

Effects of aging on circadian patterns of gene expression in the human prefrontal cortex

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With aging, significant changes in circadian rhythms occur, including a shift in phase toward a “morning” chronotype and a loss of rhythmicity in circulating hormones. However, the effects of aging on molecular rhythms in the human brain have remained elusive. Here, we used a previously described time-of-death analysis to identify transcripts throughout the genome that have a significant circadian rhythm in expression in the human prefrontal cortex [Brodmann’s area 11 (BA11) and BA47]. Expression levels were determined by microarray analysis in 146 individuals. Rhythmicity in expression was found in ~10% of detected transcripts ($P < 0.05$). Using a metaanalysis across the two brain areas, we identified a core set of 235 genes ($q < 0.05$) with significant circadian rhythms of expression. These 235 genes showed 92% concordance in the phase of expression between the two areas. In addition to the canonical core circadian genes, a number of other genes were found to exhibit rhythmic expression in the brain. Notably, we identified more than 1,000 genes (1,186 in BA11; 1,591 in BA47) that exhibited age-dependent rhythmicity or alterations in rhythmicity patterns with aging. Interestingly, a set of transcripts gained rhythmicity in older individuals, which may represent a compensatory mechanism due to a loss of canonical clock function. Thus, we confirm that rhythmic gene expression can be reliably measured in human brain and identified for the first time (to our knowledge) significant changes in molecular rhythms with aging that may contribute to altered cognition, sleep, and mood in later life.

aging | postmortem | circadian rhythms | gene expression | prefrontal cortex

Nearly all processes in the brain and body are controlled by a 24-h circadian rhythm. These rhythms are important in regulating the sleep/wake cycle, metabolism, alertness, cognition, and other processes (1). Environmental or genetic disruptions to circadian rhythms are strongly associated with chronic sleep problems, increased rates of cancer, lowered immune function, metabolic disorders, and psychiatric disorders (2, 3). The molecular clock is controlled by a transcriptional/translational feedback loop with the circadian locomotor output cycles kaput (CLOCK) and brain and muscle Arnt-like protein 1 (BMAL1; also known as ARNTL) proteins acting as the major transcriptional activators, and the Period (PER1, PER2, PER3) and Cryptochrome (CRY1, CRY2) proteins acting as the major repressors (4). This core circadian feedback loop regulates the diurnal expression patterns of many different genes as it is estimated that 10–20% of all transcripts have a circadian rhythm (1, 5). Although the master circadian pacemaker in the suprachiasmatic nucleus (SCN) of the hypothalamus synchronizes rhythms throughout the brain and body, the genes that control circadian rhythms are expressed in nearly every cell (6). In recent years, it has become apparent that these genes serve important functions in specific brain regions, including the control of daily rhythms in neuronal activity and the response to environmental stimuli (7–9).

Evidence from preclinical and clinical studies suggests rhythms in the prefrontal cortex (PFC) are particularly important for

cognitive performance and executive function. Several studies in humans have reported diurnal differences in cognitive performance and a significant decrease in performance following circadian rhythm disruption (10–12). Interestingly, these measures vary by age with older adults performing better on cognitive tasks in the morning and getting worse throughout the day (12, 13). In older women, there is a direct correlation between weak circadian activity rhythms and poorer executive function (14). In preclinical studies, mice trained in cortical-driven cognitive tasks show pronounced diurnal differences in performance (15–17). Moreover, mice housed under a shortened day (20-h light–dark cycle of 10-h light, 10-h dark) displayed reduced cognitive flexibility and a loss of dendritic length and complexity in the PFC (18).

Physiological and activity rhythms are generally known to deteriorate with aging and show a phase advance toward early morning wakening (19, 20). Daily rhythms in hormones like melatonin and cortisol are decreased as are sleep and body temperature rhythms in older individuals (21). Interestingly, the recognized stimulation of alertness and cognition by blue light seen in young people is diminished in older people, suggesting decreased input to the clock (22). Moreover, the addition of serum from older people to cultured cells that express a circadian reporter construct (*Bmal1-luciferase*) leads to a shortening of molecular rhythms and a phase advance that is not seen with serum from younger people (23). This finding suggests the presence of circulating factors that alter molecular rhythms with age.

Significance

Circadian rhythms are important in nearly all processes in the brain. Changes in rhythms that come with aging are associated with sleep problems, problems with cognition, and nighttime agitation in elderly people. In this manuscript, we identified transcripts genome-wide that have a circadian rhythm in expression in human prefrontal cortex. Moreover, we describe how these rhythms are changed during normal human aging. Interestingly, we also identified a set of previously unidentified transcripts that become rhythmic only in older individuals. This may represent a compensatory clock that becomes active with the loss of canonical clock function. These studies can help us to develop therapies in the future for older people who suffer from cognitive problems associated with a loss of normal rhythmicity.

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In the human brain, the investigation of brain region-specific transcriptional rhythms across the life span has been challenging due to the lack of control of environmental factors, such as time of death, sleep–wake cycles, and exposure to other factors known to influence rhythms. A recent study overcame some of these obstacles by ordering postmortem samples around a 24-h clock based on their time of death, essentially reconstructing a pseudo-time series by treating each individual sample as an independently sampled data point over one 24-h cycle (24). In 55 healthy controls and 34 patients with major depressive disorder (MDD), they found robust expression rhythms of hundreds of genes in several brain regions in control subjects, with many of these genes displaying significantly disrupted or altered expression rhythms in subjects with MDD. Here, we used a similar analytical approach to identify rhythmic transcripts in two areas of the PFC [Brodmann’s area 11 (BA11) and BA47] in a large sample of 146 subjects from across the life span with no history of psychiatric illness. This large sample allowed us to investigate the effects of normal aging on molecular rhythms in the human PFC and to test the prediction that older individuals display altered or even a loss of molecular rhythms in this brain region.

Materials and Methods

Human Postmortem Brain Samples. Using the resources of the University of Pittsburgh's Brain Tissue Donation Program, 210 subjects were identified. Samples were obtained after consent from next of kin during autopsies conducted at the Allegheny County Medical Examiner's Office (Pittsburgh). The absence of lifetime psychiatric disorders was determined by an independent committee of experienced clinical research scientists using information from clinical records, toxicology results, and a standardized psychological autopsy. Subjects were removed from the study if death was not witnessed because their time of death (TOD) cannot be precisely determined. Subjects that did not meet the criteria of rapid death were also removed from the study. Sixty-four subjects were removed based on these criteria. The final sample consisted of 146 individuals with the following characteristics: mean (range) age of 50.7 (16–96) years, 78% male, 85% Caucasian, mean postmortem interval (PMI) for brain collection of 17.3 h (4–28 h), mean pH of 6.7 (5.8–7.6), and RNA integrity number (RIN) of 8.0 (5.9–9.6) (Table S1).

For each subject, the right hemisphere was blocked coronally, frozen, and stored at -80°C . Blocks containing BA11 or BA47 of the orbital PFC were cut on a cryostat, and cortical gray matter was collected for RNA extraction as previously described (25). All procedures were approved by the University of Pittsburgh's Institutional Review Board for Biomedical Research and Committee for Research Involving the Dead.

