Supporting Information

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SI Methods

Quantifying and Aligning RNA-Sequencing Data. Fastq files containing raw RNA-seq reads were aligned to the mouse genome (mm9/NCBI37) by using STAR (1) (default parameters). RNA-seq quantification was performed by using HTSeq (2), which was run in stranded mode (default parameters). Protein-coding genes were quantified by using the Ensembl annotation (3). Noncoding RNAs were quantified by using data from the NONCODE v3 database (4). Quantification values were normalized by using DESeq2 (5).

Identifying Noncoding RNAs Conserved Between Humans and Mice. We began by downloading BED files listing ncRNA coordinates for humans and mice from the NONCODE v3 database. These bed files contained 33,801 human and 36,991 mouse transcripts. To prevent overlapping ncRNAs from confounding the analysis (many of these appeared to be alternative spliceforms of the same ncRNAs), we merged all overlapping ncRNAs on the same strand by using the BEDTools suite (6). This merge step resulted to 20,042 human and 27,286 mouse transcripts. Using the coordinates for these merged transcripts and the University of California, Santa Cruz (UCSC) Genome Browser (7), we downloaded the nucleotide sequences corresponding to each of these ncRNAs in FASTA format. Next, we constructed separate human and mouse BLAST libraries from these ncRNA sequences by running the makeblastdb command with default parameters. Following this operation, we used BLAST (8) to align the mouse ncRNA sequences against the human ncRNA BLAST library, and vice versa. Because ncRNAs have been shown to have relaxed constraints on sequence conservation (9), we ran *blastn* by using the more permissive dc-megablast algorithm and a minimum *e*-value cutoff of $1e^{-10}$. We then mined these BLAST results for pairs of human and mouse ncRNAs that were each other's top BLAST hit (termed "reciprocal best hits"). Filtering for these reciprocal best hits left us with 1,601 human and mouse transcript pairs, we termed conserved ncRNAs. We are confident in our ability to identify conserved ncRNAs by using these relaxed BLAST parameters as we successfully found wellknown, conserved ncRNAs like Xist, Tsix, Hotair, H19, and Gas5.

To assign names and annotation data to these conserved ncRNAs, we used BLAST to align their sequences to human and mouse RefSeq (10) transcripts. We found 585 of these conserved ncRNAs mapped to protein-coding genes (i.e., RefSeq IDs beginning with NM or XM) in the sense orientation in both humans and mice. Upon visual inspection of these ncRNAs, we found that many of these mapped along the entire length of the proteincoding transcripts. Although some ncRNAs in this list might represent noncoding isoforms of these protein-coding transcripts, we chose to take a conservative approach and removed these from further analysis. Following the removal of these transcripts, we were left with a final list of 1,016 conserved ncRNAs. We assigned biotypes [defined by GENCODE (11) and Ensembl] to these transcripts by using both Ensembl and manual annotation. Quantification and analysis of these transcripts was performed like all other RNA-seq transcript data, as described in Quantifying and Aligning RNA-Sequencing Data.

Identifying Novel ncRNAs. Given that RNA-seq data are not limited to a specific gene annotation, we sought to characterize novel transcripts. We began by collecting all reads that mapped across splice junctions (i.e., reads with large gaps in their alignments). Reads falling into this class are identified by STAR during alignment and stored in files with the *SJ.out.tab* extension. Although this strategy will cause us to miss single-exon transcripts,

we have greater confidence that the data comes from a real, expressed transcripts if we see evidence of RNA splicing. To reduce the impact of spurious reads and noise, we required that splice junctions be mapped by a minimum of 16 reads across our entire dataset (this threshold corresponds to two reads per time point in a single orgran). We chose a fairly low threshold so as not to remove junctions present in only a single organ and those circadian transcripts expressed in bursting patterns (like Dbp). Next, we used BEDTools to filter out any junction mapping within 1 kb of any Ensembl or RefSeq transcript, or overlapping with any NONCODE transcript. All of these steps left us with 10,452 junctions from putative transcripts. We merged all junctions within 500 bp of each other to form 5,154 putative, ncRNA transcript regions. These putative transcripts were quantified and analyzed like all other RNA-seq transcripts, as described in Quantifying and Aligning RNA-Sequencing Data.

