Visual effort moderates postural cascade dynamics

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26 **Abstract**

27 Standing still and focusing on a visible target in front of us is a preamble to many
 28 coordinated behaviors (e.g., reaching an object). Hiding behind its apparent simplicity is a
 29 deep layering of texture at many scales. The task of standing still laces together activities at
 30 multiple scales: from ensuring that a few photoreceptors on the retina cover the target in the
 31 visual field on an extremely fine scale to synergies spanning the limbs and joints at smaller
 32 scales to the mechanical layout of the ground underfoot and optic flow in the visual field on
 33 the coarser scales. Here, we used multiscale probability density function (PDF) analysis to
 34 show that postural fluctuations exhibit similar statistical signatures of cascade dynamics as
 35 found in fluid flow. In participants asked to stand quietly, the oculomotor strain of visually
 36 fixating at different distances moderated postural cascade dynamics. Visually fixating at a
 37 comfortable viewing distance elicited posture with a similar cascade dynamics as posture with
 38 eyes closed. Greater viewing distances known to stabilize posture showed more diminished
 39 cascade dynamics. In contrast, nearest and farthest viewing distances requiring greater
 40 oculomotor strain to focus on targets elicited a dramatic strengthening of postural cascade
 41 dynamics, reflecting active postural adjustments. Critically, these findings suggest that vision
 42 stabilizes posture by reconfiguring the prestressed poise that prepares the body to interact
 43 with different spatial layouts.

44 **Keywords:** center of pressure; ergonomics; inverse power law; multiscale PDF; postural
 45 control; quiet stance

46 1. Introduction

47 Standing still and visually fixating on a target in front of us is a seemingly simple task.
 48 However, hiding within this apparent simplicity is a deep layering of texture at many scales.
 49 On an extremely fine-scale, task completion depends only on ensuring that a few
 50 photoreceptors on the retina cover the entire target in the visual field. Standing still and
 51 visually fixating at much coarser scales rests on the mechanical layout of the ground
 52 underfoot and optic flow in the visual field before you. Between optic flow and mechanical
 53 layout, standing still relies on synergies spanning the limbs and joints at smaller scales and
 54 subtle postural perturbations, triggering reflex arcs and muscle twitches, at yet smaller scales.
 55 The task of standing still and visually fixating laces together activities at these multiple scales,
 56 entailing a close connection among events of widely varying scales, from whole-body postural
 57 fluctuations at large scales, to head sway and eye movements at medium scales, and
 58 photoreceptor activity at the finest scales [1–3]. Consequently, the postural center of pressure
 59 (CoP) fluctuations—which directly relate to sway—exhibit similar statistical signatures of
 60 cascade dynamics as found in fluid flow [4]. The metaphor of ‘cascades,’ as in tumbling water
 61 that accelerates and splashes down a rockface, captures some critical aspects of the
 62 dynamics of emergent behavior [5–7]. Destabilizing posture emphasizes the postural cascade
 63 dynamics [8,9]. Here, we propose that perturbing the visual system has a similar effect of
 64 strengthening postural cascade dynamics, in which the optical flow varies with fixation
 65 distance, as a meandering stream joins other streams and gathers momentum into rushing
 66 rapids, becoming more turbulent along the way. Whereas multiscale entropy addresses the
 67 difference of variation across different scales [10,11], cascade dynamics explicitly implicates
 68 nonlinear interactions lacing these scales together.

69 Visually guided posture presents a curious case in which light entails mechanical
 70 change in bodily center of mass [12–17]. Beyond minuscule photoreceptor responses, large-
 71 scale layout of visible surfaces supports optic flow with bodily sway. Optic flow is the
 72 expansion, contraction, or rotation of visible surfaces as the body moves forward or
 73 backward, or turns to the side, respectively. Relative accelerations of visible surfaces provide
 74 the standing participant with rich information about the layout of objects. Placing a fixation
 75 target at different viewing distances perturbs the optic flow: changing the relative
 76 accelerations of visible surfaces as well as imposing retinal-specific constraints of oculomotor
 77 convergence (i.e., higher oculomotor strain in specific or visual effort in general) [18,19],
 78 prompting new head- and torso-sway (Fig. 1). Indeed, optic flow relies on nesting of behaviors
 79 across the aforementioned range of scales, including the organism nested in the task
 80 environment at the largest scale right down to the hierarchical organization of photoreceptor
 81 response of optic flow at the finest scale [3]. Comfortable viewing distances (50-100cm)
 82 requiring least oculomotor strain should most resemble posture with eyes closed [20,21].
 83 Medium viewing distances beyond most-comfortable viewing in the range of 200 cm stabilize
 84 posture [22]. Extremely distant or extremely near targets will be harder to focus on and have a
 85 much slower or faster optic flow, respectively, requiring more sway to resolve the image [23].