Time of Death Analysis in the Zeitgeber Timescale. To analyze rhythmic gene expression, the TOD for each subject was normalized to a zeitgeber time (ZT) scale. For each subject, both place and time of death was collected, where the time zone of the place of death was used to adjust the reported TOD from local time to coordinated universal time. Daylight savings time was also incorporated when appropriate. The sunrise time was calculated according to

the date and the longitude and latitude of the place of death. Subject's TOD was set as $ZT = t$ hours after previous sunrise (if $t < 18$) or before next sunrise (if $t > -6$).

Microarray Data Preprocessing. All samples were analyzed using the Affymetrix Human Gene 1.1 ST microarray platform. Gene expression values were corrected, quantile-normalized, and \log_2 -transformed via Affymetrix Expression Console software (build 1.2.1.20) using RMA algorithm. A total of 33,297 probe sets were available on each array; only those probe sets with annotated gene symbols were selected (20,237 gene symbols). If a gene was represented by multiple probe sets, the one with the largest intensity interquartile region was selected to represent that gene. Microarray data for each brain region were analyzed separately. The raw and processed microarray data were deposited in the National Center for Biotechnology Information Gene Expression Omnibus database (GSE71620).

Detection of Circadian Gene Expression Patterns. Nonlinear regression was used to detect circadian gene expression patterns. All individual samples were ordered by their TODs. Temporal expression was fitted to a sinusoidal curve using the nonlinear least-squares method. The coefficient of determination (R^2) was used as a proxy of goodness-of-fit. The empirical P value was estimated from a null distribution of R^2 generated from 1,000 TOD-randomized expression datasets for BA11 and BA47 separately. Adaptive weighted Fisher method was adopted to combine multiple P values across brain regions (26). The q value was estimated using R package *qvalue* (27).

Analysis of Aging Effects on Expression Rhythmicity. Subjects were classified as younger (<40 y, $n = 31$) or older (>60 y, $n = 37$) and analysis of rhythmic gene expression was performed on each group independently as described above. Age effect P values were estimated from 1,000 age-shuffled data matrices for BA11 and BA47 separately (*SI Materials and Methods*).

Results

Gene Expression Rhythms in Human BA11 and BA47. In 146 subjects, we performed a comprehensive gene expression analysis in BA11 and BA47 of the PFC (Fig. S14). In BA11 2,475 genes (~12% of the genome) and in BA47 a total of 1,615 (~8% of the genome) displayed detectable circadian rhythmicity ($P < 0.05$) (Dataset S1). To identify a set of genes with consistent circadian regulation of gene transcripts across BA11 and BA47, we applied a metaanalysis approach across the brain regions and limited the false-discovery rate to 5% (i.e., $q < 0.05$). A total of 235 genes with a significant circadian expression pattern were detected at $q < 0.05$ (Dataset S1 and Table S2). Notably, these genes displayed coordinated temporal expression patterns across BA11 and BA47, as illustrated by the nearly identical patterns observed across the two areas (Fig. 1 A and B). Indeed, the peak or acrophase of expression of those 235 genes was highly concordant (92%) between BA11 and BA47 (Pearson's $r = 0.95$, $P = 5.8 \times 10^{-120}$) (Fig. 1C). The core genes that make up the molecular clock showed robust expression rhythms in the PFC (Fig. 2). Their patterns of expression were strikingly similar across the two brain regions and also to those published previously (24), demonstrating the consistency in the use of these analyses to detect significant rhythms in gene expression in human post-mortem tissue. The top 50 genes with significant circadian rhythms in expression are listed in Fig. 3. For example, *Clorf51* (more recently known as *CLART*) has the most robust expression rhythm (Fig. S2). The mouse ortholog of this gene, *Gm129*, has been recently identified as having a circadian pattern of expression in mice (28, 29). Many of these genes display circadian expression patterns in peripheral tissues of the mouse, such as the liver, heart, and/or skeletal muscle, and in the brain, including the SCN and cerebellum. For example, *DUSP4*, *ANKRD12*, *TRIM24*, and *TMEM119* display expression rhythms in the mouse SCN (30), whereas *DUSP11*, *USP2*, *SEN3*, *BACE2*, and *PEXI* are expressed rhythmically in other areas of the brain (30, 31). Notably, some of the genes we identified here as displaying rhythmicity in the human PFC are not known to be involved in circadian rhythms, or even to be expressed in a circadian pattern, suggesting these genes may have previously unidentified roles within or downstream of the molecular clock. For example, *KCNH4*

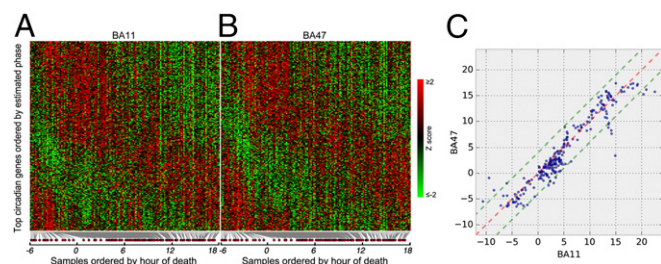
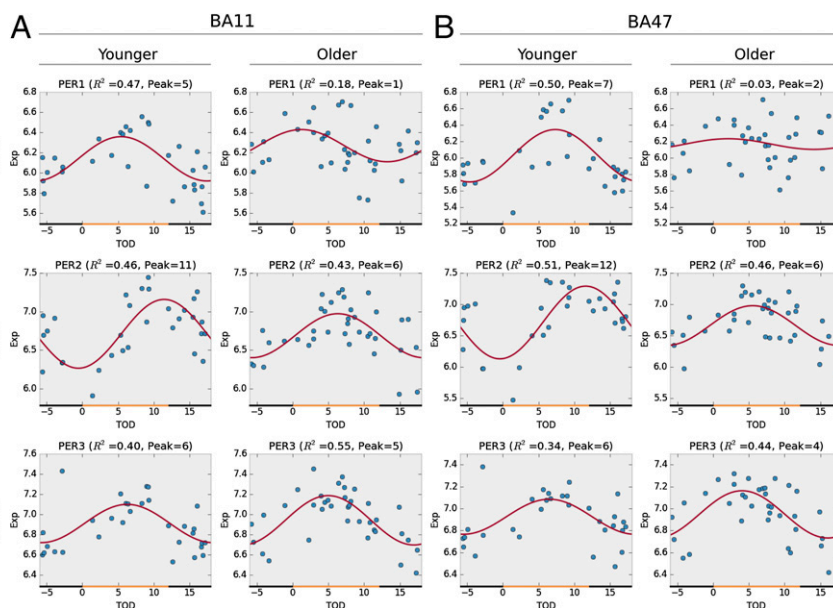


Fig. 1. Heat map of expression levels and comparison of circadian acrophase for the top circadian genes ($n = 235$, $q < 0.05$) in BA11 and BA47. (A and B) Expression levels were Z-transformed for each gene. Red indicates higher expression level; green indicates lower expression levels. (C) The circadian phase (peak hours) of 235 circa genes derived from metaanalysis are plotted on TOD axes for BA11 (x axis) and BA47 (y axis). Red dashed line: 1:1 diagonal line. Green dashed lines: ± 4 -h phase concordance boundaries. Ninety-two percent of circa genes (217 of 235) are located within the concordance interval.



