Nested Stochastic Resetting: Nonequilibrium Steady States and Exact Correlations

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Stochastic resetting breaks detailed balance and drives the formation of nonequilibrium steady states. Here, we consider a chain of diffusive processes $x_i(t)$ that interact unilaterally: at random time intervals, the process x_n stochastically resets to the instantaneous value of x_{n-1}. We derive analytically the steady-state statistics of these nested stochastic resetting processes including the stationary distribution for each process as well as its moments. We are also able to calculate exactly the steady-state two-point correlations $\langle x_n x_{n+j} \rangle$ between processes by mapping the problem to one of the ordering statistics of random counting processes. Understanding statistics and correlations in many-particle nonequilibrium systems remains a formidable challenge and our results provide an example of such tractable correlations. We expect this framework will both help build a model-independent framework for random processes with unilateral interactions and find immediate applications, e.g., in the modeling of lossy information propagation.

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Stochastic resetting, the return of a system to a predetermined state at random times, leads to striking departures from conventional stochastic dynamics. At the single-particle level, diffusive motion interposed by resetting events, where the position of the particle is moved instantaneously to one of a predetermined set of sites, is a central model in the study of minimal processes breaking detailed balance due to its simplicity and analytical tractability [1,2]. It has been shown to generically drive the formation of nonequilibrium steady states [3–7] and finds broad relevance in biological processes across length scales as a mechanism for reducing mean-first passage times in target search problems [8–23].

Yet, the role of resetting in many-body systems with interacting particles remains largely unexplored. A small number of recent works have studied the impact that resetting mechanisms can have in a variety of many-particle systems [24–29]. While most studies of resetting in many-body systems focus on global resetting [26], comparatively little is known about local resetting, where particles reset individually and independently rather than simultaneously. Whereas previous work has largely considered standard local resetting applied to otherwise interacting particles systems including aggregation, SSEP, and TASEP, our model introduces interactions mediated directly by the resetting mechanism itself [27]. It was recently reported that resetting events can serve as a way to introduce and control correlations in systems without explicit interactions between processes [25]. Particle systems for which correlations between particles can be calculated exactly remain elusive: these tractable examples provide both physical insight and potential avenues for constructing a more general framework.

Building upon the analytic formalism developed for resetting processes, we introduce in this Letter a novel many-particle model that remains analytically solvable in steady state despite the existence of strong correlations arising from its dynamics. We consider a chain of diffusive processes with unilateral interactions between nearest-neighbors on the chain enforced by a pairwise resetting mechanism. We demonstrate that this is sufficient to generate correlations between particles that are arbitrarily far apart in the chain, calculating exactly the steady-state correlations in particle positions of the form $\langle x_n x_{n+j} \rangle$ by reconstructing the problem as one on the ordering of random counting processes.

Physically, the model describes lossy information propagation: each particle in the chain can be seen as a noisy process which stochastically reads the state of the previous process on the chain, in turn diffusion captures the dynamical "forgetting" of this reading. Inaccuracies would generically accumulate down this chain of processes due to the limited nature of the interactions. This accumulation can have drastic consequences, such as in prion folding [30], where misfolded proteins can act as templates, converting neighbors into the same misfolded state: this error propagation leads to diseases such as Creutzfeldt-Jakob [31]. Similarly, the absence of proofreading in RNA viruses ensures mutation accumulation, directly contributing to their rapid evolution and adaptability [32,33].

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Perhaps the most striking example of this is misinformation propagation in social networks: the embellishment of "fake" news through unsupervised word-of-mouth communication [34,35]. Our model captures how stochastic propagation and internal fluctuations (modeling the decay in memory over time) drive correlated errors in information along such chains.

Nested stochastic resetting—We consider a system of N Brownian particles confined to the real line: $x_n(t) \in \mathbb{R}$ for $n \in \{1, \ldots, N\}$. The diffusive motion of each particle is independent and characterized in each case by the diffusion coefficient D. Each particle is independently subjected to resetting events which occur with rate r in a Poissonian manner. In the event where x_n undergoes a reset at time t, the position of x_n is set to $x_{n-1}(t)$, that is, the instantaneous position of the $(n-1)$th particle in the chain. When particle x_1 resets, it does so to the fixed time-independent distribution of positions $P_0(x)$.

