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## ON A FUNCTIONAL CENTRAL LIMIT THEOREM FOR RANDOM WALKS CONDITIONED TO STAY POSITIVE

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Let  $\{X_k : k \geq 1\}$  be a sequence of i.i.d.rv with  $E(X_i) = 0$  and  $E(X_i^2) = \sigma^2$ ,  $0 < \sigma^2 < \infty$ . Set  $S_n = X_1 + \dots + X_n$ . Let  $Y_n(t)$  be  $S_k/\sigma n^{1/2}$  for  $t = k/n$  and suitably interpolated elsewhere. This paper gives a generalization of a theorem of Iglehart which states weak convergence of  $Y_n(t)$ , conditioned to stay positive, to a suitable limiting process.

**1. Introduction.** Let  $\{X_i\}_{i \in N}$  be a sequence of i.i.d.rv with  $E(X_i) = 0$  and  $E(X_i^2) = \sigma^2$  where  $0 < \sigma^2 < \infty$ . Let  $S_k = X_1 + \dots + X_k$  and  $Y_n(t)$  be the continuous process on  $[0, 1]$  for which  $Y_n(k/n) = S_k/\sigma n^{1/2}$  and which is linearly interpolated elsewhere.

It is well known (see e.g., [2]) that  $Y_n(t)$  converges weakly in  $(C[0, 1], \rho)$  to the Brownian motion process, where  $C[0, 1]$  is the set of continuous functions on  $[0, 1]$  and  $\rho$  the supremum metric.

Let now  $C^+ = \{f \in C : f(t) \geq 0 \text{ for } t \in [0, 1]\}$ . We have  $P(Y_n \in C^+) > 0$  for each  $n$ . So the definition of conditional probabilities is elementary. Let  $Y_n^+$  be the  $Y_n$ -process conditioned to stay positive. That is for all Borel-sets  $A \subset C[0, 1]$  we set  $P(Y_n^+ \in A) = P(Y_n \in A \mid Y_n \in C^+)$ . We remark that  $C^+$  is a null set for the measure of the Brownian motion. Iglehart proved [3] weak convergence of the  $Y_n^+$  process to the Brownian meander process  $W^+$  which is defined by

$$(1.1) \quad W^+(t) = \left| \frac{1}{(1-\tau)^{1/2}} W(\tau + (1-\tau)t) \right|, \quad 0 \leq t \leq 1$$

with  $W$  the Brownian process and  $\tau = \sup\{t \in [0, 1] : W(t) = 0\}$ . (Notice that  $\tau < 1$  a.s.)

Iglehart assumed  $E|X_i|^3 < \infty$  and  $X_i$  nonlattice or integer valued with span 1. It is shown in this paper that these extra assumptions are superfluous. Iglehart calculates the finite-dimensional distributions and proves tightness. Then he identifies the process with (1.1) for which Belkin [1] calculated the finite dimensional distributions. The proof given here requires no computation. It is based on identifying  $\lim_{n \rightarrow \infty} Y_n^+(t) = W(T+t) - W(T) = W^+(t)$  for an appropriate random time  $T$  and uses only the continuous mapping theorem (Theorem 5.1 in [2]).

**2. Notations and preliminary lemmas.** For  $s \in (0, \infty]$  let  $C^s$  be the set of

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continuous functions on  $[0, s]$  (or  $[0, \infty)$  for  $s = \infty$ ) and  $\mathcal{B}^s$  the smallest  $\sigma$ -algebra such that the mappings  $C^s \ni f \rightarrow f(t) \in \mathbb{R}$  are measurable.

Let  $P^s$  be the measure of the Brownian motion on  $(C^s, \mathcal{B}^s)$ .

$T^s: C^s \rightarrow \bar{\mathbb{R}}^+ = [0, \infty]$  is the mapping with

$$(2.1) \quad T^s(f) = \inf \{t: f(u) \geq f(t) \text{ for } t \leq u \leq t + 1 \leq s\}, \quad (\inf \emptyset = \infty).$$

We set  $T = T^\infty$  and  $P = P^\infty$  for simplicity.

LEMMA 2.1. For all  $s \in (0, \infty]$   $T^s$  is  $\mathcal{B}^s$ -measurable.