Conclusions

In conclusion, our study demonstrates the power of TOD transcriptomic analysis to identify transcripts with a circadian rhythm in human postmortem brain. We find many genes to have a significant rhythm in BA11 and BA47 with a high concordance in their phase. Furthermore, we have identified age-related changes in rhythmic transcript expression and somewhat surprisingly have uncovered a previously unidentified set of genes that gain rhythmicity in older individuals. These studies will help us better understand how rhythms change during aging and how targeted

therapies that enhance molecular rhythmicity might be developed to prevent conditions like sundowning or enhance cognition. Moreover, in the future, we can use this approach to identify changes in molecular rhythms in a variety of brain regions or specific cell types that associate with psychiatric and neurological diseases.

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- Patel VR, Eckel-Mahan K, Sassone-Corsi P, Baldi P (2014) How pervasive are circadian oscillations? *Trends Cell Biol* 24(6):329–331.
- Baron KG, Reid KJ (2014) Circadian misalignment and health. *Int Rev Psychiatry* 26(2):139–154.
- Foster RG, Kreitzman L (2014) The rhythms of life: What your body clock means to you! *Exp Physiol* 99(4):599–606.
- Reppert SM, Weaver DR (2001) Molecular analysis of mammalian circadian rhythms. *Annu Rev Physiol* 63:647–676.
- Hogenesch JB, Panda S, Kay S, Takahashi JS (2003) Circadian transcriptional output in the SCN and liver of the mouse. *Novartis Found Symp* 253:171–180; discussion 52–55, 102–109, 180–183 passim.
- Albrecht U (2012) Timing to perfection: The biology of central and peripheral circadian clocks. *Neuron* 74(2):246–260.
- Logan RW, Williams WP, 3rd, McClung CA (2014) Circadian rhythms and addiction: Mechanistic insights and future directions. *Behav Neurosci* 128(3):387–412.
- Mukherjee S, et al. (2010) Knockdown of Clock in the ventral tegmental area through RNA interference results in a mixed state of mania and depression-like behavior. *Biol Psychiatry* 68(6):503–511.
- Sidor MM, et al. (2015) Daytime spikes in dopaminergic activity drive rapid mood-cycling in mice. *Mol Psychiatry* 20(11):1406–1419.
- Cho K, Ennaceur A, Cole JC, Suh CK (2000) Chronic jet lag produces cognitive deficits. *J Neurosci* 20(6):RC66.
- Marquie JC, Tucker P, Folkard S, Gentil C, Ansiau D (2015) Chronic effects of shift work on cognition: Findings from the VISAT longitudinal study. *Occup Environ Med* 72(4):258–264.
- Rouch I, Wild P, Ansiau D, Marquie JC (2005) Shiftwork experience, age and cognitive performance. *Ergonomics* 48(10):1282–1293.
- Anderson JA, Campbell KL, Amer T, Grady CL, Hasher L (2014) Timing is everything: Age differences in the cognitive control network are modulated by time of day. *Psychol Aging* 29(3):648–657.
- Walsh CM, et al. (2014) Weaker circadian activity rhythms are associated with poorer executive function in older women. *Sleep* 37(12):2009–2016.
- Mulder CK, Gerkema MP, Van der Zee EA (2013) Circadian clocks and memory: Time-place learning. *Front Mol Neurosci* 6:8.
- Mulder CK, Papantonou C, Gerkema MP, Van Der Zee EA (2014) Neither the SCN nor the adrenals are required for circadian time-place learning in mice. *Chronobiol Int* 31(9):1075–1092.
- Roedel A, Storch C, Holsboer F, Ohl F (2006) Effects of light or dark phase testing on behavioural and cognitive performance in DBA mice. *Lab Anim* 40(4):371–381.
- Karatsoreos IN, Bhagat S, Bloss EB, Morrison JH, McEwen BS (2011) Disruption of circadian clocks has ramifications for metabolism, brain, and behavior. *Proc Natl Acad Sci USA* 108(4):1657–1662.
- Youngstedt SD, Kripke DF, Elliott JA, Klauber MR (2001) Circadian abnormalities in older adults. *J Pineal Res* 31(3):264–272.
- Yoon IY, et al. (2003) Age-related changes of circadian rhythms and sleep-wake cycles. *J Am Geriatr Soc* 51(8):1085–1091.
- Hofman MA, Swaab DF (2006) Living by the clock: The circadian pacemaker in older people. *Ageing Res Rev* 5(1):33–51.
- Daneault V, et al. (2014) Aging reduces the stimulating effect of blue light on cognitive brain functions. *Sleep* 37(1):85–96.
- Pagani L, et al. (2011) Serum factors in older individuals change cellular clock properties. *Proc Natl Acad Sci USA* 108(17):7218–7223.
- Li JZ, et al. (2013) Circadian patterns of gene expression in the human brain and disruption in major depressive disorder. *Proc Natl Acad Sci USA* 110(24):9950–9955.
- Seney ML, et al. (2013) The role of genetic sex in affect regulation and expression of GABA-related genes across species. *Front Psychiatry* 4:104.
- Chang LC, Lin HM, Sibille E, Tseng GC (2013) Meta-analysis methods for combining multiple expression profiles: Comparisons, statistical characterization and an application guideline. *BMC Bioinformatics* 14:368.
- Storey JD (2003) The positive false discovery rate: A Bayesian interpretation and the q-value. *Ann Stat* 31(6):2013–2035.
- Goriki A, et al. (2014) A novel protein, CHRONO, functions as a core component of the mammalian circadian clock. *PLoS Biol* 12(4):e1001839.
- Annayev Y, et al. (2014) Gene model 129 (Gm129) encodes a novel transcriptional repressor that modulates circadian gene expression. *J Biol Chem* 289(8):5013–5024.
- Panda S, et al. (2002) Coordinated transcription of key pathways in the mouse by the circadian clock. *Cell* 109(3):307–320.
- Hughes ME, et al. (2009) Harmonics of circadian gene transcription in mammals. *PLoS Genet* 5(4):e1000442.
- Pagani M, et al. (2007) Imaging the neurobiological substrate of atypical depression by SPECT. *Eur J Nucl Med Mol Imaging* 34(1):110–120.
- Nebel K, et al. (2005) On the neural basis of focused and divided attention. *Brain Res Cogn Brain Res* 25(3):760–776.
- Dunlap JC (1999) Molecular bases for circadian clocks. *Cell* 96(2):271–290.
- Houl JH, Yu W, Dudek SM, Hardin PE (2006) *Drosophila* CLOCK is constitutively expressed in circadian oscillator and non-oscillator cells. *J Biol Rhythms* 21(2):93–103.
- Harbour VL, Weigl Y, Robinson B, Amir S (2014) Phase differences in expression of circadian clock genes in the central nucleus of the amygdala, dentate gyrus, and suprachiasmatic nucleus in the rat. *PLoS One* 9(7):e103309.
- Lamont EW, Robinson B, Stewart J, Amir S (2005) The central and basolateral nuclei of the amygdala exhibit opposite diurnal rhythms of expression of the clock protein Period2. *Proc Natl Acad Sci USA* 102(11):4180–4184.
- Miyake A, Mochizuki S, Yokoi H, Kohda M, Furuichi K (1999) New ether-à-go-go K⁺ channel family members localized in human telencephalon. *J Biol Chem* 274(35):25018–25025.
- Sewduth RN, et al. (2014) The ubiquitin ligase PDZRN3 is required for vascular morphogenesis through Wnt/planar cell polarity signalling. *Nat Commun* 5:4832.
- Honda T, Yamamoto H, Ishii A, Inui M (2010) PDZRN3 negatively regulates BMP-2-induced osteoblast differentiation through inhibition of Wnt signaling. *Mol Biol Cell* 21(18):3269–3277.
- Allen CN, et al. (1999) Orphanin-FQ/nociceptin (OFQ/N) modulates the activity of suprachiasmatic nucleus neurons. *J Neurosci* 19(6):2152–2160.
- Miyakawa K, et al. (2007) ORL1 receptor-mediated down-regulation of mPER2 in the suprachiasmatic nucleus accelerates re-entrainment of the circadian clock following a shift in the environmental light/dark cycle. *Neuropharmacology* 52(3):1055–1064.
- Burger AM, et al. (2010) Role of the BCAA2 ubiquitin E3 ligase in hormone responsive breast cancer. *Open Cancer J* 3(1):116–123.
- Stevens RG, Brainard GC, Blask DE, Lockley SW, Motta ME (2014) Breast cancer and circadian disruption from electric lighting in the modern world. *CA Cancer J Clin* 64(3):207–218.
- Stojkovic K, Wing SS, Cermakian N (2014) A central role for ubiquitination within a circadian clock protein modification code. *Front Mol Neurosci* 7:69.
- Myers BL, Badian P (1995) Changes in circadian rhythms and sleep quality with aging: Mechanisms and interventions. *Neurosci Biobehav Rev* 19(4):553–571.
- Abe T, et al. (2011) Relation between morningness-eveningness score and depressive symptoms among patients with delayed sleep phase syndrome. *Sleep Med* 12(7):680–684.
- Adan A (1994) Chronotype and personality factors in the daily consumption of alcohol and psychostimulants. *Addiction* 89(4):455–462.
- Giglio LM, et al. (2010) Circadian preference in bipolar disorder. *Sleep Breath* 14(2):153–155.
- Merikanto I, et al. (2013) Evening types are prone to depression. *Chronobiol Int* 30(5):719–725.
- Bachman D, Rabins P (2006) “Sundowning” and other temporally associated agitation states in dementia patients. *Annu Rev Med* 57:499–511.
- Klaffke S, Staedt J (2006) Sundowning and circadian rhythm disorders in dementia. *Acta Neurol Belg* 106(4):168–175.
- Tirubuzi R, et al. (2014) miR128 up-regulation correlates with impaired amyloid β (1–42) degradation in monocytes from patients with sporadic Alzheimer’s disease. *Neurobiol Aging* 35(2):345–356.
- Jin M, et al. (2014) miRNA-128 suppresses prostate cancer by inhibiting BMI-1 to inhibit tumor-initiating cells. *Cancer Res* 74(15):4183–4195.
- Guo S, et al. (2014) miR-15a inhibits cell proliferation and epithelial to mesenchymal transition in pancreatic ductal adenocarcinoma by down-regulating Bmi-1 expression. *Cancer Lett* 344(1):40–46.
- Bekris LM, et al. (2013) MicroRNA in Alzheimer’s disease: An exploratory study in brain, cerebrospinal fluid and plasma. *Biomarkers* 18(5):455–466.
- Terzibas Tozzini E, et al. (2014) Regulation of microRNA expression in the neuronal stem cell niches during aging of the short-lived annual fish *Nothobranchius furzeri*. *Front Cell Neurosci* 8:51.
- Eckel-Mahan KL, et al. (2013) Reprogramming of the circadian clock by nutritional challenge. *Cell* 155(7):1464–1478.
- Stelzer G, et al. (2011) In-silico human genomics with GeneCards. *Hum Genomics* 5(6):709–717.
- Safran M, et al. (2010) GeneCards Version 3: The human gene integrator. *Database (Oxford)* 2010:baq020.