86 Testing these hypotheses requires examining the divergence of postural fluctuations
 87 from Gaussian form. Gaussian distributions are classically the result of adding very many
 88 independent (i.e., non-interacting) variables. Interactivity amongst the participating variables
 89 promotes persistent if also intermittent, uneven growth of variance with timescale. Under the
 90 central limit theorem, homogeneity of variance keeps measurements within short, thin tails of
 91 a Gaussian distribution. But intermittent growth in variance manifests in distributions with
 92 longer, heavier tails specifically due to nonlinear temporal correlations [24,25]. Testing these

tails is even more difficult because they are by definition only populated by extreme and relatively rare values. However, fortunately, hydrodynamic-cascade research has yielded an analytical method for estimating non-Gaussianity based on querying better-populated regions of the distribution [26]. Applying this method to physiological measures produces estimates of non-Gaussianity that predict clinical outcomes [27–31] and that change with variation in both endogenous postural control (i.e., unmanipulated factors that respond to but also exert effects upon other variables of the postural system) and exogenous postural demands [8,9]. Here, we used this method to investigate how constraints imposed by visual effort affect postural cascade dynamics. Participants were asked to minimize postural sway while maintaining quiet stance for 120 s in six different viewing conditions: eyes closed and eyes fixated on a point on a screen at a distance of 25, 50, 135, 220, and 305 cm from the eyes. We predicted that postural cascade dynamics while fixating at a 50-cm distance would resemble eyes-closed posture (Hypothesis-1), and that postural cascade dynamics would be weakest while fixating at medium (i.e., 130- and 220-cm) distances (Hypothesis-2) but strongest at extremely near (i.e., 25-cm) and extremely far (i.e., 305-cm) distances (Hypothesis-3).

2. Materials and methods

The present study is a reanalysis of data from a previous study examining postural control in different viewing conditions [32].

2.1. Participants

Seven men and eight women (18–40 years old) participated after providing institutionally-approved informed consent.

2.2. Experimental setup and procedure

Each participant stood barefoot on two force plates (AMTI Inc., Watertown, MA) recording 3D moments and ground reaction forces at 100 Hz—one foot on each plate, 25 cm apart, before a white background spanning his/her visual field (Fig. 1A). A square white screen (5×5 cm) mounted on a tripod was placed at specific distances in front of the participant. From behind the participant, a laser pen projected a static light point on the screen's center.

Each participant experienced six different viewing conditions (eyes-closed and eyes fixated on the screen's light point at a distance of 25, 50, 135, 220, and 305 cm in the front), each three times in randomized order over a single 90-min session. In each trial, each participant was instructed to minimize the postural sway by maintaining visual fixation at the light point projected on the screen for 120 s. Each participant had a 5-min break for rest after every six trials.

2.3. Data processing

All data processing was performed in MATLAB 2019b (Matlab Inc., Natick, MA). Trial-by-trial ground reaction forces yielded a 2D center of pressure (CoP) series, each dimension describing anterior-posterior (AP) and medial-lateral (ML) axes. Each 60-s trial yielded 12000-sample 2D CoP series and 11999-sample 2D CoP displacement series. Finally, a 1D CoP sample-to-sample planar Euclidean displacement (PED) series described postural fluctuations along the transverse plane. Iterated Amplitude Adjusted Fourier Transformation (IAAFT) provided phase-randomized surrogates using original series' spectral amplitudes to preserve only linear temporal correlations [33].

137 2.4. Canonical indices of endogenous postural fluctuations

138 Three linear indices were computed for each CoP PED series: (i) Mean of all
139 fluctuations (CoP_PED_Mean), (ii) Standard deviation (CoP_PED_SD), and (iii) Root mean
140 square (CoP_PED_RMSE).