PROOF. If  $v = s - (u + 1) > 0$  then  $\{T^s \leq u\} = \bigcap_{n \geq 1/v} \{f \in C^s: \text{there exists a rational } r \leq u + 1/n \text{ with } f(r) < \min_{1 \leq i \leq n-1} f(r + i/n) + 1/n\}$ , which is easily seen to belong to  $\mathcal{B}^s$ .

LEMMA 2.2.  $P(T < \infty) = 1$ .

PROOF. Let  $A_\varepsilon = \{f \in C^1: \text{ex. } s \leq 1 - \varepsilon \text{ with } f(s) \leq f(u) \text{ for } s \leq u \leq s + \varepsilon\}$ . Now we have  $A_\varepsilon \downarrow \{f \in C^1: f \text{ nonincreasing}\}$  as  $\varepsilon \downarrow 0$ . We infer  $P(A_\varepsilon) \uparrow 1$  for  $\varepsilon \downarrow 0$ . If  $\varphi: C^\infty \rightarrow C^\infty$  is defined by  $\varphi(f)(t) = \varepsilon^{-1}f(\varepsilon t)$  then  $\varphi$  is measure preserving (see [5] page 246) and  $\varphi(A_\varepsilon) \subset \{T < \infty\}$  so  $P(T < \infty) \geq P(A_\varepsilon)$  for all  $\varepsilon > 0$ .

LEMMA 2.3. The following three statements are true for all  $s \in (0, \infty]$ .

$$(2.2) \quad P^s(f(T^s) = f(T^s + 1)) = 0;$$

$$(2.3) \quad P^s(T^s = s - 1) = 0;$$

$$(2.4) \quad P^s(\text{ex. } u \in (0, 1) \text{ with } f(T^s) = f(T^s + u)) = 0.$$

PROOF. We set  $m(t) = \min_{0 \leq s \leq t} W(t)$ .  $D(t) = W(t) - m(t)$  has the same finite-dimensional distributions as  $|W(t)|$  (see [5] page 193). Observe now that  $T^s = \inf \{t \leq s - 1: m(t) = m(t + 1)\}$ . Now  $T^s = s - 1$  implies  $D(s - 1) = 0$  which has  $P$  measure 0. This proves (2.3).

Let  $U = \{\text{ex. } u < v < w \text{ with } m(u) = m(v) = m(w) \text{ and } D(u) = D(v) = D(w) = 0\}$ . Then  $U \subset \bigcup_{r, s \in \mathbb{Q}} \{\min_{0 \leq t \leq r} W(t) = \min_{r \leq t \leq r+s} W(t)\}$  and the last has  $P$  measure 0. This proves (2.4).

It suffices to prove (2.2) for  $s = \infty$ . With probability one, the hitting time process  $\{T_{-x}: x \geq 0\}$  ( $T_{-x} = \inf \{t: W(t) = -x\}$ ) has no jumps of length one. This follows from its Lévy decomposition (see Section 1.7 of [4]). Together with  $P(U) = 0$  this yields (2.2).

LEMMA 2.4. For each  $s \in (0, \infty]$   $T^s$  is a continuous  $P^s$  a.e. on  $(C^s, \rho)$ .

PROOF. By (2.3) it suffices to consider the case  $s = \infty$ . Let  $f$  be such that  $T(f) < \infty$  and  $f$  does not belong to the null sets defined in (2.2)—(2.4).

(I) We first prove that for all  $\delta > 0$  there exists an  $\varepsilon > 0$  with

$$T(f') \leq T(f) + \delta \quad \text{when } \rho(f, f') < \varepsilon.$$

By (2.2) there is as  $\tau < \delta$  so that

$$\inf_{T+1 \leq u \leq T+1+\tau} f(u) > f(T) .$$

Now (2.4) gives  $\varepsilon = \frac{1}{3}(\inf_{T+\tau \leq u \leq T+\tau+1} f(u) - f(T)) > 0$ .

If  $\rho(f, f') < \varepsilon$  and  $\gamma'$  is such that  $T(f) \leq \gamma' \leq T(f) + \tau$  and  $f'(\gamma') = \inf_{T \leq u \leq T+\tau} f'(u)$  then  $T(f') \leq \gamma' \leq T(f) + \delta$ .