Supporting Information

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SI Materials and Methods

Detection of Circadian Gene Expression Patterns. Nonlinear regression was used to detect circadian gene expression patterns. All individual samples were ordered by their TODs, and for each gene, this temporal expression was fitted to a sinusoidal curve using the nonlinear least-squares method. The sinusoidal curve was defined as follows:

$$y = A \sin(Fx + \text{phase}) + \text{offset},$$

where A represents the amplitude and F represents the frequency, which was fixed at 24-h period. The nonlinear fitting was performed based on the Levenberg–Marquardt algorithm, which was implemented in SciPy's Optimization package (release 0.13.2). The peak hour of the circadian pattern was calculated directly from the fitted curve.

The Choice of Cohort Age Cutoffs. We chose age 40 and 60 as the cutoffs in the age stratification analysis for the following reasons:

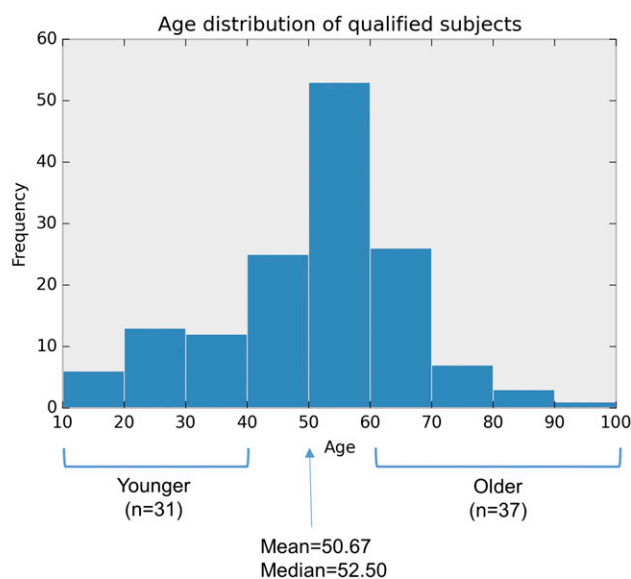
- i) Age 60 or 65 are both widely used cutoffs to define elders, and they generally agree with the typical retirement age in the developed countries (e.g., United Nations has used 60+ to define old age). We also chose >60 because it generates a sample size ($n = 37$) that is comparable to the younger group (<40) ($n = 31$).
- ii) For this type of analysis, we require strong signals to distinguish different circadian gene expression patterns between the younger and the older groups. Therefore, we have to choose relatively extreme age groups while trying to keep a level of statistical power needed to detect significant differences (i.e., the group sizes cannot be too small and should be approximately equal sizes).

- iii) Moreover, current age cutoffs (40, 60) are close to the first quartile (Q1, 25%, 42.45 y) and the third quartile (Q3, 75%, 59.75 y), respectively. In addition, they are of approximately equal distance from the mean (50.67 y) and median (52.50 y).

Analysis of Aging Effects on Expression Rhythmicity. First, subjects were classified as younger (<40 y, $n = 31$) or older (>60 y, $n = 37$) by age as mentioned above. Next, the procedures of detection of circadian gene expression patterns (mentioned in the main text) were applied to each group and each brain region separately. Then, for each gene, the absolute difference of the parameters (i.e., Δbase , $\Delta\text{amplitude}$, Δphase , and ΔR^2) between the younger and the older group can be calculated by comparing their best-fitting circadian curves ($P < 0.05$) that we obtained at the previous step. After that, we generated 1,000 age-shuffled expression data matrixes (i.e., subjects were randomly assigned to either younger or older group) for BA11 and BA47 separately, by which we repeated all of the procedures to collect a null background of the delta values and estimated the empirical P values of each observation against the null background. The age effect on circadian expression patterns between the younger and the older groups were categorized as follows: change in the level of basal expression (Δbase); change in the amplitude of oscillation ($\Delta\text{amplitude}$); change in the acrophase of rhythmicity (Δphase); a loss of rhythmicity typically observed as a disruption of circadian rhythmicity of gene expression oscillation (ΔR^2); and the gain of rhythmicity typically observed as a gain of circadian rhythmicity of gene expression oscillation (ΔR^2). These categories are not mutually exclusive except for the loss and gain of rhythmicity. Note that the comparison of ΔR^2 was not limited to rhythmic or arrhythmic genes in either age group. Any gene that showed significant R^2 decrease or increase (empirical $P < 0.05$) in the older group would be annotated as “loss of rhythmicity” or “gain of rhythmicity,” respectively.

