

# A log-linear model for non-stationary time series of counts

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- 1 GARCH and integer-valued GARCH
- 2 Models for non-stationary count processes
- 3 Mixing properties of INGARCH processes

# GARCH and integer-valued GARCH

(Classical) GARCH:

$$\begin{aligned}X_t &= \sigma_t \varepsilon_t, \\ \sigma_t^2 &= f(X_{t-1}^2, \dots, X_{t-p}^2; \sigma_{t-1}^2, \dots, \sigma_{t-q}^2),\end{aligned}$$

where  $f: \mathbb{R}_+^{p+q} \rightarrow \mathbb{R}_+$ ,  $(\varepsilon_t)_{t \in \mathbb{Z}}$  sequence of i.i.d. rv's,  $\mathbb{E}\varepsilon_t^2 = 1$ .

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Integer-valued **GARCH** (INGARCH):

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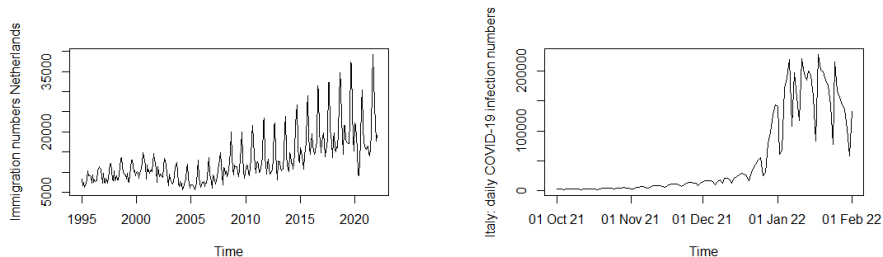
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Poisson-INGARCH:  $Q(\sigma) = \text{Poi}(\sigma) \rightsquigarrow \sigma_t = \text{var}(X_t | X_{t-1}, X_{t-2}, \dots)$

# A model for count series with a strong trend



**Figure:** left: Monthly immigration numbers for the Netherlands with increasing trend and strongly increasing seasonality; right: daily COVID-19 infection numbers from Italy with explosive trend.

# Poisson-INGARCH and trend

$$X_t \mid \text{“past”} \sim \text{Poi}(\sigma_t); \quad \sigma_{t+1} = a_t X_t + b_t \sigma_t + Z_t,$$

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- if  $\sqrt{\text{var}(X_t \mid \sigma_t)} / E(X_t \mid \sigma_t) \xrightarrow{P} 0$ , then
  - ▶  $d_{TV}(\text{Poi}(\tilde{\sigma}_t), \text{Poi}(\tilde{\sigma}'_t)) \xrightarrow{P} 1$ ,
  - ▶ mixing properties deteriorate as  $t \rightarrow \infty$

# A remedy: (nearly) scale-invariant distributions on $\mathbb{N}_0$

Classical GARCH:

$$X_t \mid \text{"past"} \sim \mathcal{N}(0, \sigma_t)$$
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Integer-valued counterparts:

$$X_\sigma = \lfloor \sigma Y \rfloor$$

$$(X_\sigma = k \iff \sigma Y \in [k, k + 1))$$

# Examples

- $Y \sim \text{Exp}(1)$ , then

$$P(X_\sigma = k) = P(\sigma Y \in [k, k + 1)) = p(1 - p)^k,$$

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- $Z \sim \mathcal{N}(0, \pi/2)$ , then  $Y := |Z|$  has a half-normal distribution,  
 $EY = 1$ ,  $X_\sigma = \lfloor \sigma Y \rfloor$

## The proposed model

$$X_t \mid \text{"past"} \stackrel{d}{=} [\sigma_t Y], \quad (2.1a)$$

$$\sigma_t = f(\sigma_{t-1}, X_{t-1}) \cdot Z_{t-1}, \quad (2.1b)$$

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Then

$$d_{TV}(P^{X_\sigma}, P^{X_{\sigma'}}) \leq \text{const.} \cdot |\ln(\sigma) - \ln(\sigma')| \quad \forall \sigma, \sigma' > 0$$

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(2.1b) equivalent to

$$\ln(\sigma_t) = \ln(f(\sigma_{t-1}, X_{t-1})) + \underbrace{\ln(Z_{t-1})}_{=: C_{t-1}} \quad (2.1c)$$

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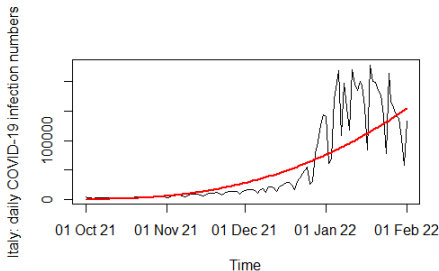
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Least squares fit:  $\hat{\theta}_n = 2.48$ ,  $t \mapsto t^{\hat{\theta}_n}$



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Applications in statistics: consistency, asymptotic normality, ...



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Applications in statistics: consistency, asymptotic normality, ...

