

# Wiener-Hopf factorization for extremal Markovian sequences connected with the Kendall convolution

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- **First order Kendall maximal autoregressive processes and their applications**
- Barbara Jasiulis-Gołdyn, PhD

# Generalized convolution of the Kendall type

## Definition 1 (Kendall convolution)

- ①  $\delta_a \triangle_{\alpha} \delta_b = T_{\max\{|a|, |b|\}} \left( (1 - z^{\alpha}) \tilde{\delta}_1 + z^{\alpha} \tilde{\pi}_{2\alpha} \right),$   
where  $z = \frac{\min\{|a|, |b|\}}{\max\{|a|, |b|\}}, \alpha \in (0, 1], \tilde{\pi}_{2\alpha}(dx) = \frac{\alpha}{|x|^{2\alpha+1}} \mathbf{1}_{(1, \infty)}(|x|) dx.$
- ②  $\nu_1 \triangle_{\alpha} \nu_2(A) = \int_{\mathbb{R}^2} (\delta_x \triangle_{\alpha} \delta_y)(A) \nu_1(dx) \nu_2(dy)$

# Kendall random walk

## Definition 2 (Rosiński et al.)

*The Kendall random walk is a Markov process  $\{X_n : n \in \mathbb{N}_0\}$  with  $X_0 = 0$  and the transition probabilities*

$$P_n(x, A) = P(X_{n+k} \in A | X_k = x) = \delta_x \Delta_\alpha \nu^{\Delta_\alpha n}$$

*where measure  $\nu \in \mathcal{P}_s$  is called the step distribution.*

# Kendall random walk representation

## Theorem 1 (Jasiulis-Gołdyn)

The Markov process  $\{X_n : n \in \mathbb{N}_0\}$  with step distribution  $Y_i \sim \nu$  has the following properties:  $X_0 = 0$ ,  $X_1 = Y_1$ ,

$$X_{n+1} = \nu(|X_n|, |Y_{n+1}|)u(X_n, Y_{n+1})\theta_n^{Q_n} \text{ a.e.},$$

where  $\theta_n$  is independent of  $\nu(|X_n|, |Y_{n+1}|)u(X_n, Y_{n+1})$ ,  $\nu(x, y) = x \vee y$ ,  
 $u(x, y) = \frac{x \wedge y}{x \vee y}$ ,

$$u(x, y) = \begin{cases} \operatorname{sgn}(x), & |x| \geq |y|, \\ \operatorname{sgn}(y), & |x| < |y|, \end{cases}$$

and

$$\mathbb{P}(Q_n = k | X_n, Y_{n+1}) = \begin{cases} (z(|X_n|, |Y_{n+1}|))^{\alpha}, & k = 1, \\ 1 - (z(|X_n|, |Y_{n+1}|))^{\alpha}, & k = 0. \end{cases}$$

# Williamson transform

## Definition 3

*Williamson transform Operation  $\nu \rightarrow \hat{\nu}$  given by*

$$\hat{\nu}(t) = \int_{\mathbb{R}} (1 - |xt|^\alpha)_+ \nu(dx), \quad \nu \in \mathcal{P}_s,$$

*where  $a_+ = a$  if  $a \geq 0$  and  $a_+ = 0$  otherwise.*

## Theorem 2

*Let  $\nu_1, \nu_2 \in \mathcal{P}_s$  be probability measures with Williamson transforms  $\hat{\nu}_1, \hat{\nu}_2$ .  
Then*

$$\int_{\mathbb{R}} (1 - |xt|^\alpha)_+ (\nu_1 \triangle_\alpha \nu_2)(dx) = \hat{\nu}_1(t) \hat{\nu}_2(t).$$

# Inverse Williamson transform

## Theorem 3 (Jasiulis-Gołdyn, Misiewicz, 2017)

*The correspondence between measure  $\nu \in \mathcal{P}_s$  and its Williamson transform is 1 – 1. Moreover, denoting by  $F$  the cumulative distribution function of  $\nu$ ,  $\nu(\{0\}) = 0$  and  $G(t) = \hat{\nu}(\frac{1}{t})$ , we have*

$$F(t) = \begin{cases} \frac{1}{2\alpha} [\alpha(G(t) + 1) + tG'(t)] & \text{if } t > 0; \\ 1 - F(-t) & \text{if } t < 0. \end{cases}$$