We define the probability distribution for the position of the nth particle as $P_n(x, t) = \mathbb{P}(x_n(t) = x)$. For all $n > 0$, the Fokker-Planck equation describing the evolution of $P_n(x, t)$ takes the form

$$\partial_t P_n(x,t) = D\partial_x^2 P_n(x,t) - rP_n(x,t) + rP_{n-1}(x,t). \qquad (1)$$

The right-hand side consists of both a diffusive term and gain-loss terms stemming from the resetting process. It is straightforward to confirm that the total probability is conserved. For the remainder of this Letter, we assume that $P_0(x)$ has zero mean $x_0 = 0$ and a variance σ_0. Our results can be mapped on to the case of finite x_0 by working with redefined variables of the form $y_n(t) = x_0 + x_n(t)$. In particular, $\langle y_n y_{n+j}\rangle = x_0^2 + \langle x_n x_{n+j}\rangle$.

Nonequilibrium steady-state distributions—We denote the steady-state distribution of particle x_n as $P_n^*(x) = \lim_{t\to\infty} P_n(x,t)$. From the Fokker-Planck equation above, we derive a hierarchy of equations for the distributions $P_n^*(x)$ by solving Eq. (1) at steady state:

$$0 = D\partial_x^2 P_n^*(x) - rP_n^*(x) + rP_{n-1}^*(x). \qquad (2)$$

We define the Fourier transform of a function $f(x)$, which we will denote by $\hat{f}(q)$, and its inverse transform, respectively, as

$$\hat{f}(q) = \int_{-\infty}^{\infty} dx\, f(x) e^{-iqx}, \qquad f(x) = \frac{1}{2\pi}\int_{-\infty}^{\infty} dq \hat{f}(q) e^{iqx}. \qquad (3)$$

Taking the Fourier transform of Eq. (2), we derive an iterative formula for the distribution functions in Fourier space: we define $\alpha = \sqrt{r/D}$ and derive

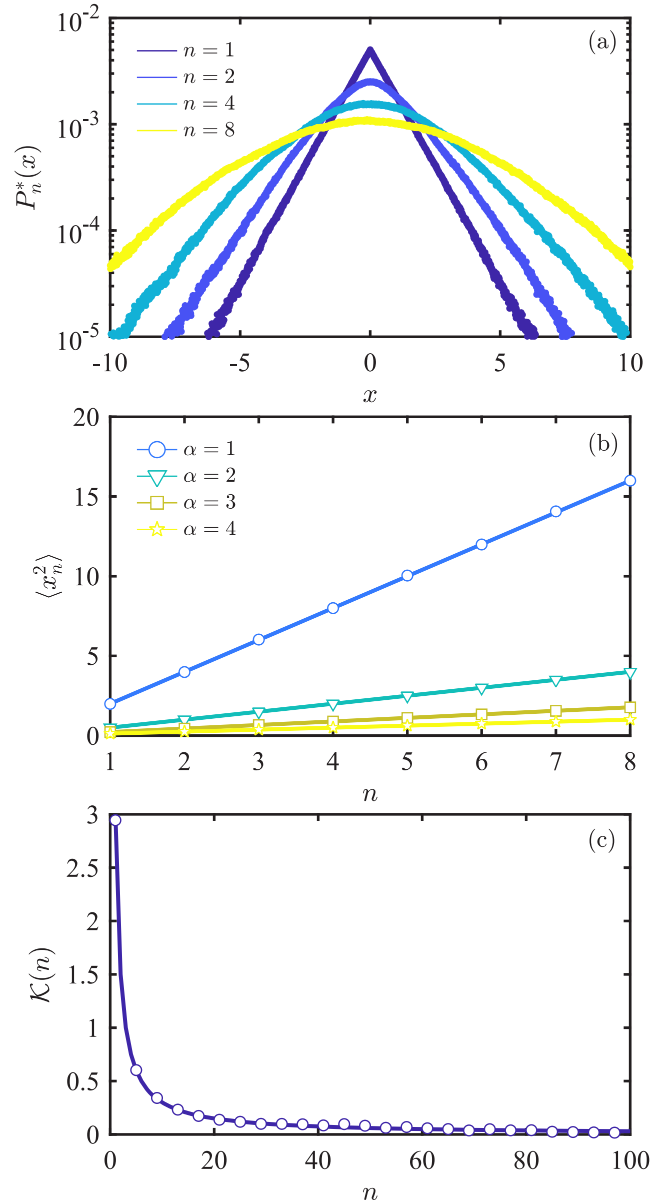

FIG. 1. Nonequilibrium steady-states and positional moments. We compare our analytic results (solid line) for (a) the stationary distribution of particle x_n, $P_n^*(x)$ [see Eq. (6)], and (b) the positional variance of particle x_n position, $\langle x_n^2\rangle$ [see Eq. (9)], to numerical simulations of the microscopic process (symbols), for $n = \{1, 2, 4, 8\}$ demonstrating the validity of our exact result (solid line). (c) Excess kurtosis $\mathcal{K}(n)$ converging to zero in the limit of large n values (solid line—analytics and symbols—numerics).