141 Four nonlinear indices were computed for each CoP PED series: (i) Sample entropy
142 (CoP_PED_SampEn), indexing the extent of complexity in the signal [34], using $m = 2$ and $r =$
143 0.2 [35]. (ii) Multiscale sample entropy (CoP_PED_MSE), indexing signal complexity over
144 multiple timescales [10], using $m = 2$, $r = 0.2$, and $\tau = 20$ [35]. (iii) We used detrended
145 fluctuation analysis [36] to compute Hurst's exponent, H_{fGn} , indexing temporal correlations in
146 original CoP PED series (CoP_PED_ $H_{fGn_Original}$) and shuffled versions of each series
147 (CoP_PED_ $H_{fGn_Shuffled}$) using scaling region: 4, 8, 12,... 1024 [37]. Shuffling destroys the
148 temporal structure of a signal. (iv) Multifractal spectrum width, $\Delta\alpha$, indexing the extent of
149 multifractal temporal correlations in the signal. Chhabra and Jensen's direct method [38] was
150 used to compute $\Delta\alpha$ for original CoP series (CoP_PED_ $\Delta\alpha_{Original}$) and IAAFT surrogate
151 (CoP_PED_ $\Delta\alpha_{Surrogate}$) [6].

152 2.5. Multiscale probability density function (PDF) analysis

153 Multiscale PDF analysis characterizes the distribution of abrupt changes in CoP PED
154 series $\{ b(t) \}$ using the PDF tail. The first step is to generate $\{ B(t) \}$ by integrating $\{$
155 $b(t) \}$ after centering by the mean b_{ave} (Fig. S1A):

$$156 \quad B(t) = \sum_{i=1}^{t/\Delta t} b(i\Delta t) - b_{ave} \quad (1)$$

157 A 3rd order polynomial detrends $\{ B(t) \}$ within k overlapping windows of length $2s$,
158 s being the timescale (Fig. S1B). Intermittent deviation $\Delta_s B(t)$ in k^{th} window from
159 $1+s(k-1)$ to sk in the detrended time series $\{ B^d(t) = B(t) - f_{fit}(t) \}$ is computed as
160 $\Delta_s B^d(t) = B^d(t+s) - B^d(t)$, where $1+s(k-1) \leq t \leq sk$ and $f_{fit}(t)$ is the polynomial
161 representing the local trend of $\{ B(t) \}$, of which the elimination assures the zero-mean
162 probability density function in the next step (Fig. S1C). Finally, $\Delta_s B$ is normalized by the
163 SD (i.e., variance is set to one) to quantify the PDF.

164 To quantify the non-Gaussianity of $\Delta_s B$ at timescale s , the standardized PDF
165 constructed from all the $\Delta_s B(t)$ values is approximated by the Castaing model [26], with
166 λ_s as a single parameter characterizing the non-Gaussianity of the PDF. λ_s is estimated
167 as

$$168 \quad \lambda_s^2 = \frac{2}{q(q-2)} [\ln(\sqrt{\pi} \langle |\Delta_s B|^q \rangle) + \ln \Gamma(\frac{q+1}{2}) - \frac{q}{2} \ln 2] \quad (2)$$

169 where $\langle |\Delta_s B|^q \rangle$ denotes an estimated value of q^{th} order absolute moment of $\{ \Delta_s B \}$. As
170 λ_s^2 increases, the PDF becomes increasingly peaked and fat-tailed (Fig. S2A). λ_s^2 can
171 be estimated by Eq. (2) based on q^{th} order absolute moment of a time series independent
172 of q . Estimating λ_s^2 based on 0.2th moment ($q = 0.2$) emphasizes the center part of
173 the PDF, reducing the effects of extreme deviations due to heavy-tails and kurtosis. We used
174 0.2th moment because estimates of λ_s^2 for a time series of ~ 12000 samples are more
175 accurate at lower values of q [39].

Cascade-type multiplicative processes yield the inverse relationship $\lambda_s^2 \sim -\log s$ (Fig. S2B) [29]. For the present purposes, we quantified λ_s^2 for each original CoP PED series and corresponding IAAFT surrogate at timescales 5 to 1000 samples (i.e., 50 ms to 10 s) at steps of 5 samples (50 ms).

We used Akaike Information Criterion (AIC) weights obtained via the maximum likelihood estimation (MLE) to determine whether the PDF at each timescale was a power law, lognormal, exponential, or gamma distribution. We include this analysis also to show how AIC-based MLE sensitivity to lognormal-like heavy tails differs from multiscale PDF sensitivity to the bulk of the distribution.

