From charged polymers to random walk in random scenery

Xia Chen¹
Department of Mathematics
University of Tennessee
Knoxville, TN 37996-1300
xchen@math.utk.edu

Davar Khoshnevisan²
Department of Mathematics
University of Utah
Salt Lake City, UT 84112-0090
davar@math.utah.edu

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Abstract

We prove that two seemingly-different models of random walk in random environment are generically quite close to one another. One model comes from statistical physics, and describes the behavior of a randomly-charged random polymer. The other model comes from probability theory, and was originally designed to describe a large family of asymptotically self-similar processes that have stationary increments.

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1 Introduction and the main results

The principal goal of this article is to show that two apparently-disparate models—one from statistical physics of disorder media [KK91, DGH92, DH94] and one from probability theory [KS79, Bol89]—are very close to one another.

In order to describe the model from statistical physics, let us suppose that $q := \{q_i\}_{i=1}^{\infty}$ is a collection of i.i.d. mean-zero random variables with finite variance $\sigma^2 > 0$. For technical reasons, we assume here and throughout that

$$\mu_6 := \mathcal{E}(q_1^6) < \infty. \tag{1.1}$$

In addition, we let $S := \{S_i\}_{i=0}^{\infty}$ denote a random walk on \mathbf{Z}^d with $S_0 = 0$ that is independent from the collection q. We also rule out the trivial case that S_1 has only one possible value.

The object of interest to us is the random quantity

$$H_n := \sum_{1 \le i < j \le n} q_i q_j \mathbf{1}_{\{S_i = S_j\}}.$$
 (1.2)

In statistical physics, H_n denotes a random Hamiltonian of spin-glass type that is used to build Gibbsian polymer measures. The q_i 's are random charges, and each realization of S corresponds to a possible polymer path; see the paper by Kantor and Kardar [KK91], its subsequent variations by Derrida et al [DGH92, DH94] and Wittmer et al [WJJ93], and its predecessos by Garel and Orland [GO88] and Obukhov [O86]. The resulting Gibbs measure then corresponds to a model for "random walk in random environment." Although we do not consider continuous processes here, the continuum-limit analogue of H_n has also been studied in the literature [BP97, MP96].

Kesten and Spitzer [KS79] introduced a different model for "random walk in random environment," which they call random walk in random scenery.¹ We can describe that model as follows: Let $Z := \{Z(x)\}_{x \in \mathbb{Z}^d}$ is a collection of i.i.d. random variables, with the same common distribution as q_1 , and independent of S. Define

$$W_n := \sum_{i=1}^n Z(S_i). (1.3)$$

The process $W := \{W_n\}_{n=0}^{\infty}$ is called random walk in random scenery, and can be thought of as follows: We fix a realization of the d-dimensional random field Z—the "scenery"—and then run an independent walk S on \mathbf{Z}^d . At time j, the walk is at S_j ; we sample the scenery at that point. This yields $Z(S_j)$, which is then used as the increment of the process W at time j.

Our goal is to make precise the assertion that if n is large, then

$$H_n \approx \gamma^{1/2} \cdot W_n$$
 in distribution, (1.4)

where

$$\gamma := \begin{cases} 1 & \text{if } S \text{ is recurrent,} \\ \sum_{k=1}^{\infty} P\{S_k = 0\} & \text{if } S \text{ is transient.} \end{cases}$$
 (1.5)

 $^{^1{}m Kesten}$ and Spitzer ascribe the terminology to Paul Shields

Our derivation is based on a classification of recurrence vs. transience for random walks that appears to be new. This classification [Theorem 2.4] might be of independent interest.

We can better understand (1.4) by considering separately the cases that S is transient versus recurrent. The former case is simpler to describe, and appears next.

Theorem 1.1. If S is transient, then

$$\frac{W_n}{n^{1/2}} \xrightarrow{\mathcal{D}} N(0, \sigma^2) \quad and \quad \frac{H_n}{n^{1/2}} \xrightarrow{\mathcal{D}} N(0, \gamma \sigma^2). \tag{1.6}$$

Kesten and Spitzer [KS79] proved the assertion about W_n under more restrictive conditions on S. Similarly, Chen [C08] proved the statement about H_n under more hypotheses.

Before we can describe the remaining [and more interesting] recurrent case, we define

$$a_n := \left(n\sum_{k=0}^n P\{S_k = 0\}\right)^{1/2}.$$
 (1.7)

It is well known [P21, CF51] that S is recurrent if and only if $a_n/n^{1/2} \to \infty$ as $n \to \infty$.

Theorem 1.2. If S is recurrent, then for all bounded continuous functions $f: \mathbf{R}^d \to \mathbf{R}$,

$$E\left[f\left(\frac{W_n}{a_n}\right)\right] = E\left[f\left(\frac{H_n}{a_n}\right)\right] + o(1), \tag{1.8}$$

where o(1) converges to zero as $n \to \infty$. Moreover, both $\{W_n/a_n\}_{n\geq 1}$ and $\{H_n/a_n\}_{n\geq 1}$ are tight.

We demonstrate Theorems 1.1 and 1.2 by using a variant of the replacement method of Liapounov [Lia00, pp. 362–364]; this method was rediscovered later by Lindeberg [Lin22], who used it to prove his famous central limit theorem for triangular arrays of random variables.

It can be proved that when S is in the domain of attraction of a stable law, W_n/a_n converges in distribution to an explicit law [KS79, Bol89]. Consequently, H_n/a_n converges in distribution to the same law in that case. This fact was proved earlier by Chen [C08] under further [mild] conditions on S and q_1 .