$$\hat{P}_n^*(q) = \frac{\alpha^2}{q^2 + \alpha^2}\hat{P}_{n-1}^*(q), \qquad (4)$$

which by recurrence leads for all n to

$$\hat{P}_n^*(q) = \hat{P}_0(q)\left(\frac{\alpha^2}{q^2+\alpha^2}\right)^n. \qquad (5)$$

Finally, we derive our result for $P_n^*(x)$ by taking the inverse Fourier transform of $\hat{P}_n^*(q)$ (see Ref. [36] for instance) leading to the following convolution in real-space:

$$P_n^*(x) = \frac{\alpha}{\sqrt{\pi}(n-1)!}\left(\frac{\alpha|x|}{2}\right)^{n-\frac{1}{2}} K_{n-\frac{1}{2}}(\alpha|x|) * P_0(x), \tag{6}$$

where K_m is a modified Bessel function of the second kind. From this, we conclude that for all finite values of n, no matter how large, particles have a well-defined nonequilibrium steady-state distribution with finite variance [see Fig. 1(a)]. We remark that $P_1^*(x)$ is exactly

$$P_1^*(x) = \frac{\alpha}{2}\exp(-\alpha|x|) * P_0(x), \tag{7}$$

which is the stationary distribution known for a particle undergoing Brownian motion with Poissonian resetting to a fixed distribution $P_0(x)$ [1,2]. In what follows, we take $P_0(x) = \delta(x)$ for illustrative purposes, but our results are easily generalizable.

Positional moments—We now calculate the moments of each particle's position. First, we note that the odd moments vanish by symmetry as $x_0 = 0$ and the dynamics are invariant under reflection ($x \to -x$). The remaining moments can be calculated directly from the expressions derived above for the stationary probability distributions.

Calling again on Refs. [36,37] (see Ref. [38] for details), we can derive the following closed-form expressions for the moment of order $2q$ of the nth particle in the nested stochastic resetting process:

$$\langle x_n^{2q}\rangle = \int_{-\infty}^{\infty} dx\, x^{2q} P_n^*(x) = \binom{n+q-1}{n-1}\frac{(2q)!}{\alpha^{2q}}. \tag{8}$$

In particular, the variance of particle x_n takes the form

$$\langle x_n^2\rangle = \frac{2n}{\alpha^2} = n\langle x_1^2\rangle, \tag{9}$$

a surprisingly simple result: the mean squared displacement from the origin grows linearly with the distance along the resetting chain [as can be seen in Fig. 1(b)].

As seen in Fig. 1(a), the steady-state distribution crosses over from double exponential tails to Gaussian tails as n increases. To confirm this, we measure the excess Kurtosis, defined as

$$\mathcal{K}(n) = \frac{\langle x_n^4\rangle}{\langle x_n^2\rangle^2} - 3, \tag{10}$$