Fig. S1. Overview of analysis flows. (A) Detection of clock-regulated genes in human prefrontal cortex (PFC) via metaanalysis. We first estimated the P values of expression rhythmicity for all of the genes in brain regions BA11 and BA47 independently. Then we combined these P values to meta- P values via AW-Fisher and corrected them into q values. A total of 235 cross-region PFC circadian genes were detected at $q < 0.05$. (B) Detection of age effect on circadian expression rhythmicity. The work flow was independent from A; i.e., the analysis in B did not rely on any *a priori* results yielded in A. It is possible that a gene shows expression rhythmicity only in younger individuals but not in older individuals (or could be vice versa). Therefore, if younger subjects were mixed with older subjects (e.g., when all 146 subjects were included as how we did in A), we might be unable to detect the expression rhythmicity of certain genes (see Fig. S4 for such examples).

Age	
count	146
mean	50.67
std	15.30
min	16
25%	42.25
50%	52.50
75%	59.75
max	96



Base shift		Amplitude change		Phase shift		Loss of rhythmicity	Gain of rhythmicity
Gene	Direction	Gene	Direction	Gene	Direction	Gene	Gene
ANKRD55	↓ -0.32	C1orf51	↓ -0.29	BACE2	Advance	SIK2	HABP2
TRIB2	↓ -0.28			C1orf51	Advance	SPATA2L	CPLX1
THRA	↓ -0.08			PER2	Advance	BACE2	C15orf44
KCNH4	↓ -0.20			SPRY4	Advance	KCTD12	MARCH3
PER1	↑ 0.13			USP2	Advance	RNF115	PECAM1
SPRY4	↓ -0.21			TRIB2	Advance	PDE7B	CCDC14
				PER1	Advance	VGF	
				NR1D1	Advance	LAPTM5	
				ANKRD55	Advance	CTNNAL1	
				KCNH4	Advance	CD34	
						IFNGR1	
						PER1	
						KIAA1549	
						CTNND1	
						ADRA1B	
						ISLR2	
						C1orf51	
						SMPD3	
						HPGDS	

Fig. S4. List of detected age effects on 235 PFC circadian genes in BA11. Upward arrow represents rise of circadian expression rhythmicity base in the older. Downward arrow represents drop of base or decrease of amplitude in the older. Phase advance means the peak hour of circadian expression rhythmicity comes earlier in the older. See Dataset S2 for full table.

Base shift		Amplitude change		Phase shift		Loss of rhythmicity	Gain of rhythmicity
Gene	Direction	Gene	Direction	Gene	Direction	Gene	Gene
TRIB2	↓ -0.37			MGC42105	Advance	PER1	RSPH1
MAPK4	↓ -0.15			KIAA1310	Advance	HERC5	SLC39A14
SPRY4	↓ -0.27			TRIB2	Advance	PDE7B	USP2
BHLHE41	↑ 0.16			BHLHE40	Reverse	IGFBP4	HR
ARNTL	↓ -0.16			C5orf51	Advance	SLCO2A1	PHTF2
DBP	↓ -0.18			NR1D1	Advance	SIK2	SHISA6
BHLHE40	↑ 0.17			SPRY4	Advance	SH3GL3	SIGLECP3
KCNH4	↓ -0.17			PER2	Advance	KIAA0776	
				C1orf51	Advance	CEP57	
				DUSP4	Advance	FBXO40	
				MAPK4	Delay	MDGA1	
						HABP2	
						RARA	
						KIAA1549	
						CD34	
						SESN3	
						LDB1	
						ANKRD55	
						MARCH7	
						OPRL1	

Fig. S5. List of detected age effects on PFC circadian genes in BA47. Upward arrows and downward arrows represent rise and drop of circadian expression rhythmicity base in the older, respectively. No instance was found with significant amplitude change. Phase advance means the peak hour of circadian expression rhythmicity comes earlier in the older. Phase delay means the peak hour comes later in the older. Phase reverse means the difference of peak hours between the younger and the older groups is nearly 12 h. See Dataset S3 for full table.

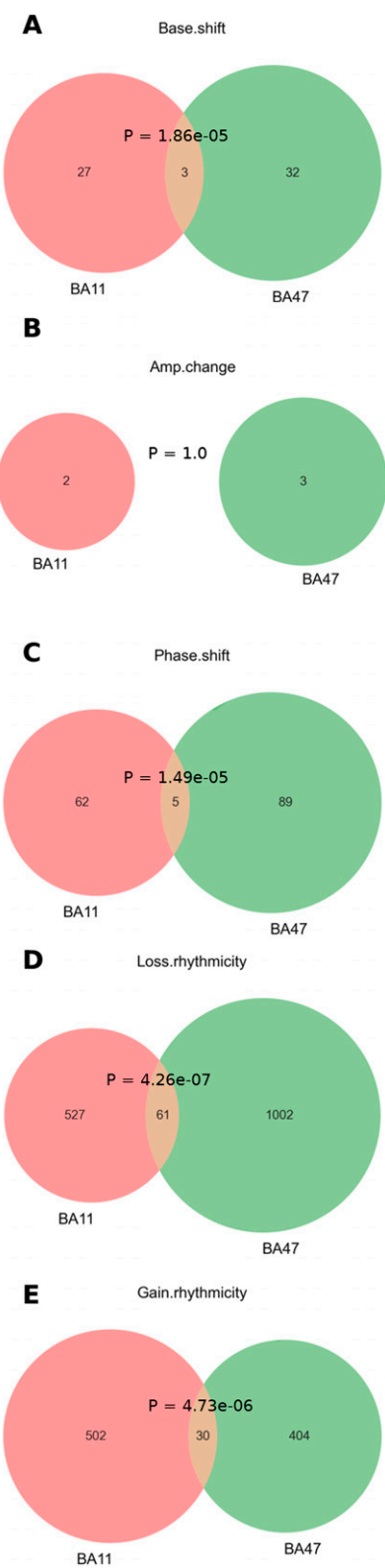


Fig. S6. Venn diagram of gene numbers in each age effect category between BA11 and BA47. Only those genes with $P < 0.05$ in each category were counted here (Datasets S2 and S3). See also Dataset S4 for complete lists. Shown are interactions between BA11 and BA47 in genes that show (A) base shift, (B) amplitude change, (C) phase shift, (D) loss of rhythmicity, or (E) gain of rhythmicity.