We conclude the introduction by describing the growth of a_n under natural conditions on S.

Remark 1.3. Suppose S is strongly aperiodic, mean zero, and finite second moments, with a nonsingular covariance matrix. Then, S is transient iff $d \geq 3$, and by the local central limit theorem, as $n \to \infty$,

$$\sum_{k=1}^{n} P\{S_k = 0\} \sim \text{const} \times \begin{cases} n^{1/2} & \text{if } d = 1, \\ \log n & \text{if } d = 2. \end{cases}$$
 (1.9)

See, for example Spitzer [S76, **P9** on p. 75]. Consequently,

$$a_n \sim \text{const} \times \begin{cases} n^{3/4} & \text{if } d = 1, \\ (n \log n)^{1/2} & \text{if } d = 2. \end{cases}$$
 (1.10)

This agrees with the normalization of Kesten and Spitzer [KS79] when d=1, and Bolthausen [Bol89] when d=2.

2 Preliminary estimates

Consider the local times of S defined by

$$L_n^x := \sum_{i=1}^n \mathbf{1}_{\{S_i = x\}}.$$
 (2.1)

A little thought shows that the random walk in random scenery can be represented compactly as

$$W_n = \sum_{x \in \mathbf{Z}^d} Z(x) L_n^x. \tag{2.2}$$

There is also a nice way to write the random Hamiltonian H_n in local-time terms. Consider the "level sets,"

$$\mathcal{L}_n^x := \{ i \in \{1, \dots, n\} : \ S_i = x \}. \tag{2.3}$$

It is manifest that if $j \in \{2, ..., n\}$, then $L_j^x > L_{j-1}^x$ if and only if $j \in \mathcal{L}_n^x$. Thus, we can write

$$H_n = \frac{1}{2} \left(\sum_{x \in \mathbf{Z}^d} \left| \sum_{i=1}^n q_i \mathbf{1}_{\{S_i = x\}} \right|^2 - \sum_{i=1}^n q_i^2 \right)$$

$$= \sum_{x \in \mathbf{Z}^d} h_n^x,$$
(2.4)

where

$$h_n^x := \frac{1}{2} \left(\left| \sum_{i \in \mathcal{L}_n^x} q_i \right|^2 - \sum_{i \in \mathcal{L}_n^x} q_i^2 \right). \tag{2.5}$$

We denote by $\widehat{\mathbf{P}}$ the conditional measure, given the entire process S; $\widehat{\mathbf{E}}$ denotes the corresponding expectation operator. The following is borrowed from Chen [C08, Lemma 2.1].

Lemma 2.1. Choose and fix some integer $n \ge 1$. Then, $\{h_n^x\}_{x \in \mathbb{Z}^d}$ is a collection of independent random variables under \widehat{P} , and

$$\widehat{\mathbf{E}}h_{n}^{x}=0 \quad and \quad \widehat{\mathbf{E}}\left(\left|h_{n}^{x}\right|^{2}\right)=\frac{\sigma^{2}}{2}L_{n}^{x}\left(L_{n}^{x}-1\right) \qquad \text{P-a.s.} \tag{2.6}$$

Moreover, there exists a nonrandom positive and finite constant $C = C(\sigma)$ such that for all $n \ge 1$ and $x \in \mathbf{Z}^d$,

$$\widehat{\mathrm{E}}\left(\left|h_{n}^{x}\right|^{3}\right) \le C\mu_{6}\left|L_{n}^{x}\left(L_{n}^{x}-1\right)\right|^{3/2}$$
 P-a.s. (2.7)

Next we develop some local-time computations.

Lemma 2.2. For all $n \geq 1$,

$$\sum_{x \in \mathbf{Z}^d} EL_n^x = n \quad and \quad \sum_{x \in \mathbf{Z}^d} E\left(|L_n^x|^2\right) = n + 2\sum_{k=1}^{n-1} (n-k) P\{S_k = 0\}. \tag{2.8}$$

Moreover, for all integers $k \geq 1$,

$$\sum_{x \in \mathbf{Z}^d} \mathbf{E}\left(|L_n^x|^k\right) \le k! \, n \left| \sum_{j=0}^n \mathbf{P}\{S_j = 0\} \right|^{k-1}. \tag{2.9}$$

Proof. Since $EL_n^x = \sum_{j=1}^n P\{S_j = x\}$ and $\sum_{x \in \mathbb{Z}^d} P\{S_j = x\} = 1$, we have $\sum_x EL_n^x = n$. For the second-moment formula we write

$$E(|L_n^x|^2) = \sum_{1 \le i \le n} P\{S_i = x\} + 2 \sum_{1 \le i < j \le n} P\{S_i = S_j = x\}$$

$$= \sum_{1 \le i \le n} P\{S_i = x\} + 2 \sum_{1 \le i < j \le n} P\{S_i = x\} P\{S_{j-i} = 0\}.$$
(2.10)

We can sum this expression over all $x \in \mathbf{Z}^d$ to find that

$$\sum_{x \in \mathbf{Z}^d} E\left(|L_n^x|^2\right) = n + 2 \sum_{1 \le i < j \le n} P\{S_{j-i} = x\}.$$
 (2.11)

This readily implies the second-moment formula. Similarly, we write

$$\begin{split}
& E\left(\left|L_{n}^{x}\right|^{k}\right) \\
& \leq k! \sum_{1 \leq i_{1} \leq \dots \leq i_{k} \leq n} P\{S_{i_{1}} = \dots = S_{i_{k}} = x\} \\
& = k! \sum_{1 \leq i_{1} \leq \dots \leq i_{k} \leq n} P\{S_{i_{1}} = x\} P\{S_{i_{2}-i_{1}} = 0\} \dots P\{S_{i_{k}-i_{k-1}} = 0\} \\
& \leq k! \sum_{i=1}^{n} P\{S_{i} = x\} \cdot \left|\sum_{j=1}^{n} P\{S_{j} = 0\}\right|^{k-1}.
\end{split} \tag{2.12}$$

Add over all $x \in \mathbf{Z}^d$ to finish.