(II) To show the other inequality note that

$$\lim_{n \rightarrow \infty} (\inf \{T(f') : \rho(f, f') < 1/n\}) = \lambda \leq T(f) .$$

Let  $\{f_n\}_{n \in \mathbb{N}}$  be a sequence with  $\rho(f, f_n) \leq 1/n$  and  $\lim_{n \rightarrow \infty} T(f_n) = \lambda$ . Let  $\varepsilon > 0$ . By the continuity of  $f$  and the uniform convergence of  $f_n$ , there exists  $n_0$  such that for  $n \geq n_0$  we have:

$$\begin{aligned} \inf_{\lambda \leq u \leq \lambda+1} f(u) &\geq \inf_{T(f_n) \leq u \leq T(f_n)+1} f(u) - \varepsilon \\ &\geq \inf_{T(f_n) \leq u \leq T(f_n)+1} f_n(u) - 2\varepsilon \\ &\geq f_n(T(f_n)) - 2\varepsilon \geq f(T(f_n)) - 3\varepsilon \geq f(\lambda) - 4\varepsilon . \end{aligned}$$

So  $\inf_{\lambda \leq u \leq \lambda+1} f(u) \geq f(\lambda)$  which implies  $T(f) \leq \lambda$  completing the proof of Lemma 2.4.

Let  $u$  be the function in  $C^1$  which is everywhere equal  $-1$ . We define a map  $\Phi_s : C^s \rightarrow C^1$

$$\begin{aligned} \Phi_s(f)(t) &= f(T^s(f) + t) && \text{for } T^s(f) < \infty \\ &= u && \text{for } T^s(f) = \infty . \end{aligned}$$

We write  $\Phi = \Phi_\infty$  for simplicity.

A straightforward conclusion of Lemma 2.4 is

LEMMA 2.5. For each  $s \in (0, \infty]$   $\Phi_s$  is continuous  $P^s$  a.s. on  $(C^s, \rho)$ .

**3. Sums of independent random variables conditioned to stay positive.** Let  $X_1, X_2, \dots$ , be i.i.d.rv with  $E(X_i) = 0$ ;  $E(X_i^2) = \sigma^2 < \infty$  ( $\sigma^2 > 0$ ) and  $S_k = \sum_{j=1}^k X_j$ .  $T_n = \inf \{k : S_{k+i} \geq S_k \text{ for } i = 1, \dots, n\}$ . Clearly  $T_n < \infty$  holds a.s. We set  $Z_k = S_{T_n+k} - S_{T_n}$ .

LEMMA 3.1. For each sequence of real numbers  $a_1, \dots, a_n$

$$(3.1) \quad \begin{aligned} P(S_k \leq a_k, k = 1, \dots, n | S_k \geq 0, k = 1, \dots, n) \\ = P(Z_k \leq a_k, k = 1, \dots, n) . \end{aligned}$$

PROOF. This is an easy consequence of the independence and identical distribution of the  $X_i$ :

If  $B_j = \bigcup_{s=0}^{j-1} \{S_s \leq S_r \text{ for } s+1 \leq r \leq \min(j, s+n)\}$  we have

$$\begin{aligned} P(S_{T_n+k} - S_{T_n} \leq a_k \text{ for } k = 1, \dots, n) \\ = \sum_{j=0}^{\infty} P(S_{j+k} - S_j \leq a_k \text{ for } k = 1, \dots, n | T_n = j) P(T_n = j) \end{aligned}$$

$$\begin{aligned}
 &= \sum_{j=0}^{\infty} P(S_{j+k} - S_j \leq a_k \text{ for } k = 1, \dots, n | S_{j+k} \geq S_j \\
 &\quad \text{for } k = 1, \dots, n \text{ and } B_j^c) P(T_n = j) \\
 &= P(S_k \leq a_k, k = 1, \dots, n | S_k \geq 0, k = 1, \dots, n) \\
 &\hspace{15em} \text{since } T_n < \infty \text{ a.s.}
 \end{aligned}$$

We set  $Y_n(k/n) = (1/n^{\frac{1}{2}}\sigma)S_k$  for  $k \geq 0$  and  $Y_n(t)$  linearly interpolated.

Let  $Q_n$  be the probability measure defined on  $(C^\infty, \mathcal{B}^\infty)$  by this process. Let  $\Pi_s: C^\infty \rightarrow C^s$  be the projection map and  $\Phi, C^+$  defined as above. We remark that  $P^s = P\Pi_s^{-1}$ .