Category	Base shift	Amp change	Phase shift	Loss of rhythmicity	Gain of rhythmicity
Base shift		n=0 (P=1.0)	n=25 (P=8.25e-60)	n=1 (P=5.87e-01)	n=1 (P=5.51e-01)
Amp change	n=1 (P=6.9e-03)		n=2 (P=1.08e-05)	n=2 (P=8.34e-04)	n=0 (P=1.0)
Phase shift	n=30 (P=1.83e-67)	n=3 (P=3.87e-07)		n=6 (P=1.31e-02)	n=1 (P=1.0)
Loss of rhythmicity	n=1 (P=1.0)	n=0 (P=1.0)	n=5 (P=8.19e-01)		n/a
Gain of rhythmicity	n=0 (P=1.0)	n=0 (P=1.0)	n=0 (P=2.73e-01)	n/a	

Fig. S7. Co-occurrence of age effects on circadian expression rhythmicity. Shown in each cell is the number of co-occurrence and the associated *P* value (by Fisher's exact test) between every two age effect categories. Note that the loss of rhythmicity and the gain of rhythmicity are two mutually exclusive categories by definition. Color code: blue cells, cases in BA11; green cells, cases in BA47.

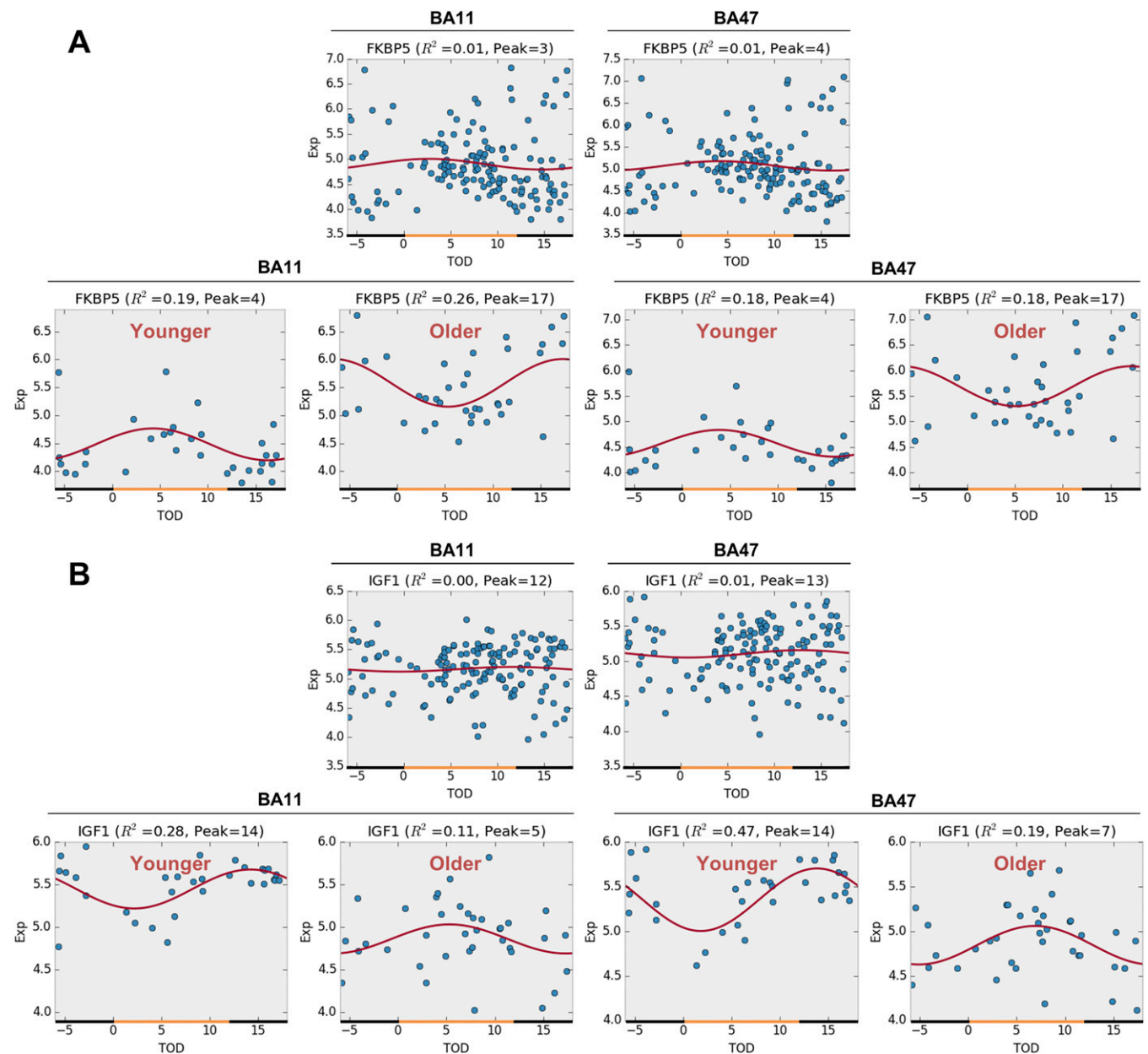


Fig. S8. Rhythmicity expression profiles before and after age stratification. (A) FKBP5. (B) IGF1. (Upper) Before age stratification ($n = 146$). (Lower) After age stratification ($n = 31$ in younger and $n = 37$ in older).

