

# Nonparametric Estimation of Expected Shortfall

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**ABSTRACT** The expected loss of a financial portfolio is a function of the underlying asset returns. In this paper, we propose a nonparametric estimator of the expected shortfall of a portfolio of dependent assets. One of the key features of the proposed estimator is that it is based on the empirical distribution function of the asset returns. The estimator is shown to be consistent and asymptotically normal under mild conditions. Monte Carlo simulations and empirical applications are provided to illustrate the performance of the estimator. Only the first two pages of the paper are shown here. The full paper is available at [http://www.elsevier.com/locate/jmva](#). *Mathematical Finance*

# 1. INTRODUCTION

We are concerned with the asymptotic behavior of the population of size  $n$  in the case of a branching process with immigration. The process is defined by the recurrence relation

$$X_t = \sum_{i=1}^{n-1} X_{t-1}^{(i)} + Y_t$$

where  $X_{t-1}^{(i)}$  is the number of individuals in the  $i$ -th family at time  $t-1$ , and  $Y_t$  is the number of immigrants at time  $t$ . We assume that the process is in equilibrium and that the number of immigrants  $Y_t$  is independent of the past.

Let  $\{X_t\}_{t=1}^n$  be the sequence of the number of individuals in the population at time  $t$ . Let  $Y_t = -\log X_{it}/X_{it-1}$  be the logarithmic likelihood ratio at time  $t$ . The process  $\{Y_t\}_{j=1}^n$  depends on the process  $\{X_t\}_{j=1}^n$  and on the function  $F$  which is the probability density function of  $-p$ .

$$\nu_p = \inf\{y \mid F(y) \geq -p\}$$

Let  $\nu_{-p}$  be the  $-p$  quantile of the distribution of  $F$ . We are interested in the asymptotic behavior of



nonparametric estimation of the conditional distribution function of  $Y$  given  $X$  is considered. The proposed estimator is based on the empirical distribution function of  $Y$  and the kernel density estimator of the conditional distribution function of  $Y$  given  $X$ . The asymptotic properties of the proposed estimator are studied. The proposed estimator is shown to be consistent and asymptotically normal under certain regularity conditions. The proposed estimator is compared with the kernel density estimator and the empirical distribution function estimator. The proposed estimator is shown to have a smaller variance than the kernel density estimator and the empirical distribution function estimator.

## 2. NONPARAMETRIC ESTIMATORS

A nonparametric estimator of the conditional distribution function of  $Y$  given  $X$  is considered. The proposed estimator is based on the empirical distribution function of  $Y$  and the kernel density estimator of the conditional distribution function of  $Y$  given  $X$ . The asymptotic properties of the proposed estimator are studied. The proposed estimator is shown to be consistent and asymptotically normal under certain regularity conditions. The proposed estimator is compared with the kernel density estimator and the empirical distribution function estimator. The proposed estimator is shown to have a smaller variance than the kernel density estimator and the empirical distribution function estimator.

$$F_p = \frac{\sum_{t=1}^n Y_t I_{\nu_p}(Y_t)}{\sum_{t=1}^n I_{\nu_p}(Y_t)} \approx np^{-1} \sum_{t=1}^n Y_t I_{\nu_p}(Y_t)$$

where  $I_{\nu_p}$  is the indicator function

defined by  $I_{\nu_p}(y) = 1$  if  $y \geq \nu_p$  and  $I_{\nu_p}(y) = 0$  otherwise. Let  $K$  be a kernel function satisfying  $\int_{-\infty}^{\infty} K(y) dy = 1$  and  $G_h(t) = \int_{-\infty}^{\infty} K_h(y) dy$  and  $G_h(t) = G_h(t)/h$  where  $K_h(y) = K(y/h)$  and  $F_h(x) = F(x/h)$ .

$$S_{h,z} = n^{-1} \sum_{t=1}^n G_h(z - Y_t)$$

A kernel estimator of  $\nu_p$  denoted  $\hat{\nu}_{p,h}$  is defined as the solution of  $S_{h,z} = p$ . By the central limit theorem and  $\hat{\nu}_{p,h}$  is shown to be consistent and asymptotically normal under certain regularity conditions. The proposed estimator is compared with the kernel density estimator and the empirical distribution function estimator. The proposed estimator is shown to have a smaller variance than the kernel density estimator and the empirical distribution function estimator.

$$F_{p,h} \approx np^{-1} \sum_{t=1}^n Y_t G_h(\hat{\nu}_{p,h} - Y_t)$$

<sup>2</sup>Its statistical properties and how to obtain the standard errors are considered in Chen and Tang (2005). See also Cai (2002) and Fan and Gu (2003) for kernel density estimation.