Let  $Q_n \Pi_1^{-1}(dx | C^+)$  be the probability measure on  $C^1$  which is defined by

$$Q_n \Pi_1^{-1}(A | C^+) = Q_n(\Pi_1^{-1}(A \cap C^+)) / Q_n(\Pi_1^{-1}(C^+))$$

for  $A \in \mathcal{B}^1$ .

**THEOREM 3.2.** *The probability measures  $Q_n \Pi_1^{-1}(dx | C^+)$  converge weakly to  $P\Phi^{-1}$  (on  $(C^1, \rho)$ ).*

**PROOF.** We have proved in Lemma 3.1 that

$$(3.2) \quad Q_n \Pi_1^{-1}(dx | C^+) = Q_n \Phi^{-1}(dx) \text{ holds.}$$

Now by Donsker's theorem (see [2]),  $Q_n \Pi_s^{-1}$  converges weakly to  $P^s$  for  $s < \infty$ . With regard to Lemma 2.5 we have for  $s < \infty$

$$(3.3) \quad Q_n(\Phi_s \Pi_s)^{-1} \rightarrow P^s \Phi_s^{-1} \text{ weakly.}$$

(Theorem 5.1 in [2].)

Let  $A$  be a continuity set in  $\mathcal{B}^1$ , that is  $P\Phi^{-1}(\partial A) = 0$ . We are going to show that

$$(3.4) \quad \lim_{n \rightarrow \infty} Q_n \Phi^{-1}(A) = P\Phi^{-1}(A).$$

The theorem then follows. (3.4) doesn't follow directly from (3.3) because we have there the assumption  $s < \infty$ . Set

$$D = \{f \in C^1 : \min_{0 \leq t \leq 1} f(t) \geq -\frac{1}{2}\}.$$

Without loss of generality we can assume  $A \subset D$ . (If not: replace  $A$  by  $A \cap D$  noticing  $Q_n \Phi^{-1}(D^c) = P\Phi^{-1}(D^c) = P\Phi^{-1}(\partial D) = 0$ ).

Let  $\varepsilon > 0$  be given. According to Lemma 2.2 we have  $P(T < \infty) = 1$ . So there exists a real number  $c > 0$  such that  $P(T \leq c - 1) \geq 1 - \varepsilon$ .

We choose  $n_0$  such that for  $n \geq n_0$

$$(3.5) \quad |Q_n \Pi_c^{-1}(T^c < \infty) - P^c(T^c < \infty)| \leq \varepsilon.$$

(According to Lemma 2.4  $\{T^c < \infty\}$  is a continuity set with respect to  $P^c$ . (3.5) then follows by Donsker's theorem.)

We infer from (3.5) and the setting of  $c$ :

$$(3.6) \quad P(\Phi_c \Pi_c \neq \Phi) \leq \varepsilon,$$

$$(3.7) \quad Q_n(\Phi_c \Pi_c \neq \Phi) \leq 2\varepsilon .$$

(We have  $\{\Phi_c \Pi_c = \Phi\} \cap \{T < \infty\} = \{T^c \Pi_c < \infty\} = \{T \leq c - 1\}$ .)

We choose  $n_1 \geq n_0$  such that for  $n \geq n_1$

$$(3.8) \quad |Q_n(\Phi_c \Pi_c)^{-1}(A) - P^c \Phi_c^{-1}(A)| \leq \varepsilon .$$

(The element  $u$  doesn't belong to  $\partial A$  because we assumed  $A \subset D$ . It is easily seen that  $(\Phi_c \Pi_c)^{-1}(\partial A) \subset \Phi^{-1}(\partial A)$  holds, so we infer that  $P(\Phi_c \Pi_c)^{-1}(\partial A) = P^c \Phi_c^{-1}(\partial A) = 0$  and the existence of an  $n_1$ , such that (3.8) holds then follows from (3.3).)