Our next lemma provides the first step in a classification of recurrence [versus transience] for random walks.

Lemma 2.3. It is always the case that

$$\lim_{n \to \infty} \frac{1}{n} \sum_{x \in \mathbf{Z}^d} \mathbf{E}\left(|L_n^x|^2\right) = 1 + 2 \sum_{k=1}^{\infty} \mathbf{P}\{S_k = 0\}.$$
 (2.13)

Proof. Thanks to Lemma 2.2, for all $n \geq 1$,

$$\frac{1}{n} \sum_{x \in \mathbf{Z}^d} \mathbf{E}\left(|L_n^x|^2\right) = 1 + 2 \sum_{k=1}^{n-1} \left(1 - \frac{k}{n}\right) \mathbf{P}\{S_k = 0\}.$$
 (2.14)

If S is transient, then the monotone convergence theorem ensures that

$$\lim_{n \to \infty} \frac{1}{n} \sum_{x \in \mathbf{Z}^d} \mathbf{E}\left(|L_n^x|^2\right) = 1 + 2 \sum_{k=1}^{\infty} \mathbf{P}\{S_k = 0\}.$$
 (2.15)

This proves the lemma in the transient case.

When S is recurrent, we note that (2.14) readily implies that for all integers $m \geq 2$,

$$\liminf_{n \to \infty} \frac{1}{n} \sum_{x \in \mathbf{Z}^d} \mathbf{E}\left(|L_n^x|^2\right) \ge 1 + 2 \sum_{k=1}^{m-1} \left(1 - \frac{k}{m}\right) \mathbf{P}\{S_k = 0\}
\ge 1 + \sum_{1 \le k \le m/2} \mathbf{P}\{S_k = 0\}.$$
(2.16)

Let $m \uparrow \infty$ to deduce the lemma.

Next we "remove the expectation" from the statement of Lemma 2.3.

Theorem 2.4. As $n \to \infty$,

$$\frac{1}{n} \sum_{x \in \mathbf{Z}^d} (L_n^x)^2 \to 1 + 2 \sum_{k=1}^{\infty} P\{S_k = 0\} \quad in \ probability. \tag{2.17}$$

Remark 2.5. The quantity $I_n := \sum_{x \in \mathbf{Z}^d} (L_n^x)^2$ is the socalled *self-intersection local time* of the walk S. This terminology stems from the following elementary calculation: For all integers $n \geq 1$,

$$I_n = \sum_{1 \le i, j \le n} \mathbf{1}_{\{S_j = S_i\}}.$$
 (2.18)

Consequently, Theorem 2.4 implies that a random walk S on \mathbf{Z}^d is recurrent if and only if its self-intersection local time satisfies $I_n/n \to \infty$ in probability. \square

Remark 2.6. Nadine Guillotin–Plantard has kindly pointed out to us that the mode of convergence in Theorem 2.4 can be strengthened to almost-sure convergence. This requires a direct subadditivity argument [GP04]. It follows also from the estimates that follow, together with a classical blocking argument, which we skip.

Proof. First we study the case that $\{S_i\}_{i=0}^{\infty}$ is transient. Define

$$Q_n := \sum_{1 \le i < j \le n} \mathbf{1}_{\{S_i = S_j\}}.$$
 (2.19)

Then it is not too difficult to see that

$$\sum_{x \in \mathbf{Z}^d} (L_n^x)^2 = 2Q_n + n \quad \text{for all } n \ge 1.$$
 (2.20)

This follows immediately from (2.18), for example. Therefore, it suffices to prove that, under the assumption of transience,

$$\frac{Q_k}{k} \to \sum_{j=1}^{\infty} P\{S_j = 0\} \quad \text{in probability as } k \to \infty.$$
 (2.21)

Lemma 2.3 and (2.20) together imply that

$$\lim_{k \to \infty} \frac{EQ_k}{k} = \sum_{j=1}^{\infty} P\{S_j = 0\}.$$
 (2.22)

Hence, it suffices to prove that $\operatorname{Var} Q_n = o(n^2)$ as $n \to \infty$. In some cases, this can be done by making an explicit [though hard] estimate for $\operatorname{Var} Q_n$; see, for instance, Chen [C08, Lemma 5.1], and also the technique employed in the proof of Lemma 2.4 of Bolthausen [Bol89]. Here, we opt for a more general approach that is simpler, though it is a little more circuitous. Namely, in rough terms, we write Q_n as $Q_n^{(1)} + Q_n^{(2)}$, where $\mathrm{E}Q_n^{(1)} = o(n)$, and $\mathrm{Var}\,Q_n^{(2)} = o(n^2)$. Moreover, we will soon see that $Q_n^{(1)}, Q_n^{(2)} \geq 0$, and this suffices to complete the proof. For all $m := m_n \in \{1, \ldots, n-1\}$ we write

$$Q_n = Q_n^{1,m} + Q_n^{2,m}, (2.23)$$

where

$$Q_n^{1,m} := \sum_{\substack{1 \le i < j \le n: \\ j > i + m}} \mathbf{1}_{\{S_i = S_j\}} \quad \text{and} \quad Q_n^{2,m} := \sum_{\substack{1 \le i < j \le n: \\ j < i + m}} \mathbf{1}_{\{S_i = S_j\}}. \tag{2.24}$$