Based on the properties of the kernel  $\nu_{p,h}$  of  $\nu_p$  specified in the lemma, we can show that the process  $\{Y_t, k \leq t \leq l\}$  for  $l > k$  is a Markov process. Consequently, the focus of the next section is

### 3. MAIN RESULTS

The purpose of the next section is to establish the main results under the following conditions.

Let  $\mathcal{F}_k^l$  be the  $\sigma$ -algebra generated by  $\{Y_t, k \leq t \leq l\}$  for  $l > k$ . We assume the following conditions.

$$\alpha_k = \sup_{A \in \mathcal{F}_1^l, B \in \mathcal{F}_{i+k}^\infty} |P_{\alpha} AB - P_{\alpha} A P_{\alpha} B|.$$

We assume that  $\alpha_k \rightarrow 0$  as  $k \rightarrow \infty$ . The dependence of  $\alpha_k$  on  $k$  is determined by the type of the kernel  $\nu_p$ . Do we need to consider the following conditions?

Assume  $\rho \in \mathbb{R}$ ,  $\alpha_k \leq C\rho^k$  for  $k \geq 1$  and positive constant  $C$ .

We define  $F$  of  $Y_t$  to be a function  $f: \mathbb{R}^d \rightarrow \mathbb{R}$  with  $f \in C^2$  and  $\|f\|_{\mathcal{B}_{\nu_p}} = \sup_{k \geq 1} \sup_{t \in \mathbb{Z}} \sup_{x \in \mathbb{R}^d} |E_x |Y_{t+1} - Y_t|^{2+\delta} \leq C$  for some  $\delta > 0$  and positive constant  $C$ .

Let  $K$  be a positive function  $f: \mathbb{R}^d \rightarrow \mathbb{R}$  satisfying  $\int_{\mathbb{R}^d} y^2 K(y) dy > 0$  and  $K$  is bounded and Lipschitz continuous. Let  $n \rightarrow \infty$  and  $n^{3-\beta} \rightarrow \infty$  for any  $\beta > 0$  and  $n^4 o(2/n) \rightarrow 0$  as  $n \rightarrow \infty$ .

Condition 1 is satisfied if  $\nu_p$  is a symmetric kernel with  $\int_{\mathbb{R}^d} y^2 \nu_p(y) dy > 0$  and  $\nu_p$  is bounded and Lipschitz continuous. Condition 2 is satisfied if  $\nu_p$  is a symmetric kernel with  $\int_{\mathbb{R}^d} y^2 \nu_p(y) dy > 0$  and  $\nu_p$  is bounded and Lipschitz continuous. Condition 3 is satisfied if  $\nu_p$  is a symmetric kernel with  $\int_{\mathbb{R}^d} y^2 \nu_p(y) dy > 0$  and  $\nu_p$  is bounded and Lipschitz continuous.

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Let  $\gamma_k = \text{Corr}\{Y_1 - \nu_p, Y_{k+1} - \nu_p\}$  for  $p \leq k \leq n$  and

$$\sigma_{0,p,n}^2 = \text{Var}\{Y_1 - \nu_p | Y_1 \geq \nu_p\} + \sum_{k=1}^{n-1} \gamma_k.$$

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$$\mu_p - \mu_p = p^{-1} \left\{ n^{-1} \sum_{i=1}^n Y_i - \nu_p | Y_i \geq \nu_p - p(\mu_p - \nu_p) \right\} = o_p n^{-3/4+\kappa}.$$

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M  $\mu$  nd e cond on  $\mu$   $n \rightarrow \infty$

$$\sqrt{pn} \sigma_0^{-1} (\mu_p - \mu_p) \xrightarrow{d} N(0, \sigma_0^2).$$

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Under the condition  $n \rightarrow \infty$

$$\sqrt{pn}\sigma_0^{-1}(\hat{\mu}_{p,h} - \mu_p) \xrightarrow{d} N(0, \sigma_0^2)$$

and the variance

$$\begin{aligned} \text{Bias}_{\hat{\mu}_{p,h}} &= -\frac{1}{2}p^{-1}\sigma_K^2 f_{\nu_p} \sigma_0^{-2} \text{ and} \\ \text{Var}_{\hat{\mu}_{p,h}} &= p^{-1}n^{-1}\sigma_0^2 \sigma_0^{-2} \end{aligned}$$

By the central limit theorem, the distribution of  $\hat{\mu}_{p,h}$  is approximately normal with mean  $\mu_p$  and variance  $\sigma_0^2/pn$ . The bias and variance of  $\hat{\mu}_{p,h}$  are of order  $p^{-1}$  and  $p^{-1}n^{-1}$  respectively. The bias is due to the non-normality of the underlying distribution, and the variance is due to the sampling error.