For  $n \geq n_1$  we have:

$$\begin{aligned} |Q_n \Phi^{-1}(A) - P \Phi^{-1}(A)| &\leq |Q_n \Phi^{-1}(A) - Q_n(\Phi_c \Pi_c)^{-1}(A)| \\ &\quad + |Q_n(\Phi_c \Pi_c)^{-1}(A) - P^c \Phi_c^{-1}(A)| \\ &\quad + |P(\Phi_c \Pi_c)^{-1}(A) - P \Phi^{-1}(A)| \\ &\leq Q_n(\Phi \neq \Phi_c \Pi_c) + \varepsilon + P(\Phi \neq \Phi_c \Pi_c) \leq 4\varepsilon . \end{aligned}$$

So  $\lim_{n \rightarrow \infty} Q_n \Phi^{-1}(A) = P \phi^{-1}(A)$  which is (3.4) and the proof is complete.

So far we have proved that  $Y_n^+$  converges weakly to  $P \Phi^{-1}$  which is  $W(T+t) - W(T)$   $0 \leq t \leq 1$ . It remains to identify  $W(T+\cdot) - W(T)$  with the Brownian meander  $W^+$ . But this clearly follows from Iglehart's result. We give a sketch of a proof using the methods of the present paper: Let  $X_i = \pm 1$  each with probability  $\frac{1}{2}$ . Set  $\mu_n = \inf \{k \leq n : \text{the sequence } S_k, \dots, S_n \text{ does not change sign}\}$  and let  $\nu_n = n - \mu_n$  (remark that  $\nu_n \geq 1$ ). We define  $\tilde{Y}_n(t)$  as follows:  $\tilde{Y}_n(k/\nu_n) = (1/\nu_n)^{\frac{1}{2}} |S_{\mu_n+k}|$  for  $0 \leq k \leq \nu_n$  and linearly interpolated elsewhere.  $\tilde{Y}_n(\cdot)$  has the same distribution as  $Y_{\nu_n}^+(\cdot)$  where  $\{Y_k^+\}_{k \in \mathbb{N}}$  and  $\nu_n$  are independent. Define  $\tau' : C^1 \rightarrow [0, 1]$  by  $\tau'(f) = \inf \{t \in [0, 1] : f(s) \text{ does not change sign for } s \in [t, 1]\}$ . Further, define  $\Psi : C^1 \rightarrow C^1$  by  $\Psi(f)(t) = |(1 - \tau')^{-\frac{1}{2}} f(\tau' + (1 - \tau')t)|$  for  $\tau' \in [0, 1)$ , and  $\Psi(f)$  identically zero for  $\tau' = 1$ . We then have  $\tilde{Y}_n = \Psi(Y_n)$ , which is identical in law to  $Y_{\nu_n}^+$ . Now  $\tau' = \tau = \sup \{t \in [0, 1] : f(t) = 0\}$   $P^1$ -a.s. (This can be proved in the same way as the statements of Lemma 2.3). So  $W^+$  has the same distribution as  $\Psi(W)$ . It can be shown by the same methods as in Lemma 2.4 and 2.5 that  $\Psi$  is  $P^1$ -a.s. continuous on  $(C^1, \rho)$ . The continuous mapping theorem implies  $\tilde{Y}_n \rightarrow W^+$  and so  $Y_{\nu_n}^+ \rightarrow W^+$  in distribution. By Theorem 3.2  $Y_n^+ \rightarrow W(T+\cdot) - W(T)$ . Clearly  $\nu_n \rightarrow \infty$  in distribution. This is sufficient for  $Y_{\nu_n}^+ \rightarrow W(T+\cdot) - W(T)$  because  $\{Y_n^+\}$  and  $\nu_n$  are independent. It follows that  $W^+$  and  $W(T+\cdot) - W(T)$  have the same distribution.

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REFERENCES

[1] BELKIN, B. (1972). An invariance principle for conditioned random walks attracted to a stable law. *Z. Wahrscheinlichkeitstheorie und Verw. Gebiete* **21** 45-64.  
 [2] BILLINGSLEY, P. (1968). *Convergence of Probability Measures*. Wiley, New York.

- [3] IGLEHART, D. L. (1974). Functional central limit theorems for random walks conditioned to stay positive. *Ann. Probability* 2 608–619.
- [4] ITO, K. and MCKEAN, H. P. (1965). *Diffusion Processes and Their Sample Paths*. Springer-Verlag, Berlin.
- [5] LÉVY, P. (1945). *Processus Stochastique et Mouvement Brownian*. Gauthier-Villars, Paris.

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