplementary Data are available at NAR Online: Supplementary Table 1 and Supplementary Figures 1–3.

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