and using Eq. (8), we obtain

$$\mathcal{K}(n) = \frac{3}{n}, \tag{11}$$

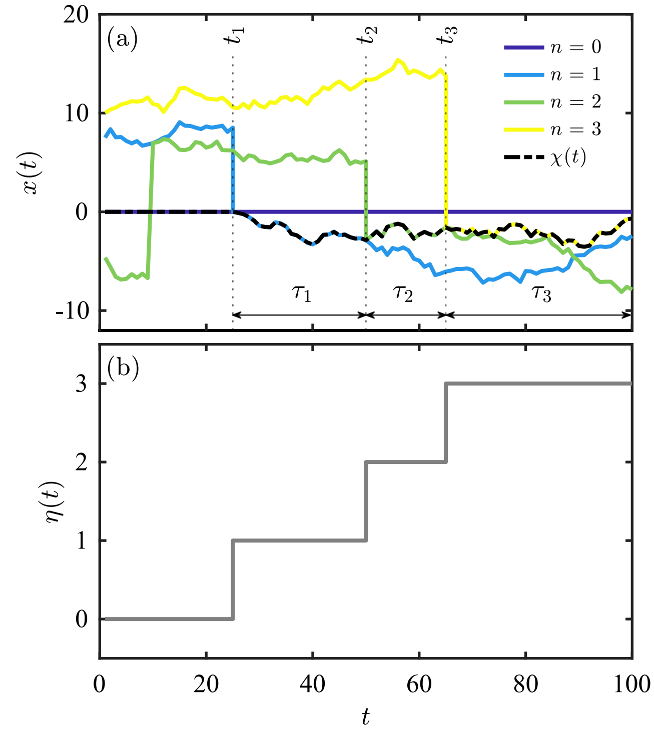

FIG. 2. Mapping to diffusive trajectory. (a) Example realization of the nested resetting process for $N = 3$. The diffusive trajectory $\chi(t)$ constructed from the coupled microscopic dynamics as instructed from Eq. (12) is shown as a black dashed line. (c) The associated index from this trajectory, $\eta(t)$, such that $\chi(t) = x_{\eta(t)}(t)$ for all t.

which shows that the excess Kurtosis indeed converges to 0 when $n \to \infty$ [see Fig. 1(c)]. Note that $\mathcal{K}$ is a measure of non-Gaussianity; indeed, we have $\mathcal{K} \equiv 0$ for a Gaussian distribution. Our results thus imply that the stationary distributions for x_n converge toward a Gaussian distribution with zero mean and variance given by Eq. (9) as n increases.

Static two-point correlation functions—Going further, we now compute exactly the two-point correlations of the form $\langle x_n x_{n+j}\rangle$, where n and j are positive integers. To find an expression for this correlator, we recognize that $x_n(T)$ at some large time T can be understood as the displacement of a purely diffusive particle over n exponentially distributed waiting times. Indeed, at large time T (such that the initial conditions have been forgotten and the system is in its nonequilibrium steady state), we know that x_n last reset to the position of x_{n-1} at some time $t_n = T - \tau_n$, where τ_n is an exponentially distributed random variable with rate r as dictated by the statistics of the resetting mechanism. In the time interval $t \in (t_n, T]$, the motion of $x_n(t)$ is entirely diffusive. At time t_n, we have that $x_n(t_n) = x_{n-1}(t_n)$. Similarly, we can identify a time $t_{n-1} = T - \tau_n - \tau_{n-1}$ (where τ_{n-1} is independent of τ_n but identically distributed) such that the motion of x_{n-1} is entirely diffusive over $t_{n-1} < t \le t_n$. This process can be iterated until reaching

$x_0 = 0$, which happens at time $t_1 = T - \sum_{m=1}^{n} \tau_m$ (see Fig. 2).

Following this procedure, we can construct (for any realization of the resetting events) an entirely diffusive trajectory that originates at 0 and arrives at $x_n(T)$ at time T, which we denote by $\chi(t)$

$$\chi(t) = \begin{cases} 0, & t \leq t_1 \\ x_m(t), & t \in (t_m, t_{m+1}], (1 \leq m \leq n-1) \\ x_n(t), & t \in (t_n, T]. \end{cases} \tag{12}$$

In doing so, we also define the counting process $\eta(\tau)$, which describes the indices associated with the progression of the diffusive trajectory through resetting events:

$$\eta(t) = \begin{cases} 0 & t \leq t_1 \\ m & t \in (t_m, t_{m+1}], (1 \leq m \leq n-1) \\ n & t \in (t_n, T]. \end{cases} \tag{13}$$

Using these definitions, we write $\chi(t) = x_{\eta(t)}(t)$ or equivalently, $x_n(t) = \{\chi(t), \eta(t)\}$. In [38], we show that we can easily rederive results (6) and (8) in this framework.

Now consider the two processes $x_n(t) = \{\chi(t), \eta(t)\}$ and $x_{\bar{n}}(t) = \{\bar{\chi}(t), \bar{\eta}(t)\}$, with $\bar{n} = n + j$, $j > 0$. By definition of χ and η, we conclude that if $\eta(t) = \bar{\eta}(t) \equiv m$ for some time $t < T$, then the two diffusive processes are at the same location at t, leading to $\chi(t) = \bar{\chi}(t)$. We also argue that in this case, the jumping events of the two processes N and $\bar{N}$ are synchronized before t, thus the processes are identical for all $t' \leq t$. This implies that the static correlator (i.e., in the limit of large T) between two particles on the resetting chain is entirely controlled by t_ℓ the last time before T such that the $\eta(t_\ell) = \bar{\eta}(t_\ell)$. Note that for $t \in (t_\ell, T]$, $\chi(t)$, and $\bar{\chi}(t)$ are uncorrelated as $\eta(t) \neq \bar{\eta}(t)$. In what follows, we denote for simplicity $n_\ell = \eta(t_\ell)$.