Because n > m, we have

$$EQ_n^{1,m} \le n \sum_{k=-\infty}^{\infty} P\{S_k = 0\}.$$
 (2.25)

We estimate the variance of $Q_n^{2,m}$ next. We do this by first making an observa-

Throughout the remainder of this proof, define for all subsets Γ of \mathbb{N}^2 ,

$$\Upsilon(\Gamma) := \sum_{(i,j)\in\Gamma} \mathbf{1}_{\{S_i = S_j\}}.$$
(2.26)

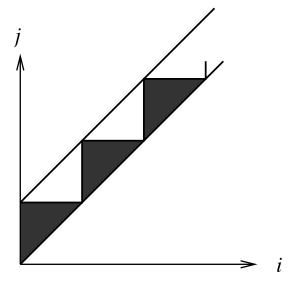


Figure 1: A decomposition of Q_n

Suppose $\Gamma_1, \Gamma_2, \ldots, \Gamma_{\nu}$ are finite disjoint sets in \mathbf{N}^2 , with common cardinality, and the added property that whenever $1 \leq a < b \leq \nu$, we have $\Gamma_a < \Gamma_b$ in the sense that i < k and j < l for all $(i,j) \in \Gamma_a$ and $(k,l) \in \Gamma_b$. Then, it follows that

$$\{\Upsilon(\Gamma_{\nu})\}_{\mu=1}^{\nu}$$
 is an i.i.d. sequence. (2.27)

For all integers $p \ge 0$ define

$$B_p^m := \{(i,j) \in \mathbf{N}^2 : (p-1)m < i < j \le pm \},$$

$$W_p^m := \{(i,j) \in \mathbf{N}^2 : (p-1)m < i \le pm < j \le (p+1)m \}.$$
(2.28)

In Figure 1, $\{B_p^m\}_{p=1}^{\infty}$ denotes the collection black and $\{W_p^m\}_{p=1}^{\infty}$ the white triangles that are inside the slanted strip.

We may write

$$Q_{(n-1)m}^{2,m} = \sum_{p=1}^{n-1} \Upsilon(B_p^m) + \sum_{p=1}^{n-1} \Upsilon(W_p^m).$$
 (2.29)

Consequently,

$$\operatorname{Var} Q_{(n-1)m}^{2,m} \le 2\operatorname{Var} \sum_{p=1}^{n-1} \Upsilon(B_p^m) + 2\operatorname{Var} \sum_{p=1}^{n-1} \Upsilon(W_p^m). \tag{2.30}$$

If $1 \le a < b \le m-1$, then $B^m_a < B^m_b$ and $W^m_a < W^m_b$. Consequently, (2.27) implies that

$$\operatorname{Var} Q_{(n-1)m}^{2,m} \le 2(n-1) \left[\operatorname{Var} \Upsilon(B_1^m) + \operatorname{Var} \Upsilon(W_1^m) \right].$$
 (2.31)

Because $\Upsilon(B_1^m)$ and $\Upsilon(W_1^m)$ are individually sums of not more than $\binom{m}{2}$ -many ones,

$$\operatorname{Var} Q_{(n-1)m}^{2,m} \le 2(n-1)m^2. \tag{2.32}$$

Let $Q_n^{(1)} := Q_n^{1,m}$ and $Q_n^{(2)} := Q_n^{2,m}$, where $m = m_n := n^{1/4}$ [say]. Then, $Q_n = Q_n^{(1)} + Q_n^{(2)}$, and (2.25) and (2.32) together imply that $\mathrm{E}Q_{(n-1)m}^{(1)} = o((n-1)m)$. Moreover, $\mathrm{Var}\,Q_{(n-1)m}^{(2)} = o((nm)^2)$. This gives us the desired decomposition of $Q_{(n-1)m}$. Now we complete the proof: Thanks to (2.22),

$$EQ_{(n-1)m}^{(2)} \sim nm \cdot \sum_{j=1}^{\infty} P\{S_j = 0\} \text{ as } n \to \infty.$$
 (2.33)

Therefore, the variance of $Q_{(n-1)m}^{(2)}$ is little-o of the square of its mean. This and the Chebyshev inequality together imply that $Q_{(n-1)m}^{(2)}/(nm)$ converges in probability to $\sum_{j=1}^{\infty} P\{S_j = 0\}$. On the other hand, we know also that $Q_{(n-1)m}^{(1)}/(nm)$ converges to zero in $L^1(P)$ and hence in probability. Consequently, we can change variables and note that as $n \to \infty$,

$$\frac{Q_{nm}}{nm} \to \sum_{j=1}^{\infty} P\{S_j = 0\} \quad \text{in probability.}$$
 (2.34)

If k is between (n-1)m and nm, then

$$\frac{Q_{(n-1)m}}{nm} \le \frac{Q_k}{k} \le \frac{Q_{nm}}{(n-1)m}. (2.35)$$

This proves (2.21), and hence the theorem, in the transient case.