*except for the countable many  $t \in \mathbb{R}$ .*

# Definitions

- $\tau_a^+ = \inf\{i \geq 0 : X_i > a\}$
- $\tau_a^- = \inf\{i \geq 0 : X_i < a\}$
- Convention:  $\min \emptyset = \infty$
- Notation:  $H(x) = 2F(x) - 1 - G(x)$
- Notation:  $\Psi(t) = (1 - |t|^\alpha)_+$



# Useful lemmas

## Lemma 4 (Jasiulis-Gołdyn, Misiewicz)

$$\begin{aligned}\delta_x \triangle_{\alpha} \delta_y(0, t) &:= \frac{1}{2} \left( 1 - \left| \frac{xy}{t^2} \right|^{\alpha} \right) \mathbf{1}_{\{|x| < t, |y| < t\}} \\ &= \frac{1}{2} \left[ \psi\left(\frac{x}{t}\right) + \psi\left(\frac{y}{t}\right) - \psi\left(\frac{x}{t}\right) \psi\left(\frac{y}{t}\right) \right] \mathbf{1}_{\{|x| < t, |y| < t\}}\end{aligned}$$

## Lemma 5 (Jasiulis-Gołdyn, Misiewicz)

$$\begin{aligned}\delta_x \triangle_{\alpha} \nu(0, t) &= P_1(x, [0, t)) \\ &= \left[ \psi\left(\frac{x}{t}\right) \left( F(t) - \frac{1}{2} \right) + \frac{1}{2} G(t) - \frac{1}{2} \psi\left(\frac{x}{t}\right) G(t) \right] \mathbf{1}_{\{|x| < t\}} \\ &= \frac{1}{2} \left[ \psi\left(\frac{x}{t}\right) H(t) + G(t) \right] \mathbf{1}_{\{|x| < t\}}\end{aligned}$$

# Useful lemmas

## Lemma 6 (Jasiulis-Gołdyn, Staniak)

$$F_n(t) = \begin{cases} \frac{1}{2\alpha} [\alpha(G(t)^n + 1) + tnG(t)^{n-1}G'(t)] & , t > 0, \\ 1 - F_n(-t) & , t < 0. \end{cases}$$

## Lemma 7 (Jasiulis-Gołdyn, Staniak)

$$\begin{aligned} \delta_x \Delta_\alpha \nu^n(0, t) &= P_n(x, [0, t)) \\ &= \left[ \psi\left(\frac{x}{t}\right) \left(F_n(t) - \frac{1}{2}\right) + \frac{1}{2}G(t)^n - \frac{1}{2}\psi\left(\frac{x}{t}\right) G(t)^n \right] \mathbf{1}_{\{|x| < t\}} \end{aligned}$$

## Results for $a = 0$

### Theorem 8 ((Jasiulis-Gołdyn, Misiewicz))

*R. v.  $\tau_0^+$  (and, by symmetry of the Kendall random walk, also variable  $\tau_0^-$ ) has geometric distribution  $P(\tau_0^+ = k) = \frac{1}{2^k}$ ,  $k = 1, 2, \dots$ .*

*Generating function for  $\tau_0^+$  is given by*

$$\mathbf{E}s^{\tau_0^+} = \frac{s^{\frac{1}{2}}}{1 - \frac{s}{2}}, \quad 0 \leq s < 2.$$

## More results

- $\Phi_n(t) := \mathbf{P}\{X_1 \leq 0, \dots, X_{n-1} \leq 0, 0 < X_n < t\} = \frac{1}{2^n} G(t)^{n-1} \left[ 2n \left( F(t) - \frac{1}{2} \right) - (n-1)G(t) \right]$

### Theorem 9 (Jasiulis-Gołdyn, Misiewicz)

$$\mathbf{P}\{X_{\tau_0^+} < t\} = \sum_{k=1}^{\infty} \mathbf{P}\{X_{\tau_0^+} < t, \tau_0^+ = k\} = \sum_{k=1}^{\infty} \Phi_k(t) = \frac{1}{(2-G(t))^2} \left[ 4F(t) - 2 - G(t)^2 \right]$$