Disease Genes, Drug Targets, and Other Data Sources. Disease-gene annotations were aggregated from the following sources: Online Mendelian Inheritance in Man (12), Universal Protein Resource (13), Comparative Toxicogenomics Database (14), Pharmaco-genomics KnowledgeBase (15), and Literature-Derived Human Gene-Disease Network (16). Drug target genes were pulled from the DrugBank database (17). List of WHO essential medicines were downloaded from the WHO website (18). National Institutes of Health (NIH) funding estimates were for fiscal year 2013 from the NIH Research Condition, and Disease Categories system (19). MicroRNA target predictions for PTGS1 were from TargetScan (20).

Tissue Culture and Cell Maintenance. NIH 3T3 cells were purchased from ATCC. These cells were maintained in growth media containing 10% FBS (Atlanta Biologicals) by volume, $1 \times$ Penicillin/Streptomycin/Glutamine (Gibco), and $1 \times$ nonessential amino acids (NEAA; Gibco) in Dulbecco's modified Eagle's medium (DMEM; Gibco). Cells were grown in a humidified incubator at 37 °C and 5% (vol/vol) CO₂.

Transfections. All transfections were performed in the forward format. Briefly, cells were seeded in six-well dishes at a density of 2.5×10^5 cells per well, in media containing no antibiotics [DMEM, 10% FBS by volume, 1× Glutamine (Gibco), and 1× NEAA]. Cells were incubated overnight at 37 °C and 5% (vol/vol) CO₂. On the following day, cells were transfected by using Opti-MEM (Gibco) and the RNAiMAX (Invitrogen) reagent, according to the manufacturers' protocol. Cells were transfected with mirVana Negative Control #1, mmu-miR-22–3p mimic, or mmu-miR-22–5p mimic (Life Technologies) at a final concentration of 50 nM. Transfected cells were incubated for 72 h at 37 °C and 5% (vol/vol) CO₂. RNA and protein were harvested from the same well by collecting cells in ice-cold PBS and dividing these cell suspensions into two aliquots. For each well, one aliquot was processed for protein, and the other was processed for RNA.

Western blot. Whole-cell protein extracts were isolated from cells by using ice-cold RIPA buffer (Sigma), supplemented with Complete protease inhibitor mixture (Roche). Protein concentrations were quantified by using the DC protein assay (BioRad). Four micrograms of protein was resolved on precast 7.5% polyacrylamide, Tris-HCl/Glycine/SDS gels (BioRad) and transferred to PVDF membranes. Membranes were blocked for 1 h at room temperature in blocking solution [5% (wt/vol) milk, 0.05% Tween 20, 1× Tris-buffer saline], followed by overnight incubation at 4 °C with primary antibody in blocking solution. Primary antibodies used were as follows: anti-PTGS1 (160110; Cayman Chemical) and anti-GAPDH (sc-25778; Santa Cruz). Membranes were then rinsed twice each with TBS-0.05% Tween and blocking solution. Following rinses, membranes were probed with secondary antibody at room temperature for 70 min. Those membranes treated with anti-PTGS1 were incubated with antimouse IgG HPR-linked secondary antibodies (NA931V; GE Healthcare), whereas membranes treated with anti-GAPDH were incubated with anti-rabbit IgG HPR-linked secondary antibodies (NA934-1ML; GE Healthcare). Membranes were then rinsed five times for 10 min in TBS-0.05% Tween, and then imaged by using standard autoradiograph techniques after the application of Western Lightning Plus ECL (PerkinElmer) Western blotting detection reagent.

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RNA extraction and quantitative PCR. RNA was extracted from cells by using TRIzol reagent (Life Technologies) with Direct-zol RNA MiniPrep kit (Zymo Research), according to manufacturer's protocol, cDNA was generated from 500 ng of RNA by using the qScript cDNA Synthesis Kit (Quanta Biosciences), and qPCR was performed on the ViiA 7 Real-Time PCR System (Life Technologies) using the PerfeCTa FastMix II, Low ROX reagent (Quanta Biosciences), according to the manufacturer's protocols. Relative expression quantification of the qPCR data were performed by using the $\Delta\Delta$ CT method with the ViiA 7 analysis software v1.2 (Life Technologies). *Ptgs1* (Mm00477214_m1; Life Technologies) was quantified by using *Gapdh* (4352661; Life Technologies) as the endogenous reference.

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Fig. S1. Identifying oscillating transcripts across different organs. (*A*) The number of oscillating transcripts identified in each tissue as a function of the JTK_CYCLE significance cutoff. (*B*) The average total number of oscillating genes detected as a function of the number of organs sampled. This figure is a repetition of the calculation performed in Fig. 1*C*, using only data from organs with a more homogeneous composition (liver, kidney, lung, heart, adrenal gland, and skeletal muscle). Error bars represent SD. Best-fit model has been overlayed in red. (*C*) Radial diagrams showing the phase distribution of oscillating genes in each organ. These are enlarged versions of those included down the right side of Fig. 2*A*.