In order to derive the recurrent case, it suffices to prove that $Q_n/n \to \infty$ in probability as $n \to \infty$.

Let us choose and hold an integer $m \geq 1$ —so that it does *not* grow with n—and observe that $Q_n \geq Q_n^{2,m}$ as long as n is sufficiently large. Evidently,

$$EQ_n^{2,m} = \sum_{\substack{1 \le i < j \le n: \\ j < i + m}} P\{S_j = S_i\}$$

$$= (n - 1) \sum_{k=1}^{m-1} P\{S_k = 0\}.$$
(2.36)

We may also observe that (2.32) continues to hold in the present recurrent setting. Together with the Chebyshev inequality, these computations imply that as $n \to \infty$,

$$\frac{Q_{n(m-1)}^{2,m}}{n} \to \sum_{k=1}^{m-1} P\{S_k = 0\} \text{ in probability.}$$
 (2.37)

Because $Q_{n(m-1)} \geq Q_{n(m-1)}^{2,m}$, the preceding implies that

$$\lim_{n \to \infty} P\left\{ \frac{Q_{n(m-1)}}{n} \ge \frac{1}{2} \sum_{k=1}^{m} P\{S_k = 0\} \right\} = 1.$$
 (2.38)

A monotonicity argument shows that $Q_{n(m-1)}$ can be replaced by Q_n without altering the end-result; see (2.35). By recurrence, if $\lambda > 0$ is any predescribed positive number, then we can choose [and fix] our integer m such that $\sum_{k=1}^{m} P\{S_k = 0\} \geq 2\lambda$. This proves that $\lim_{n\to\infty} P\{Q_n/n \geq \lambda\} = 1$ for all $\lambda > 0$, and hence follows the theorem in the recurrent case.

3 Proofs of the main results

Now we introduce a sequence $\{\xi_x\}_{x\in\mathbf{Z}^d}$ of random variables, independent [under P] of $\{q_i\}_{i=1}^{\infty}$ and the random walk $\{S_i\}_{i=0}^{\infty}$, such that

$$\mathrm{E}\xi_0 = 0$$
, $\mathrm{E}\left(\xi_0^2\right) = \sigma^2$, and $\widehat{\mu}_3 := \mathrm{E}\left(\left|\xi_0\right|^3\right) < \infty$. (3.1)

Define

$$\widehat{h}_n^x := \left| \frac{L_n^x \left(L_n^x - 1 \right)}{2} \right|^{1/2} \xi_x \quad \text{for all } n \ge 1 \text{ and } x \in \mathbf{Z}^d.$$
 (3.2)

Evidently, $\{\widehat{h}_n^x\}_{x \in \mathbf{Z}^d}$ is a sequence of [conditionally] independent random variables, under $\widehat{\mathbf{P}}$, and has the same [conditional] mean and variance as $\{h_n^x\}_{x \in \mathbf{Z}^d}$.

Lemma 3.1. There exists a positive and finite constant $C_* = C_*(\sigma)$ such that if $f : \mathbf{R}^d \to \mathbf{R}$ is three time continuously differentiable, then for all $n \geq 1$,

$$\left| \operatorname{E} f \left(\sum_{x \in \mathbf{Z}^d} \widehat{h}_n^x \right) - \operatorname{E} f(H_n) \right| \le C_* M_f(\widehat{\mu}_3 + \mu_6) n \left| \sum_{j=0}^n \operatorname{P} \{ S_j = 0 \} \right|^2, \tag{3.3}$$

with $M_f := \sup_{x \in \mathbf{R}^d} |f'''(x)|$.

Proof. Temporarily choose and fix some $y \in \mathbf{Z}^d$, and notice that

$$f(H_n)$$

$$= f\left(\sum_{x \in \mathbf{Z}^d \setminus \{y\}} h_n^x\right) + f'\left(\sum_{x \in \mathbf{Z}^d \setminus \{y\}} h_n^x\right) h_n^y + \frac{1}{2} f''\left(\sum_{x \in \mathbf{Z}^d \setminus \{y\}} h_n^x\right) \left|h_n^y\right|^2$$
(3.4)
+ R_n ,

where $|R_n| \leq \frac{1}{6} ||f'''||_{\infty} |h_n^y|^3$. It follows from this and Lemma 2.1 that

$$\widehat{\mathrm{E}}f(H_n)$$

$$=\widehat{\mathrm{E}}f\left(\sum_{x\in\mathbf{Z}^d\setminus\{y\}}h_n^x\right)+\frac{\sigma^2}{2}L_n^y\left(L_n^y-1\right)\widehat{\mathrm{E}}f''\left(\sum_{x\in\mathbf{Z}^d\setminus\{y\}}h_n^x\right)+R_n^{(1)},\tag{3.5}$$

where

$$\left| R_n^{(1)} \right| \le \frac{CM_f \mu_6}{12} \left| L_n^x \left(L_n^x - 1 \right) \right|^{3/2}$$
 P-a.s.
 $\le \frac{CM_f \mu_6}{12} \left| L_n^y \right|^3.$ (3.6)