## Even more results

- Let  $\{X_n : n \in \mathbb{N}_0\}$  be the Kendall random walk
- Let  $N_{s/2}$  be geometric r.v. independent of  $(X_n)$ .
- Define geometric-Kendall r.v.:  $Z_{s/2} = \sum_{k=1}^{\infty} X_k \mathbf{1}_{\{N_{s/2}=k\}}$
- Notice that  $\mathbf{E}\Psi(X_k/t) = G(t)^k$  and  $\mathbf{E}\Psi(Z_{s/2}/t) = \frac{G(t)(1-\frac{s}{2})}{1-\frac{s}{2}G(t)}$ .

### Theorem 10 (Jasiulis-Gołdyn, Misiewicz)

Let  $\{X_n : n \in \mathbb{N}_0\}$  be a random walk under the Kendall convolution with the unit step  $X_1 \sim F$  such that  $F(0) = \frac{1}{2}$ . Then

$$\mathbf{E}s^{\tau_0^+} \Psi(uX_{\tau_0^+}) = \frac{\frac{s}{2}}{1 - \frac{s}{2}} \cdot \frac{(1 - \frac{s}{2})G(1/u)}{1 - \frac{s}{2}G(1/u)} = \mathbf{E}s^{\tau_0^+} \mathbf{E}\Psi(uZ_{s/2}).$$

# Distribution of the first ladder moment

## Theorem 11 (Jasiulis-Gołdyn, Staniak)

*The distribution of  $\tau_a^+$  is given by*

$$\begin{aligned}\mathbb{P}(\tau_a^+ = k) &= \left(\frac{1}{2}\right)^{k-1} \left[ \frac{F(a)(2G(a) - 1)^2 + G(a)[2F(a) - 2 - G(a)^2]}{(2G(a) - 1)^2} \right] \\ &+ G(a)^{k-1} \frac{(k-1)(2G(a) - 1 - 2G(a)^2)}{(2G(a) - 1)^2} \\ &+ G(a)^{k-1} \frac{(1 - G(a))(2F(a) - 1)(2G(a) - 1)^2}{(2G(a) - 1)^2}\end{aligned}$$

- $\mathbb{P}(\tau_a^+ = k) = \mathbb{P}(X_0 \leq a, X_1 \leq a, \dots, X_{k-1} \leq a, X_k > a)$   
 $= \int_{-\infty}^a \dots \int_{-\infty}^a \int_a^{-\infty} P_1(x_{k-1}, dx_k) P_1(x_{k-2}, dx_{k-1}) \dots P_1(0, dx_1)$
- Define  
 $I_1 = \int_a^\infty P_1(x_{k-1}, dx_k) = \frac{1}{2} - \frac{1}{2} \left[ \Psi\left(\frac{x_{k-1}}{a}\right) H(a) + G(a) \right] \mathbf{1}(|x_{k-1}| < a)$

# Proof: recurrence equations

- Assume that  $I_j$  is of the form

$$I_j = A_j + \mathbf{1}(|x_{k-j}| < a) \left[ \Psi\left(\frac{x_{k-j}}{a}\right) H(a) B_j + C_j G(a) \right]$$

- $I_{j+1} = \int_{-\infty}^a I_j (\delta_{x_{k-j-1}} \Delta_\alpha \nu)(d_{x_{k-j}})$

- $$\begin{cases} A_{j+1} = \frac{1}{2} A_j, \\ B_{j+1} = \frac{1}{2} A_j + G(a)(B_j + C_j), \\ C_{j+1} = \frac{1}{2} A_j + C_j G(a) \end{cases}$$

- $A_1 = \frac{1}{2}, B_1 = C_1 = -\frac{1}{2}$



# Solutions

- $$A_j = \left(\frac{1}{2}\right)^j$$

- $$\begin{aligned} B_j &= G(a)^{j-1} B_1 + \sum_{m=2}^j G(a)^{j-m} \left(\frac{1}{2}\right)^m + \sum_{m=1}^{j-1} G(a)^{j-m} C_m \\ &= \sum_{m=1}^j G(a)^{j-m} C_m \end{aligned}$$