2.6. Statistical analysis

A linear mixed-effect (LME) model using lmer [40] in R package *lme4* tested λ_s^2 vs. log-timescale curves for orthogonal linear and quadratic polynomials, for interactions with grouping variables (Viewing condition $\times$ Original, where Original encoded differences in original series from surrogates) and with indices of endogenous postural fluctuations (Section 2.4.). Statistical significance was assumed at the alpha level of 0.05 using R package *lmerTest* [41]. To test how lognormality changed with log-timescale, a generalized linear mixed-effect (GLME) fit changes in Lognormality as a dichotomous variable using orthogonal linear, quadratic, and cubic polynomials and tested interaction effects of grouping variables (Viewing condition $\times$ Original) with those polynomials using glmer [42] in *lme4*.

3. Results

The eyes-closed condition elicited nonlinearity in non-Gaussianity with log-timescale, showing a stronger linear increase in λ_s^2 up to the timescale of roughly 75 samples or 750 ms ($B = 0.95$, $P = 0.031$) and a stronger negative quadratic, downward-facing parabolic form ($B = -3.78$, $P < 0.001$) for the original CoP PED series than the surrogates (Table S1; Fig. 3A). Fixating at 25 and 305 cm elicited a stronger linear increase ($B = 2.43$, $P < 0.001$; and $B = 3.09$, $P < 0.001$, respectively) in the 25- and 305- cm viewing conditions while reversing the downward-facing parabolic form of the eyes-closed condition more weakly ($B = 4.42$, $P < 0.001$; and $B = 1.85$, $P = 0.003$, respectively) of λ_s^2 vs. log-timescale curves (Figs. 3B and 3F). Fixating the eyes at 135 and 220 cm elicited a reversal of linear ($B = -2.98$, $P < 0.001$; and $B = -2.32$, $P < 0.001$, respectively) and downward-facing parabolic forms ($B = 1.81$, $P = 0.004$; and $B = 2.00$, $P = 0.001$, respectively) of λ_s^2 vs. log-timescale curves in Figs. 3D and 3E. In contrast, fixating at 50 cm neither affected the linear form ($B = -0.09$, $P = 0.879$) nor the downward-facing parabolic form ($B = 0.73$, $P = 0.244$; Fig. 3C). Thus, the λ_s^2 vs. log-timescale curves differ between the eye-closed condition and all the eyes-open conditions except the eyes-fixated-at-50-cm condition. Furthermore, whereas the 50- and 305-cm viewing conditions show significant growth of the λ_s^2 vs. log-timescale curves, the 135- and 220-cm viewing conditions exhibit significant decay of this curve with scale.

All indices, except sample entropy of postural fluctuations, showed predictive effects on λ_s^2 . λ_s^2 decreased with increases in root mean square, and increased with increases in mean, standard deviation, and multiscale entropy of postural fluctuations (Table S2). Nonetheless, greater 'original-minus-shuffled/surrogate' differences in fractality and

multifractality diminished λ_s^2 . Hence, evidence of multifractality with weak difference from the surrogates suggests heavy-tailed distributions and thus non-Gaussianity [30,31].

Interactions of these indices with linear and quadratic terms in the first model significantly improved the model fit ($\chi^2_{315} = 153961$, $P < 0.001$; Table S2). Most variability in the quadratic form of the λ_s^2 vs. log-timescale curves depended on these indices, as all but two of 41 significant ($P < 0.05$) quadratic effects relate to interactions of these indices with log-timescale. That is, the parabolic tempering of non-Gaussianity across viewing conditions depended on endogenous postural control. A cubic polynomial improved model fit ($\chi^2(120) = 2061.8$, $P < 0.001$), reflecting 17 significant interactions with the cubic effect, but left all lower-order terms unchanged in coefficients and significance (Table S3).

Postural instability typically weakens the growth of lognormality in postural fluctuations with log-timescale [8,9]. The original CoP PED series exhibited less lognormality than the surrogates ($B = -4.28$, $P < 0.001$; Table S4; Fig. 4). Lognormality grew with log-timescale: a linear increase ($B = 2219.40$, $P = 0.016$), quadratic decrease ($B = -1678.38$, $P = 0.052$), and cubic increase ($B = 559.57$, $P = 0.051$) in the original CoP PED series than the surrogates. However, polynomial profiles of the growth of lognormality with log-timescale did not differ among the conditions. Hence, observed differences in the λ_s^2 vs. log-timescale curves reflect differences in the bulk of the postural-fluctuations distributions rather than in the tail.