We proceed as in (3.4) and write

$$f\left(\widehat{h}_{n}^{y} + \sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right)$$

$$= f\left(\sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) + f'\left(\sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) \widehat{h}_{n}^{y} + \frac{1}{2}f''\left(\sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) \left|\widehat{h}_{n}^{y}\right|^{2}$$

$$+ \widehat{R}_{n},$$

$$(3.7)$$

where $|\widehat{R}_n| \leq \frac{1}{6} M_f |\widehat{h}_n^y|^3 \leq \frac{1}{12\sqrt{2}} M_f |L_n^y|^3 |\xi_y|^3$. It follows from this and Lemma 2.1 that

$$\widehat{\mathbf{E}}f\left(\widehat{h}_{n}^{y} + \sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) \\
= \widehat{\mathbf{E}}f\left(\sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) + \frac{\sigma^{2}}{2} L_{n}^{y} \left(L_{n}^{y} - 1\right) \widehat{\mathbf{E}}f''\left(\sum_{x \in \mathbf{Z}^{d} \setminus \{y\}} h_{n}^{x}\right) + R_{n}^{(2)}, \tag{3.8}$$

where $|R_n^{(2)}| \leq \frac{1}{12\sqrt{2}}\widehat{\mu}_3 M_f |L_n^y|^3$. Define $C_* := (C+1)/2$ to deduce from the preceding and (3.5) that P-a.s.,

$$\left| \widehat{\mathbf{E}} f \left(\widehat{h}_n^y + \sum_{x \in \mathbf{Z}^d \setminus \{y\}} h_n^x \right) - \widehat{\mathbf{E}} f \left(\sum_{x \in \mathbf{Z}^d} h_n^x \right) \right| \le \frac{A}{6} |L_n^y|^3, \tag{3.9}$$

where $A := C_* M_f(\widehat{\mu}_3 + \mu_6)$. The preceding computes the effect of replacing the contribution of h_n^x to H_n but the independent quantity \widehat{h}_n^y , for each fixed y, and uses only the fact that the \widehat{h} 's are a conditionally independent sequence with the same means and variances as their corresponding h's. Therefore, if we choose and fix another point $y \in \mathbf{Z}^d \setminus \{y\}$, then the very same constant A satisfies the following: Almost surely [P],

$$\left| \widehat{\mathbb{E}} f \left(\widehat{h}_n^z + \widehat{h}_n^y + \sum_{x \in \mathbf{Z}^d \setminus \{y, z\}} h_n^x \right) - \widehat{\mathbb{E}} f \left(\widehat{h}_n^y + \sum_{x \in \mathbf{Z}^d \setminus \{y\}} h_n^x \right) \right| \le \frac{A}{6} |L_n^z|^3. \quad (3.10)$$

And hence, the triangle inequality yields the following: P-a.s.,

$$\left| \widehat{\mathbf{E}} f \left(\widehat{h}_n^z + \widehat{h}_n^y + \sum_{x \in \mathbf{Z}^d \setminus \{y, z\}} h_n^x \right) - \widehat{\mathbf{E}} f \left(\sum_{x \in \mathbf{Z}^d} h_n^x \right) \right|$$

$$\leq \frac{A}{6} \left(|L_n^y|^3 + |L_n^z|^3 \right).$$
(3.11)

Because $\sum_{x \in \mathbf{Z}^d} h_n^x = H_n$, it is now possible to see how we can iterate the previous inequality to find that P-a.s.,

$$\left| \widehat{\mathbb{E}} f \left(\sum_{x \in \mathbf{Z}^d} \widehat{h}_n^x \right) - \widehat{\mathbb{E}} f(H_n) \right| \le \frac{A}{6} \sum_{y \in \mathbf{Z}^d} |L_n^y|^3.$$
 (3.12)

We take expectations and appeal to Lemma 2.2 to finish.

Next, we prove Theorem 1.1.

Proof of Theorem 1.1. We choose, in Lemma 3.1, the collection $\{\xi_x\}_{x\in\mathbf{Z}^d}$ to be i.i.d. mean-zero normals with variance σ^2 . Then, we apply Lemma 3.1 with $f(x) := g(x/n^{1/2})$ for a smooth bounded function g with bounded derivatives. This yields,

$$\left| \operatorname{E}g(H_n/n^{1/2}) - \operatorname{E}g\left(\frac{1}{n^{1/2}} \sum_{x \in \mathbf{Z}^d} \widehat{h}_n^x\right) \right| \le \frac{\operatorname{const}}{n^{1/2}}.$$
 (3.13)

In this way,

$$\sum_{x \in \mathbf{Z}^d} \widehat{h}_n^x \stackrel{\mathcal{D}}{=} \frac{\sigma}{\sqrt{2}} \left| \sum_{x \in \mathbf{Z}^d} L_n^x (L_n^x - 1) \right|^{1/2} N(0, 1) \quad \text{under } \widehat{P}$$

$$= \frac{\sigma}{\sqrt{2}} \left| -n + \sum_{x \in \mathbf{Z}^d} (L_n^x)^2 \right|^{1/2} N(0, 1), \tag{3.14}$$

where $\stackrel{\mathcal{D}}{=}$ denotes equality in distribution, and N(0,1) is a standard normal random variable under \widehat{P} as well as P. Therefore, in accord with Theorem 2.4,

$$\frac{1}{n^{1/2}} \sum_{x \in \mathbf{Z}^d} \widehat{h}_n^x \stackrel{\mathcal{D}}{=} \frac{\sigma}{\sqrt{2}} \left| -1 + \frac{1}{n} \sum_{x \in \mathbf{Z}^d} (L_n^x)^2 \right|^{1/2} N(0, 1)
= o_{\widehat{\mathbf{p}}}(1) + \gamma^{1/2} \cdot N(0, \sigma^2),$$
(3.15)

where $o_{\widehat{\mathbf{P}}}(1)$ is a term that converges to zero as $n \to \infty$ in $\widehat{\mathbf{P}}$ -probability a.s. [P]. Equation (3.13) then completes the proof in the transient case.