Table S1. Cohort demographic and clinical information

HU	Age	PMI	pH	RIN	Sex	Race	Cause	Manner	TOD
510	63	12.4	6.5	7.5	M	W	Gastrointestinal bleeding	Natural	−5.83
516	20	14	7.1	8.4	M	B	Gunshot wound to chest	Homicide	16.66
545	65	13.1	6.9	6.2	M	B	Pancreatic carcinoma with pulmonary metastasis	Natural	14.90
546	37	23.5	6.7	8.6	F	W	ASCVD	Natural	6.07
551	61	16.4	6.6	8.3	M	W	Cardiac tamponade	Natural	11.35
567	46	15	6.8	8.9	F	W	Mitral valve prolapse	Natural	14.11
568	60	9.5	6.9	8.7	F	W	ASCVD	Natural	−5.47
575	55	11.3	6.8	9.6	F	B	ASCVD	Natural	15.78
585	26	16	6.7	8.3	M	W	Trauma	Accidental	15.60
604	39	19.3	7.1	8.6	M	W	Hypoplastic coronary artery	Natural	9.27
615	62	7.2	6.4	7.8	M	W	Ruptured abdominal aortic aneurysm	Natural	−3.38
627	43	14.1	7.1	7	F	B	Chronic obstructive pulmonary disease	Natural	14.62
630	65	21.2	7	9	M	W	ASCVD	Natural	6.39
634	52	16.2	7	8.5	M	W	ASCVD	Natural	13.54
643	50	24	6.2	8	M	W	ASCVD	Natural	4.34
645	69	23	6.7	8	M	W	ASCVD	Accidental	4.91
681	51	11.6	7.2	8.9	M	W	Hypertrophic cardiomyopathy	Natural	16.00
688	55	21.5	7	7.2	M	W	Hypertrophic cardiomyopathy	Natural	7.61
694	38	20.7	7	7.7	M	W	Subarachnoid hemorrhage	Natural	8.95
700	42	26.1	7	8.7	M	W	ASCVD	Natural	3.64
704	70	20.6	7	8.7	M	W	ASCVD	Natural	10.56
727	19	7	7.4	9.2	M	B	Multiple trauma	Accidental	−2.83
731	63	10.5	6.8	8.2	F	W	ASCVD	Natural	−4.11
737	66	18.2	7.3	7.5	M	W	ASCVD	Natural	10.81
739	40	15.8	6.9	8.4	M	W	ASCVD	Natural	11.25
746	64	20.8	6.7	7.6	F	B	Peritonitis	Natural	7.90
784	58	5.5	7.1	9.1	M	W	ASCVD	Natural	−2.70
794	52	20	6.8	8.4	M	B	End-stage dilated cardiomyopathy	Natural	6.68
795	68	11.8	6.8	8.2	M	W	Ruptured abdominal aortic aneurysm	Natural	15.13
806	57	24	6.9	7.8	M	W	Pulmonary embolism	Natural	4.31
812	55	23	6.7	8.5	M	W	ASCVD	Natural	4.37
818	67	24	7.1	8.4	F	W	Anaphylactic reaction to cef0tan	Accidental	5.35
825	59	16.9	7.1	7.8	M	W	Cardiac tamponade	Natural	12.60
838	58	16.5	7	8.5	M	W	ASCVD	Natural	12.43
839	74	5.3	7.1	8.9	F	W	Massive BFT	Accidental	−1.15
840	41	15.4	6.8	9.1	F	W	ASCVD	Natural	13.97
841	70	22.3	7.2	7.2	M	W	Hypertrophic cardiomyopathy	Natural	7.69
855	62	11.5	6.7	8.4	M	B	Hypertrophic cardiomyopathy	Natural	17.28
857	48	16.6	6.7	8.9	M	W	ASCVD	Natural	10.13
866	66	12.2	7	8.5	M	W	ASCVD	Natural	15.24
869	51	6.5	7.2	8.9	M	W	Severe ASCVD	Natural	−3.46
871	28	16.5	7.1	8.5	M	W	Trauma (chest)	Accidental	12.04
895	39	15.4	7.6	8.8	M	W	ASCVD	Natural	14.25
902	60	23.6	6.7	7.7	M	W	ASCVD	Natural	4.45
920	60	23	7.2	8.5	M	W	ASCVD	Natural	3.93
932	68	25.9	6.8	8.3	M	W	Cardiac tamponade	Natural	2.23
952	62	5.5	6.6	8.7	M	W	ASCVD	Natural	4.08
953	54	18.6	6.2	7.1	M	W	Extensive BFT (head, torso, and limbs)	Accidental	9.38
969	27	10.6	7	7.7	M	W	Trauma to trunk and extremities	Accidental	−4.91
970	42	25.9	6.4	7.2	M	W	ASCVD	Natural	4.38
972	72	16.4	6.3	7.7	M	W	Trauma (cervical/upper thoracic vertebra)	Accidental	11.71
980	52	11	6.4	8.3	M	W	ASCVD	Natural	−5.96
998	25	6.3	5.9	7.6	M	W	Pulmonary thromboembolism	Natural	2.24
1026	59	19.8	6.3	7.4	M	W	ASCVD	Natural	9.64
1030	96	13.2	6.3	6.8	F	W	Fractured cervical spinal column	Accidental	16.16
1031	53	23.2	6.8	8.9	M	W	Arteriosclerotic and hypertensive CVD	Natural	6.71
1038	56	14.6	6.5	7	M	W	Rupture of dissecting hematoma of aorta	Natural	14.64
1047	43	13.8	6.6	9	M	W	ASCVD	Natural	15.15
1054	44	17.1	6.6	8.8	F	W	ASCVD	Natural	10.20
1065	85	20.2	6.3	7.1	M	B	Pulmonary embolism	Accidental	7.32
1067	49	6	6.6	8.2	M	W	Hypertensive heart disease	Natural	−1.95
1083	20	19.9	6.6	8.8	M	W	Trauma (head and trunk)	Accidental	9.20
1091	58	16.5	6.6	8.1	M	W	ASCVD	Natural	6.67

Table S1. Cont.

HU	Age	PMI	pH	RIN	Sex	Race	Cause	Manner	TOD
1092	40	16.6	6.8	8	F	B	Mitral valve prolapse	Natural	11.81
1099	24	9.1	6.5	8.6	F	W	Cardiomyopathy not otherwise specified	Natural	1.37
1103	89	22.9	6.8	7.8	M	W	BFT of head and trunk	Accidental	8.12
1108	60	23.3	6.3	8.1	M	W	ASCVD	Natural	6.92
1114	29	11.4	6.8	9.4	F	W	Trauma (trunk)	Accidental	-5.57
1119	57	20.2	6.8	8	M	W	ASCVD	Natural	8.62
1122	55	15.4	6.7	7.9	M	W	Cardiac tamponade	Natural	13.18
1129	54	21	6.8	9	M	W	ASCVD	Natural	7.91
1141	54	19.2	6.6	8.5	M	W	Arteriosclerotic and hypertensive CVD	Natural	9.48
1142	44	12.3	5.8	6.1	M	B	Hypertensive and arteriosclerotic CVD	Natural	15.98
1144	75	21.4	6.7	7.3	M	W	Arteriosclerotic and hypertensive CVD	Natural	7.75
1153	55	28	6.6	8	M	W	Atherosclerotic and hypertensive heart disease	Natural	3.69
1159	51	16.7	6.5	7.6	M	W	Hypertensive heart disease	Natural	11.81
1165	67	21	6.6	7.5	F	W	Cardiac tamponade	Natural	10.49
1171	56	19.2	6.5	8.5	M	W	Cardiac tamponade	Natural	8.55
1172	52	16.8	6.5	7.7	F	B	Hypertensive heart disease	Natural	11.79
1191	59	19.4	6.2	8.4	M	B	Atherosclerotic and hypertensive heart disease	Natural	9.24
1193	31	12.8	6.5	7.6	M	W	Myocardial infarction due to ASCVD	Natural	15.64
1194	27	16.4	6.4	8.8	M	W	ASCVD	Natural	12.63
1196	36	14.5	6.4	8.2	F	W	Positional asphyxia	Accidental	17.15
1201	52	16.4	6.2	8.1	F	W	ASCVD	Natural	12.51
1212	49	9.2	6.6	8.2	M	B	Massive subarachnoid hemorrhage	Natural	-4.42
1214	57	16.4	6.4	7.5	M	W	Arteriosclerotic and hypertensive CVD	Natural	12.56
1219	56	14.9	6.5	8.5	M	W	ASCVD	Natural	14.77
1237	64	8.7	6.4	7.7	M	W	ASCVD	Natural	0.70
1239	22	9.5	6.7	7.4	M	W	BFT to the head and neck	Accidental	-5.42
1245	59	21.6	6.6	7.4	M	W	ASCVD	Natural	7.37
1247	58	22.7	6.4	8.4	F	W	ASCVD	Natural	8.46
1264	38	21.1	6.7	8.6	M	W	Cardiomyopathy	Natural	5.60
1270	73	19.7	6.7	7.7	F	W	BFT of neck and trunk	Accidental	8.62
1276	57	14.9	6	6.1	F	W	Arteriosclerotic CVD	Natural	13.90
1280	50	23.5	6.7	7.7	F	W	Pulmonary thromboembolism	Natural	3.95
1288	59	19.7	6.9	7.4	M	W	Atherosclerotic and hypertensive heart disease	Natural	9.49
1293	65	18.5	6.6	7	F	W	BFT of trunk	Accidental	11.51
1298	48	24.5	6.8	7.9	M	W	ASCVD	Natural	4.78
1300	56	16.5	6	6.9	F	W	Pulmonary thromboembolism	Natural	13.22
1306	18	16	6.6	7.9	M	W	Congenital heart anomaly	Natural	13.54
1307	32	4.8	6.7	7.6	M	B	Hypertensive cardiomyopathy	Natural	4.03
1308	58	20.2	6	6.2	M	W	Hepatocellular carcinoma	Natural	8.43
1317	56	22.9	6.5	8.8	M	W	Arteriosclerotic and hypertensive CVD	Natural	4.80
1326	58	16.4	6.7	8	M	W	ASCVD	Natural	13.47
1333	46	18.2	6.8	8.7	M	W	Arteriosclerotic and hypertensive CVD	Natural	10.65
1335	18	14.6	7	8.7	M	W	BFT of head and trunk	Accidental	16.06
1350	21	24.2	6.4	7.3	M	W	BFT of trunk	Accidental	6.62
1371	33	13	6.2	8.5	M	B	Eosinophilic myocarditis	Natural	-5.61
1374	43	21.7	6.6	7.2	M	W	Coronary atherosclerotic disease	Natural	7.91
1378	53	20.1	6.5	7.8	F	B	Coronary artery disease	Natural	8.46
1382	73	25.3	6.6	7.9	F	W	BFT of head with ponto-midbrain transection	Accidental	2.87
1391	51	7.8	6.6	7.1	F	W	Atherosclerotic coronary artery disease	Natural	-0.59
1394	45	17.3	6.6	7.3	M	W	Atherosclerotic coronary artery disease	Natural	10.12
1400	50	16	5.8	6.8	M	W	Coronary atherosclerotic disease	Natural	11.40
1410	54	15.3	6.9	7.8	M	W	Atherosclerotic coronary artery disease	Natural	13.11
1433	65	24.1	6.8	7.5	M	W	Acute subdural hematoma with skull fracture	Accidental	7.18
1434	25	25.5	6.7	7.5	M	B	Cardiac arrhythmia while exercising	Natural	5.35
1441	57	22.3	6.5	8.5	M	W	Arteriosclerotic CVD	Natural	7.88
1444	46	22	6.5	8.4	M	W	Pulmonary thromboembolus	Natural	5.25
1447	51	16.2	6.5	8.5	M	W	Calcified atherosclerotic coronary artery disease	Natural	15.53
1460	53	21.3	6.2	7.3	M	W	Severe ASCVD	Natural	6.28
1462	47	17.2	6.6	8.5	M	W	ASCVD	Natural	10.58
1466	64	20	6.7	8.8	F	B	BFT to trunk	Accidental	9.33
1482	25	20.2	6.6	9.1	M	W	ASCVD	Natural	8.26
1488	39	21.5	6.4	8.7	M	B	Bilateral pulmonary thromboemboli	Natural	6.38