4. Discussion

Visual effort moderates postural cascade dynamics, given that standing still and visually fixating at shorter and longer distances unleashed stronger cascade dynamics than standing still (Hypothesis-3) and visually fixating at an optimal distance or standing still without visually fixating (i.e., with eyes closed; Hypotheses-1 & 2). Importantly, these effects are not reducible to the mere availability of visual information, as standing still and visually fixating at an optimal distance and standing still with eyes closed showed similar, if not identical cascade dynamics. Nor is this effect reducible to postural stability, as the growth of lognormality in postural fluctuations with timescale did not depend on the viewing condition. Instead, these effects reflect endogenous postural control, as known indices of endogenous postural fluctuations moderated the effect of viewing condition on postural cascade dynamics. In short, the moderating of postural cascade dynamics by visual effort is an endogenous phenomenon that is difficult to counteract.

Past work has shown that variability in postural fluctuations is reduced when visually fixating at near as opposed to distant targets [12,13,22], an effect that has been directly attributed to the precision demands of viewing distance [32]. The present finding significantly adds to this work by showing that this effect is not linear. Visually fixating at too-close and too-far targets may introduce ambiguity between sway and optic flow: too-close targets making head-sway more likely to destabilize the posture, and too-far targets might recruit more torso-sway. However, visually fixating at an optimally placed target may resolve this ambiguity as the body courses with fluctuations ferrying information across the body. Furthermore, the stark similarities in the cascade dynamics between standing still and visually fixating at an optimal distance and standing still with eyes closed adds a novel dimension to the family of perception-action couplings in postural control. Postural control does not depend on vision per se. Instead, it depends on how visual information is laced together with activities at multiple

262 scales: subtle fluctuations of the head, torso, and the whole body and photoreceptor support
263 of the target's retinal image.

264 Postural cascade dynamics is rooted in the known physiology. Indeed, the biophysical
265 substrate supporting postural control is imagined as a neurally-tunable bodywide multifractal
266 tensegrity (MFT) network consisting of the connective-tissue net and extra-cellular matrix
267 (ECM) in which components hang together by tensional and compression forces at multiple
268 scales, from micro (e.g., cells and membranes) to macro (e.g., muscles and bones) [43–45].
269 This network cooperates directly and uninterruptedly with the nervous system and exhibits
270 similar cascade-like dynamics as in “neuronal avalanches” [46,47]. It is no small coincidence
271 that tensegrity and avalanche models all converge on multiplicativity [48,49] that inspired
272 multiscale quantification of non-Gaussianity [27–29]. Hence, MFT approaches suggest
273 multiple points of entry through which stimulation elicits cascades to spread across scales—
274 from the surface underfoot [8] to the loads at hand [9] and now from the incoming visual
275 information. As the cascade metaphor entails, multiple scales are not merely coexisting but
276 explicitly interacting, with influences of one spreading to others. If mechanically and visually
277 perturbing posture engender cascade dynamics similarly [8,9], then postural control may
278 emerge from the perceptuomotor sensitivity of specifically multiplicative fluctuations to the
279 environment. The methods introduced here would enable future investigations into how
280 different suprapostural tasks lace together deep texture at very many scales.

281 In short, the present findings suggest that visual perception by no means is a passive
282 function proceeding in parallel to still posture—the poise carried by the body as it stands and
283 looks suggests that moving visual targets nearer or farther brings a reorganization of postural
284 interactions across scales. This standing-and-looking preamble to action brims with dynamic
285 redistributions of tensional and compression forces. Indeed, the participants completed no
286 task beyond standing still and maintaining visual fixation. But these cascades affecting a
287 dynamic balance of forces across the body seem to be essential foundations for how the body
288 reaches out beyond itself to engage with the environment [7,50–52]. So, the present findings
289 show how vision plays not only upon the photoreceptors in the eyes but also across the full-
290 body postural system.

Supplementary material

Table S1. Coefficients of linear mixed-effect (LME) model examining the effect of Viewing condition on λ_s^2 vs. log-timescale curves.

Table S2. Coefficients of LME model examining the effects of Viewing condition on λ_s^2 vs. log-timescale curves for orthogonal linear and quadratic polynomials, for interactions with indices of endogenous postural fluctuations.

Table S3. Coefficients of LME model examining the effects of Viewing condition on λ_s^2 vs. log-timescale curves for orthogonal linear, quadratic, and cubic polynomials, for interactions with indices of endogenous postural fluctuations.

Table S4. Coefficients of generalized linear mixed-effect (GLME) model examining the effect of Viewing condition on the growth of lognormality in postural fluctuations with log-timescale.