- (strictly) stationary processes  
ergodicity (plus some structure) suffices: ergodic theorem, CLT for martingale differences
- non-stationary processes  
ergodicity does not help, mixing (or “weak dependence”)

## Absolute regularity ( $\beta$ -mixing)

- $(\Omega, \mathcal{F}, P)$  probab. space,  $\mathcal{A}, \mathcal{B}$  sub- $\sigma$ -algebras of  $\mathcal{F}$ . Then

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$$= \sup_k \mathbb{E} \left[ \sup_C |P((Y_{k+n}, Y_{k+n+1}, \dots) \in C | Y_k, Y_{k-1}, \dots) - P((Y_{k+n}, Y_{k+n+1}, \dots) \in C)| \right]$$

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$Y$  is absolutely regular ( $\beta$ -mixing) if

$$\beta^Y(n) \xrightarrow{n \rightarrow \infty} 0.$$

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Method of proof:

- $((X_t, \sigma_t))_t$  time-homogeneous Markov chain
- MC technology can be used



## Here: Mixing of INGARCH(1,1)

- $((X_t, \sigma_t))_t$  is a Markov chain
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### Consequences:

- Cannot use MC technology; use coupling arguments instead
- Revision of (a possible) original goal: Prove mixing only for the count process  $(X_t)_t$

## Non-mixing of $(\sigma_t)_t$

Counterexample (Neumann, 2011, *Bernoulli*):

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- $g$  strictly monotone  $\rightsquigarrow$  we can recover  $\sigma_{t-1}$  from  $\sigma_t$   
 $\rightsquigarrow$  we can recover from  $\sigma_t$  the complete past,  $(\sigma_s)_{s < t}$
- $(\sigma_t)_t$  is not purely non-random  
 $\rightsquigarrow$  not strong ( $\alpha$ -) mixing  $\rightsquigarrow$  not  $\beta$ -mixing

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$\beta^X(k, n)$

$$\leq \tilde{E} \left[ \sup_{C \in \sigma(C)} \{ |\tilde{P}((\tilde{X}_{k+n}, \tilde{X}_{k+n+1}, \dots) \in C \mid \tilde{X}_0, \dots, \tilde{X}_k) - \tilde{P}((\tilde{X}'_{k+n}, \tilde{X}'_{k+n+1}, \dots) \in C \mid \tilde{X}'_0, \dots, \tilde{X}'_k)| \} \right]$$

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# Mixing of “Scale-invariant” INGARCH

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Contractive condition:

$$|\ln(f(x, \sigma)) - \ln(f(x', \sigma'))| \leq a |\ln(\sigma) - \ln(\sigma')| + b |\ln(x+1) - \ln(x'+1)|.$$

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$$\ln(\sigma_t) = \ln(f(\sigma_{t-1}, X_{t-1})) + \underbrace{\ln(Z_{t-1})}_{=: C_{t-1}} \quad (3.1b)$$

Contractive condition:

$$|\ln(f(x, \sigma)) - \ln(f(x', \sigma'))| \leq a |\ln(\sigma) - \ln(\sigma')| + b |\ln(x+1) - \ln(x'+1)|.$$

## Theorem 3.1 (Leucht & N., 2023+).

If  $a + \gamma b < 1$ ,  $\sup\{E|C_t - EC_t| : t \in \mathbb{N}_0\} < \infty$ , and  $E|\ln(\sigma_0)| < \infty$ , then

$$\beta^X(n) = O(\rho^n)$$

for some  $\rho < 1$ .

## Proof of Theorem 3.1

For  $t \geq k$ , couple  $\tilde{X}_t$  and  $\tilde{X}'_t$  such that

$$\begin{aligned}\tilde{P}(\tilde{X}_t \neq \tilde{X}'_t \mid \tilde{\sigma}_t, \tilde{\sigma}'_t) &= d_{TV}(P^{[\tilde{\sigma}_t Y]}, P^{[\tilde{\sigma}'_t Y]}) \\ &= O(|\ln(\tilde{\sigma}_t) - \ln(\tilde{\sigma}'_t)|)\end{aligned}$$

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Then

$$\begin{aligned}\beta^X(k, n) &\leq \underbrace{\tilde{P}(\tilde{X}_{k+n} \neq \tilde{X}'_{k+n})}_{\leq c_1(a+\gamma b)^n} \\ &\quad + \underbrace{\sum_{r=1}^{\infty} \tilde{P}(\tilde{X}_{k+n+r} \neq \tilde{X}'_{k+n+r}, \tilde{X}_{k+n+r-1} = \tilde{X}'_{k+n+r-1}, \dots, \tilde{X}_{k+n} = \tilde{X}'_{k+n})}_{\leq c_2(a+\gamma b)^n a^r}.\end{aligned}$$



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- INGARCH: proof of mixing via coupling rather than existing MC results
- Poisson-INGARCH: a moderate trend leaves mixing properties intact
- “scale-invariant” INGARCH:
  - ▶ closer to classical GARCH
  - ▶ contraction at a logarithmic scale  $\rightsquigarrow$  explosive behavior does not affect mixing properties