Table S1. Cont.

HU	Age	PMI	pH	RIN	Sex	Race	Cause	Manner	TOD
1497	38	8.5	6.3	9.1	M	W	ASCVD	Natural	−2.80
1511	48	23.5	6.8	7.2	M	W	Severe ASCVD	Natural	4.30
1514	60	25	6.4	6.6	F	W	Bilateral pulmonary emboli	Natural	2.91
1524	66	9.4	6.4	8.1	M	W	Acute small intestinal ischemic infarction	Natural	−4.21
1541	80	10.5	6.5	8	M	W	Pulmonary fibrosis	Natural	17.40
1554	50	23.2	6.5	7.6	M	W	Acute myocardial infarction	Natural	7.67
1555	17	15.1	6.9	7.9	M	W	BFT to head, thorax, abdomen, right	Accidental	16.70
1558	54	24.4	6.9	7.7	M	W	ASCVD	Natural	4.60
1559	45	8.9	6	6.9	M	W	Cardiomegaly	Natural	−1.66
1564	48	19.9	6.8	7.5	M	W	BFT to trunk	Accidental	8.99
1574	52	26.7	6.3	7	M	W	Bilateral pulmonary embolism	Natural	2.07
1583	58	19.1	6.8	8.2	M	W	BFT of the trunk	Accidental	9.10
1598	50	23.8	6.9	7.8	M	W	Acute myocardial infarction	Natural	10.12
1623	52	25.7	6.3	6.6	M	W	BFT of head and neck	Accidental	4.86
1637	46	16.6	6.9	8.2	M	W	Coronary artery atherosclerosis	Natural	15.86
10003	49	21.2	6.5	8.4	M	W	Multiple blunt force injuries	Accidental	9.82
10005	42	23.5	6.7	7.4	M	W	Multiple blunt force injuries	Accidental	7.43
10013	16	9.3	6.7	9	F	W	Trauma (multiple blunt force injuries)	Accidental	−3.88
10016	18	16.3	6.8	5.9	M	B	Gunshot wound of abdomen	Homicide	15.46
10021	38	12.7	6.3	7.2	M	W	Multiple blunt force injuries	Accidental	16.86
10027	53	13.1	6.2	6.6	F	B	Congestive heart failure	Natural	17.13

ASCVD, atherosclerotic cardiovascular disease; B, African American; BFT, blunt force trauma; CVD, cardiovascular disease; F, female; HU, subject no.; M, male; pH, brain tissue pH; PMI, postmortem interval; RIN, RNA integrity number; TOD, time of death (zeitgeber time); W, Caucasian.

Table S2. Numbers of significant circadian genes across BA11 and BA47 at different q value cutoffs after metaanalysis

Cutoff	No. of genes*	Concordant phase (%) [†]	Average R^2
$q < 0.01$	84	80 (95%)	0.13
$q < 0.05$	235	217 (92%)	0.09
$q < 0.1$	465	411 (88%)	0.07

*The total number of genes is 20,237.

[†]Concordant phase was defined as the difference of peak hour ≤ 4 h between BA11 and BA47.

Table S3. Summary of detected age effects on circadian gene expression patterns in BA11 and BA47

Class	n	Age effects					No effect
		Base shift	Amp change	Phase shift	Loss of rhythmicity	Gain of rhythmicity	
BA11							
PFC circa genes	235	6	1	10	19	6	201
Others	20,002	24	1	57	569	527	18,849
Total	20,237	30	2	67	588	533	19,051
BA47							
PFC circa genes	235	8	0	11	20	7	193
Others	20,002	27	3	83	1,043	427	18,453
Total	20,237	35	3	94	1,063	434	18,646

Note that the age effects are not necessary mutually exclusive. The total numbers of genes with age effects on expression rhythmicity are $20,237 - 19,051 = 1,186$ in BA11 and $20,237 - 18,646 = 1,591$.

Dataset S1. Circadian gene expression patterns

Dataset S1

This spreadsheet file contains the best-fitted circadian curve parameters for all genes in BA11 and BA47 (sheet 1), and also the top 235 PFC circadian genes across BA11 and BA47 (sheet 2). Functional enrichment result using DAVID for the 235 circadian genes can be found in sheet 3.

Dataset S2. BA11 age effects on circadian gene expression rhythmicity[Dataset S2](#)

This spreadsheet file contains five categories of age effects on the circadian gene expression rhythmicity detected from brain tissue BA11.

Dataset S3. BA47 age effects on circadian gene expression rhythmicity[Dataset S3](#)

This spreadsheet file contains five categories of age effects on the circadian gene expression rhythmicity detected from brain tissue BA47.

Dataset S4. Overlaps of genes with detectable age effects on circadian gene expression rhythmicity between BA11 and BA47[Dataset S4](#)

This spreadsheet file contains the overlaps of five categories of age effects on the circadian gene expression rhythmicity between BA11 and BA47.