In [38], we show that using this mapping we can write the correlator in the form

$$\langle x_n x_{n+j} \rangle = \sum_{m=1}^{n} \alpha_m^{n,n+j} \langle x_m^2 \rangle, \tag{14}$$

where the coefficients are given by the following probabilities:

$$\alpha_m^{n,n+j} \equiv \mathbb{P}(n_\ell = m | \{n, n+j\}), \tag{15}$$

where $\mathbb{P}(n_\ell = m | \{n, n+j\})$ is the probability that $n_\ell = m$ given that the two particles of interest are n and $\bar{n} = n + j$. Said differently, $\alpha_m^{n,n+j}$ represents exactly the probability that $\eta(t) = \bar{\eta}(t) = m$ at some time t, but also crucially that there is no time t' for which $\eta(t') = \bar{\eta}(t') = m'$ for some $m' \in \{m+1, \ldots, n-1, n\}$.

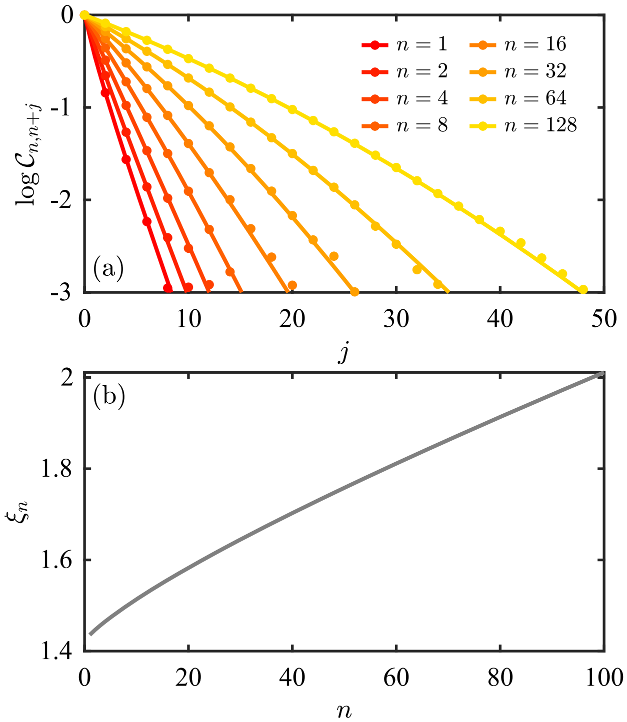

FIG. 3. Rescaled correlation function $\mathcal{C}_{n,n+j}$. (a) Rescaled correlation function $\mathcal{C}_{n,n+j}$, analytical results (solid lines) as defined in Eq. (17) showing an exponential decay at large j values of the form $\mathcal{C}_{n,n+j} \sim \exp(-j/\xi_n)$ are compared to the results of direct numerical simulations (dots). (b) Correlation length ξ_n extracted by fitting the curves in (a).

The problem of calculating $\alpha_m^{n,n+j}$ can be mapped to a discrete-time random walk (DTRW) on a 1D lattice, where two particles start at sites n and $n + j$ and at each step, one of the two particles is chosen to make a step to the left with equal probability (until it reaches 0, at which point it stops). Eventually, the particle initially at $n + j$ will hop on the site occupied by the particle initially at n: the probability that this happens at site m for the first time is exactly $\alpha_m^{n,n+j}$ and is written

$$\alpha_n^{n,n+j} = \mathcal{B}(j, j) = 2^{-j}, \tag{16a}$$

$$\alpha_{n-k}^{n,n+j} = \mathcal{B}(k, j+2k) - \sum_{l=1}^{k} \alpha_{n-k+l}^{n,n+j} \mathcal{B}(l, 2l), \tag{16b}$$

where $\mathcal{B}(m, n) = 2^{-n}\binom{n}{m}$ as shown in [38]. We can intuitively understand Eq. (16) as follows: Eq. (16a) states that the two particles meet at n only if the particle at $n + j$ hops exactly j times; further, Eq. (16b) states that to meet at $n - k$, the particles must meet at $n - k$ (first term) without having met first at another site $n - k'$ where $k' < k$ (second term).