Fig. S2. Conserved circadian ncRNAs. (A) Method overview for identifying conserved ncRNAs. (B) Functional types of circadian conserved ncRNAs. Types were defined by GENCODE and Ensembl biotypes, assigned by using Ensembl and manual annotation.



Fig. S3. Representative examples of conserved circadian ncRNAs and antisense transcripts. (A) RNA-seq coverage plot for *Galt* (red) and its antisense transcript (blue). The gene model for *Galt* is displayed above the coverage plots. (B) Expression profiles for *Galt* (red; data from microarrays) and the antisense transcripts (blue; data from RNA-seq). Gray regions indicate subjective night. (C) RNA-seq coverage plot for *Snhg12*. The gene model is displayed below the coverage plot. Note the locations of the mature snoRNA sequences located in the introns of *Snhg12*. (D) RNA-seq expression profiles for *Snhg12* in brown adipose and hypothalamus. (E) RNA-seq coverage plot for *Arnt1* (red; data from microarrays) and the antisense transcript (blue), from white adipose. The gene model for *Arnt1* is displayed below the coverage plots. (F) Expression profiles for *Arnt1* (red; data from microarrays) and the antisense transcript (blue), from white adipose. The gene model for *Per2* (red) and its antisense transcript (blue), from white adipose. The gene model for *Per2* is displayed below the coverage plots. (H) Expression profiles for *Per2* (red) and the antisense transcript (blue) from liver, adrenal gland, lung, and kidney.



Fig. S4. Genomic characteristics of circadian genes. (*A*) Genomic clustering of each organ's oscillatory genes. The test statistic used was the sum of the squared number of oscillatory genes within a sliding nine-gene window (intergenic distance disregarded). Significance values were derived by using null distributions determined by randomly shuffling gene positions 1 million times for each organ-chromosome pair. (*B*) Total length of circadian vs. noncircadian genes. Length of circadian vs. noncircadian genes across 5'UTRs (*C*), coding sequence (*D*), and 3'UTRs (*E*). Spliceform counts of circadian vs. noncircadian genes for detected spliceforms (*F*), unique sets of spliceforms expressed across organs (*G*), and unique, dominant spliceforms expressed across organs (*H*). (*I*) Number of genes having the given maximum phase difference between any two organs. *Vegfa* is shown as an example.



Fig. S5. Expression of core circadian oscillator genes across organs. (A) Expression of each gene in all organs superimposed. (B) Heatmap representation of expression from A.



Fig. S6. Discovering oscillation influence on pathways. Nodes represent Reactome pathways, with size corresponding to total number of genes in a pathway and color corresponding to percent of genes with rhythmic expression at the organism level. Edges convey pathway hierarchy. Heatmap depicts significance of pathways' oscillatory fractions by Fisher's exact test at the organ level. Network displayed in this figure is available as a Cytoscape file (bioinf.itmat.upenn. edu/circa/circadian_oscillations_in_reactome_pathways.cys).



Fig. 57. *Mir22* reduces endogenous PTGS1 in NIH 3T3 cells. (A) Representative Western blot analysis of lysates from NIH 3T3 cells transfected with mirNeg, mir-22–3p, or mir-22–5p. *, nonspecific bands. (*B*) Densitometric quantification of PTGS1 protein expression from Western blots, normalized to GAPDH protein expression. Values are mean intensities relative to the mirNeg condition, \pm SD. (*C*) Quantification of *Ptgs1* mRNA by qPCR from the same samples assayed in *B*. Expression values were normalized by *Gapdh*, and presented as mean abundance relative to mirNeg condition, \pm SD *n* = 3 for *B* and *C*. n.s., not significant; **P* < 0.0001, relative to mirNeg by one-sided, homoscedastic Student *t* test.



Fig. S8. Correlation between association significance of diseases with circadian genes and NIH research funding toward each disease.

Dataset S1. Drugs from the top-100 best-selling drugs list that target circadian genes

Dataset S1

AC PNAS

Dataset S2. Drugs from the WHO Essential Medicines list that target circadian genes

Dataset S2

Dataset S3. Half-life notes on all drugs from Datasets S1 and S2

Dataset S3

Dataset S4. Oscillation phases of all conserved, non-coding RNAs

Dataset S4

Dataset S5. Antisense transcripts

Dataset S5