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456 **Fig. 1.** Schematic of the task and effects of eye-to-target distance on postural sway. (A) The
 457 suprapostural viewing task of standing quietly with the eyes fixated at a distant visual
 458 element. (B and C) Visual angle gain for short vs. long eye-to-target distances along the
 459 anterior-posterior (AP) and medial-lateral (ML) axes. (D and E) Visual angle gain as a function
 460 of eye-to-target distance for different sway magnitudes. Closer targets increase *AP* sway,
 461 whereas farther targets increase *ML* sway.

Fig. 2. Multiscale PDF characterization of postural fluctuations in a representative participant maintaining quiet stance for 120 s with eyes closed, and eyes fixated at a point at a distance of 25, 50, 135, 220, and 305 cm from the eyes. From to bottom: CoP trajectories along the anterior-posterior (AP) and medial-lateral (ML) axes. CoP PED series. $\{ \Delta_s B(i) \}$ for $s = 0.5, 2, \text{ and } 8$ s. Standardized PDFs (in logarithmic scale) of $\{ \Delta_s B(i) \}$ for $s = 0.5, 2, \text{ and } 8$ s (from top to bottom), where σ_s denotes the SD of $\{ \Delta_s B(i) \}$ for $s = 0.5, 2, \text{ and } 8$ s (from top to bottom), where σ_s denotes the SD of $\{ \Delta_s B(i) \}$.

Fig. 3. Log-timescale dependence of the non-Gaussianity index λ_s^2 . Mean values of λ_s^2 for the participants standing quietly for 120 s in different viewing conditions. (A) Eyes closed. (B) Eyes fixated at 25 cm. (C) Eyes fixated at 50 cm. (D) Eyes fixated at 135 cm. (E) Eyes fixated at 220 cm. (F) Eyes fixated at 305 cm. Vertical bars indicate ± 1 SEM (N = 15). Notice that the λ_s^2 vs. log-timescale curves differ between the eye-closed condition all the eyes-open conditions except the eyes-fixated-at-50-cm condition.

475 **Fig. 4.** Log-timescale dependence of the mean proportion of trials with a lognormal
476 distribution for the participants standing quietly for 120 s in different viewing conditions. (A)
477 Eyes closed. (B) Eyes fixated at 25 cm. (C) Eyes fixated at 50 cm. (D) Eyes fixated at 135 cm.
478 (E) Eyes fixated at 220 cm. (F) Eyes fixated at 305 cm. Vertical bars indicate $\pm 1 SEM$ ($N = 15$).
479 Notice that the polynomial profiles of the growth of lognormality with log-timescale do not
480 differ between the eyes-closed condition and any of the eyes-open conditions.

Fig. S1. Schematic illustration of multiscale probability density function (PDF) analysis. (A) The first step is to generate $\{ B(t) \}$ by integrating $\{ b(t) \}$ after centering by the mean b_{ave} : $B(t) = \sum_{i=1}^{t/\Delta t} b(i\Delta t) - b_{\text{ave}}$. (B) A 3rd order polynomial detrends $\{ B(t) \}$ within k overlapping windows of length $2s$, s being the timescale. (C) Intermittent deviation $\Delta_s B(t)$ in k^{th} window from $1+s(k-1)$ to sk in the detrended time series $\{ B^d(t) = B(t) - f_{\text{fit}}(t) \}$ is computed as $\Delta_s B^d(t) = B^d(t+s) - B^d(t)$, where $1+s(k-1) \leq t \leq sk$ and $f_{\text{fit}}(t)$ is the polynomial representing the local trend of $\{ B(t) \}$, of which the elimination assures the zero-mean probability density function in the next step.

489

490 **Fig. S2.** Schematic illustration of non-Gaussianity index λ_s^2 . (A) The relationship between
 491 λ_s^2 and shapes of PDF plotted in linear-log coordinates for $\lambda_s^2 = 0.9, 0.33$, and 0.13 (from
 492 top to bottom). For clarity, the PDFs have been shifted vertically. As λ_s^2 increases, the PDF
 493 becomes increasingly peaked and fat-tailed. As λ_s^2 decreases, the PDF increasingly
 494 resembles the Gaussian (dashed line), assuming a perfect Gaussian as λ_s^2 approaches 0.
 495 (B) Cascade-type multiplicative processes yield the inverse relationship $\lambda_s^2 \sim -\log s$.