Importantly, Eq. (16) provides an exact, fully analytic expression for all coefficients $\alpha_m^{n,n+j}$ and thus exact results for the correlations of the form $\langle x_n x_{n+j}\rangle$ through Eq. (14) which constitutes one of our main results. We note that while in principle these correlations are tractable through the so-called last renewal approach (see details in Ref. [38]), calculations quickly become arduous for increasing n and j; the present approach circumvents this issue and is thus more generally applicable.

As seen in Fig 3, the rescaled correlation function $\mathcal{C}_{n,n+j}$ defined as

$$\mathcal{C}_{n,n+j} = \frac{\langle x_n x_{n+j}\rangle}{\sqrt{\langle x_n^2\rangle\langle x_{n+j}^2\rangle}} \tag{17}$$

decays exponentially for large enough value of j, taking the form $\mathcal{C}_{n,n+j} \sim \exp(-j/\xi_n)$, where ξ_n represents the effective separation in particle indices down the chain over which correlations decay. Counterintuitively, we show that ξ_n increases with n. In other words, particles in the chain of resetting processes separated by j particles, say particles x_n and x_{n+j}, become *more* correlated as n increases.

To understand this result, considering the evolution of the stationary distributions for the rescaled variables with zero mean and unit variance: $z_n = x_n/\sqrt{\langle x_n^2\rangle}$. The fact that ξ_n increases with n suggests that the stationary distributions for z_n and z_{n+j} themselves become more similar as n increases. To ascertain this convergence in the distributions of the rescaled variables, we quantify the relative difference in excess Kurtosis between particles n and $n+j$ in the chain. Using Eq. (11), we derive the difference in the excess Kurtosis, written as

$$|\mathcal{K}(n+j) - \mathcal{K}(n)| = \frac{3j}{n(n+j)}, \tag{18}$$

which decreases monotonically with n, as expected.

Discussion and outlook—In this Letter, we define what we call the nested stochastic resetting process and study its steady-state properties obtaining a number of exact analytical results including probability distributions for the position of all particles in the resetting chain, moments of the distributions, as well as static two-point correlators. Exact correlations for many-particle systems with broken detailed balance at the microscopic scale are often intractable and crucially missing from the literature. Altogether, we provide here an example of such tractable correlations for a many-body interacting resetting process for which correlations can be evaluated exactly. To do so, we exploited the unidirectional nature of the interactions to construct effective diffusive trajectories as dynamical descriptions of the position of the nth particle in the chain.

We find that the correlation length (along the chain) increases as one moves down the chain. In the context of information propagation, this implies the misinformation at particle x_n is shared with more particles than the misinformation of particle x_1, an effect that persists even after re-scaling to account for the different levels of misinformation. We coin this phenomenon "the least informed are heard the loudest": agents furthest away from the target state share a larger fraction of common errors than those close to the source due to a limited interaction network. Perhaps most commonly observed in social networks [34,35], signaling or developmental pathways in biological systems are vulnerable to this phenomenon: cells invest time and energy employing mechanisms like kinetic proofreading [40] to increase the accuracy of sequential processes, such as DNA replication or protein folding, to avoid the accruing of misinformation predicted by our minimal model.

The framework developed here for calculating exact pairwise correlations extends generically to systems with the following features: (i) independent motion between resetting events for each particle, (ii) independence between resetting events and particle positions, and (iii) an "anchor": a fixed distribution for particle zero to ensure a steady state can be reached.

Future work will seek to address the dynamical properties of nested resetting processes. Indeed, resetting mechanisms ensure a finite mean-first passage time for diffusive search processes [1,9–23]. One natural question to ask would be how these first-passage times vary across particles in our system. Similarly, the extreme value statistics of coupled processes pose a formidable challenge for our framework of correlated random variables [41,42]. Finally, the breakdown of time reversal symmetry in microscopic (Markovian) processes is quantified through the evaluation of the entropy production rate [43–47]. This diverges for the classical single-particle stochastic resetting process when there is only one resetting site. Recent work has considered extensions to these processes that ensure finite measurements of the entropy production (ensuring a physically relevant dynamical system) [48,49]. Analysis of the current model in this context, in particular for $n > 1$, may offer one system in which calculating the exact many-body entropy production is not out of reach.

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Data availability—The data that support the findings of this article are openly available [50].

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