- $$C_j = G(a)^{j-1} C_1 + \sum_{m=2}^j G(a)^{j-m} \left(\frac{1}{2}\right)^m = \sum_{m=1}^j G(a)^{j-m} \left(\frac{1}{2}\right)^m - G(a)^{j-1}$$

# Closed form solutions

- $A_j = \left(\frac{1}{2}\right)^j$
- $B_j = G(a)^{j-1} \frac{(1-G(a)(2G(a)-1)-G(a))}{(2G(a)-1)^2} j + \left(\frac{1}{2}\right)^j \frac{1}{(2G(a)-1)^2}$
- $C_j = \frac{G(a)^{j-1}(1-G(a))-2^{-j}}{2G(a)-1} = G(a)^{j-1} \frac{1-G(a)}{2G(a)-1} + \left(\frac{1}{2}\right)^j \frac{-1}{2G(a)-1}$

# Corollary

[Jasiulis-Góldyn, Staniak]

## Lemma 1

Generating function for  $\tau_a^+$  is given by

$$\begin{aligned} H(s) &= \frac{\frac{s}{2}}{1 - \frac{s}{2}} \left[ 2F(a) + \frac{4G(a)^2(2F(a) - 1)}{(2G(a) - 1)^2} \right] \\ &+ \frac{s}{(1 - sG(a))^2} \left[ \frac{(2G(a) - 1 - 2G(a)^2)H}{(2G(a) - 1)^2} \right] \\ &+ \frac{s}{1 - sG(a)} \left[ \frac{(2F(a) - 1)(G(a) + 1) - G(a)(2G(a) - 1 - 2G(a)^2)}{(2G(a) - 1)^2} \right] \end{aligned}$$

# Mean of the first ladder moment

## Lemma 2

Mean of the random variable  $\tau_a^+$  is given by

$$\begin{aligned}\mathbb{E}\tau_a^+ &= \frac{1}{4} \left[ 2F(a) + \frac{4G(a)^2(2F(a) - 1)}{(2G(a) - 1)^2} \right] \\ &+ \frac{1 - G(a)^2}{(1 - G(a))^4} \left[ \frac{(2G(a) - 1 - 2G(a)^2)H}{(2G(a) - 1)^2} \right] \\ &+ \frac{1}{(1 - G(a))^2} \left[ \frac{(2F(a) - 1)(G(a) + 1) - G(a)(2G(a) - 1 - 2G(a)^2)}{(2G(a) - 1)^2} \right]\end{aligned}$$

- $\mathbb{P}(X_{\tau_a^+} < t, \tau_a^+ = k)$ : complicated formula
- $\mathbb{E} s^{\tau_a^+} \Psi(uX_{t_a^+})$ : the final goal

- Renewal theory for Kendall convolution
- Limit properties of Kendall random walks
- More analogies with classical theory
- Applications



# Bibliography

- ① **A. Lachal**, *A note on Spitzer identity for random walk*, *Statistics & Probability Letters*, **78**(2), 97–108, 2008.
- ② **T. Nakajima**, *Joint distribution of first hitting time and first hitting place for random walk*, *Kodai Math. J.* **21**, 192–200, 1998.
- ③ **B.H. Jasiulis-Gołdyn, J.K. Misiewicz**, *Kendall random walk, Williamson transform and the corresponding Wiener-Hopf factorization*, in press: *Lith. Math. J.*, 2016, arXiv: <http://arxiv.org/pdf/1501.05873.pdf>.
- ④ **B.H. Jasiulis-Gołdyn, M. Staniak**, *Spitzer identity for Kendall random walk*, 2017, in preparation.
- ⑤ **M. Borowiecka-Olszewska, B.H. Jasiulis-Gołdyn, J.K. Misiewicz, J. Rosiński**, *Lévy processes and stochastic integrals in the sense of generalized convolutions*, *Bernoulli*, **21**(4), 2513–2551, 2015.