Theorem 1.2 relies on the following "coupled moderate deviation" result.

Proposition 3.2. Suppose that S is recurrent. Consider a sequence $\{\epsilon_j\}_{j=1}^{\infty}$ of nonnegative numbers that satisfy the following:

$$\lim_{n \to \infty} \epsilon_n^3 n \left| \sum_{k=1}^n P\{S_k = 0\} \right|^2 = 0.$$
 (3.16)

Then for all compactly supported functions $f: \mathbf{R}^d \to \mathbf{R}$ that are infinitely differentiable,

$$\lim_{n \to \infty} |\operatorname{E}\left[f\left(\epsilon_n W_n\right)\right] - \operatorname{E}\left[f\left(\epsilon_n H_n\right)\right]| = 0, \tag{3.17}$$

Proof. We apply Lemma 3.1 with the ξ_x 's having the same common distribution as q_1 , and with $f(x) := g(\epsilon_n x)$ for a smooth and bounded function g with bounded derivatives. This yields,

$$\left| \operatorname{E} \left[g \left(\epsilon_n \sum_{x \in \mathbf{Z}^d} |L_n^x (L_n^x - 1)|^{1/2} Z(x) \right) \right] - \operatorname{E} \left[g \left(\epsilon_n H_n \right) \right] \right| \\
\leq 2C_* M_g \mu_6 n \epsilon_n^3 \left| \sum_{k=0}^n \operatorname{P} \left\{ S_k = 0 \right\} \right|^2$$

$$= o(1), \tag{3.18}$$

owing to Lemma (3.4).

According to Taylor's formula,

$$g\left(\epsilon_{n} \sum_{x \in \mathbf{Z}^{d}} \left| L_{n}^{x} \left(L_{n}^{x} - 1\right) \right|^{1/2} Z(x) \right)$$

$$= g\left(\epsilon_{n} \sum_{x \in \mathbf{Z}^{d}} Z(x) L_{n}^{x} \right) + \epsilon_{n} \sum_{x \in \mathbf{Z}^{d}} \left(\left| L_{n}^{x} \left(L_{n}^{x} - 1\right) \right|^{1/2} - L_{n}^{x} \right) Z(x) \cdot R,$$

$$(3.19)$$

where $|R| \leq \sup_{x \in \mathbf{R}^d} |g'(x)|$. Thanks to (2.2), we can write the preceding as follows:

$$g\left(\epsilon_{n} \sum_{x \in \mathbf{Z}^{d}} \left| L_{n}^{x} \left(L_{n}^{x} - 1 \right) \right|^{1/2} Z(x) \right) - g\left(\epsilon_{n} W_{n}\right)$$

$$= \epsilon_{n} \sum_{x \in \mathbf{Z}^{d}} \left(\left| L_{n}^{x} \left(L_{n}^{x} - 1 \right) \right|^{1/2} - L_{n}^{x} \right) Z(x) \cdot R.$$

$$(3.20)$$

Consequently, P-almost surely,

$$\left| \widehat{\mathbf{E}} \left[g \left(\epsilon_n \sum_{x \in \mathbf{Z}^d} |L_n^x (L_n^x - 1)|^{1/2} Z(x) \right) \right] - \widehat{\mathbf{E}} \left[g \left(\epsilon_n W_n \right) \right] \right|$$

$$\leq \sup_{x \in \mathbf{R}^d} |g'(x)| \sigma \cdot \epsilon_n \left\{ \widehat{\mathbf{E}} \left(\sum_{x \in \mathbf{Z}^d} \left(|L_n^x (L_n^x - 1)|^{1/2} - L_n^x \right)^2 \right) \right\}^{1/2}.$$
(3.21)

We apply the elementary inequality $(a^{1/2} - b^{1/2})^2 \le |a - b|$ —valid for all $a, b \ge 0$ —to deduce that P-almost surely,

$$\left| \widehat{\mathbf{E}} \left[g \left(\epsilon_n \sum_{x \in \mathbf{Z}^d} |L_n^x (L_n^x - 1)|^{1/2} Z(x) \right) \right] - \widehat{\mathbf{E}} \left[g \left(\epsilon_n W_n \right) \right] \right|$$

$$\leq \sup_{x \in \mathbf{R}^d} |g'(x)| \sigma \cdot \epsilon_n \left\{ \widehat{\mathbf{E}} \left(\sum_{x \in \mathbf{Z}^d} L_n^x \right) \right\}^{1/2}$$

$$= \sup_{x \in \mathbf{R}^d} |g'(x)| \sigma \cdot \epsilon_n n^{1/2}.$$

$$(3.22)$$

We take E-expectations and apply Lemma (3.4) to deduce from this and (3.18) that

$$|E[g(\epsilon_n W_n)] - E[g(\epsilon_n H_n)]| = o(1). \tag{3.23}$$

This completes the proof.

Our proof of Theorem 1.2 hinges on two more basic lemmas. The first is an elementary lemma from integration theory.

Lemma 3.3. Suppose $X := \{X_n\}_{n=1}^{\infty}$ and $Y := \{Y_n\}_{n=1}^{\infty}$ are \mathbf{R}^d -valued random variables such that: (i) X and Y each form a tight sequence; and (ii) for all bounded infinitely-differentiable functions $g : \mathbf{R}^d \to \mathbf{R}$,

$$\lim_{n \to \infty} |\operatorname{E}g(X_n) - \operatorname{E}g(Y_n)| = 0.$$
(3.24)

Then, the preceding holds for all bounded continuous functions $g: \mathbf{R}^d \to \mathbf{R}$.

Proof. The proof uses standard arguments, but we repeat it for the sake of completeness.

Let $K_m := [-m, m]^d$, where m takes values in \mathbb{N} . Given a bounded continuous function $g : \mathbf{R}^d \to \mathbf{R}$, we can find a bounded infinitely-differentiable function $h_m : \mathbf{R}^d \to \mathbf{R}$ such that $h_m = g$ on K_m . It follows that

$$|Eg(X_n) - Eg(Y_n)| \le |Eh_m(X_n) - Eh_m(Y_n)|$$

 $+ 2 \sup_{x \in \mathbf{R}^d} |g(x)| (P\{X_n \notin K_m\} + P\{Y_n \notin K_m\}).$ (3.25)

Consequently,

$$\limsup_{n \to \infty} |\operatorname{E}g(X_n) - \operatorname{E}g(Y_n)|$$

$$\leq 2 \sup_{x \in \mathbf{R}^d} |g(x)| \sup_{j \geq 1} \left(\operatorname{P}\{X_j \notin K_m\} + \operatorname{P}\{Y_j \notin K_m\} \right).$$
(3.26)

Let m diverge and appeal to tightness to conclude that the left-had side vanishes.

The final ingredient in the proof of Theorem 1.1 is the following harmonic-analytic result.

Lemma 3.4. If $\epsilon_n := 1/a_n$, then (3.16) holds.

Proof. Let ϕ denote the characteristic function of S_1 . Our immediate goal is to prove that $|\phi(t)| < 1$ for all but a countable number of $t \in \mathbf{R}^d$. We present an argument, due to Firas Rassoul-Agha, that is simpler and more elegant than our original proof.

Suppose S_1' is an independent copy of S_1 , and note that whenever $t \in \mathbf{R}^d$ is such that $|\phi(t)| = 1$, $D := \exp\{it \cdot (S_1 - S_1')\}$ has expectation one. Consequently, $\mathrm{E}(|D-1|^2) = \mathrm{E}(|D|^2) - 1 = 0$, whence D=1 a.s. Because S_1 is assumed to have at least two possible values, $S_1 \neq S_1'$ with positive probability, and this proves that $t \in 2\pi \mathbf{Z}^d$. It follows readily from this that

$$\{t \in \mathbf{R}^d : |\phi(t)| = 1\} = 2\pi \mathbf{Z}^d,$$
 (3.27)

and in particular, $|\phi(t)| < 1$ for almost all $t \in \mathbf{R}^d$.

By the inversion theorem [S76, **P3**(b), p. 57], for all $n \ge 0$,

$$P\{S_n = 0\} = \frac{1}{(2\pi)^d} \int_{(-\pi,\pi)^d} \{\phi(t)\}^n dt.$$
 (3.28)

This and the dominated convergence theorem together tell us that $P\{S_n = 0\} = o(1)$ as $n \to \infty$, whence it follows that

$$\sum_{k=1}^{n} P\{S_k = 0\} = o(n) \text{ as } n \to \infty.$$
 (3.29)

For our particular choice of ϵ_n we find that

$$\epsilon_n^3 n \left| \sum_{k=1}^n P\{S_k = 0\} \right|^2 = \left(\frac{1}{n} \sum_{k=1}^n P\{S_k = 0\} \right)^{1/2}, \tag{3.30}$$

and this quantity vanishes as $n \to \infty$ by (3.29). This proves the lemma.

Proof of Theorem 1.2. Let $\epsilon_n := 1/a_n$. In light of Proposition 3.2, and Lemmas 3.3 and 3.4, it suffices to prove that the sequences $n \mapsto \epsilon_n W_n$ and $n \mapsto \epsilon_n H_n$ are tight.

Lemma 2.2, (2.2), and recurrence together imply that for all n large,

$$E\left(\left|\epsilon_{n}W_{n}\right|^{2}\right) = \sigma^{2}\epsilon_{n}^{2} \sum_{x \in \mathbf{Z}^{d}} E\left(\left|L_{n}^{x}\right|^{2}\right)$$

$$\leq \operatorname{const} \cdot \epsilon_{n}^{2} n \sum_{k=1}^{n} P\{S_{k} = 0\}$$

$$= \operatorname{const.}$$
(3.31)

Thus, $n \mapsto \epsilon_n W_n$ is bounded in $L^2(P)$, and hence is tight.

We conclude the proof by verifying that $n \mapsto \epsilon_n H_n$ is tight. Thanks to (2.4) and recurrence, for all n large,

$$E(|\epsilon_n H_n|^2) \le \operatorname{const} \cdot \epsilon_n^2 E \sum_{x \in \mathbf{Z}^d} (L_n^x)^2$$

$$\le \operatorname{const} \cdot \epsilon_n^2 n \sum_{k=1}^n P\{S_k = 0\}$$

$$= \operatorname{const}.$$
(3.32)

Confer with Lemma 2.2 for the penultimate line. Thus, $n \mapsto \epsilon_n H_n$ is bounded in $L^2(P)$ and hence is tight, as was announced.

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