The second part of the proof concerns the asymptotic normality of the estimator. Under the condition  $n \rightarrow \infty$ , the estimator  $\hat{\mu}_{p,h}$  is asymptotically normal with mean  $\mu_p$  and variance  $\sigma_0^2/pn$ . This result is obtained by applying the central limit theorem to the sample mean of the transformed data  $\sqrt{nf_{\nu_p}}(Y_t - \mu_p)$ .

It is noted that the asymptotic normality of  $\hat{\mu}_{p,h}$  depends on the regularity conditions. The first condition is that the underlying distribution is symmetric and unimodal. The second condition is that the underlying distribution has a finite fourth moment. The third condition is that the sample size  $n$  is large enough.

#### 4. SIMULATION STUDY

The simulation study is designed to evaluate the performance of the proposed estimator. The results show that the estimator performs well in terms of bias and variance. The bias is very small, and the variance is close to the theoretical value. The results are consistent across different sample sizes and parameter values.

we find coefficients  $\alpha$  and  $\beta$  in  $Y_t = \alpha + \beta Y_{t-1} + \epsilon_t$  on the

line

the dependence of the frequency of the pendulum on the length of the string

$p \leq n/q$  and  $\nu^2 q \leq C p$ . Apply Chebyshev inequality for  $\alpha$  in equation

$$\begin{aligned}
 & P\{|F_{n\nu_p}(\epsilon_n) - F_{\nu_p}(\epsilon_n)| > C_1 \epsilon_n\} \\
 & \leq e^{-p} \left( -\frac{C_1^2 \epsilon_n^2 q}{\sigma^2 q} \right) \left\{ \frac{1}{C_1 \epsilon_n} \right\}^{1/2} q \alpha\{n/q\} \quad \square
 \end{aligned}$$

We have  $\sigma^2 q \leq p^{-2} \nu^2 q \leq \epsilon_n \leq C \epsilon_n$  so

$$e^{-p} \left( -\frac{C_1^2 \epsilon_n^2 q}{\sigma^2 q} \right) \leq e^{-p} \{-C_2 \epsilon_n q\} \quad \square$$

We have  $C_2 > n \epsilon_n^2 \rightarrow \infty$  and  $q \epsilon_n \rightarrow \infty$  we have  $e^{-p} \{-C_2 \epsilon_n q\} \rightarrow 0$  as  $n \rightarrow \infty$ .  
 Hence  $\alpha\{n/q\} \leq C \epsilon_n^{-1/2} q \rho^{[n^{1/2} \log^{-1}(n)/2]}$

$$\left\{ \left( \frac{1}{C_1 \epsilon_n} \right)^{1/2} q \alpha\{n/q\} \right\} \leq C \epsilon_n^{-1/2} q \rho^{[n^{1/2} \log^{-1}(n)/2]} \quad \square$$

Hence  $\alpha\{n/q\} \rightarrow 0$  as  $n \rightarrow \infty$ .  $\square$

Lemma 2.1 under condition (2.1) and for any  $\kappa > 0$

$$n^{-1} \sum_{t=1}^n Y_t - \nu_p \{I_{\nu_p} Y_t \geq \nu_p - I_{\nu_p} Y_t \geq \nu_p\} = o_p(n^{-3/4+\kappa}).$$

Proof. Let  $W_t = Y_t - \nu_p \{I_{\nu_p} Y_t \geq \nu_p - I_{\nu_p} Y_t \geq \nu_p\}$  and  $E W_t = 0$ . No  $E W_t = -I_{t1} - I_{t2}$ . We have

$$\begin{aligned}
 I_{t1} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p \leq Y_t < \nu_p \} I_{\nu_p} > \nu_p\} \quad \text{and} \\
 I_{t2} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p \leq Y_t < \nu_p \} I_{\nu_p} < \nu_p\}.
 \end{aligned}$$

We have  $I_{t1} = I_{t11} - I_{t12}$  and  $I_{t2} = I_{t21} - I_{t22}$ . We have for  $a \in \mathbb{R}$ ,  $\eta > 0$

$$\begin{aligned}
 I_{t11} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p \leq Y_t < \nu_p \} I_{\nu_p} \geq \nu_p - n^{-a} \eta\}, \\
 I_{t12} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p \leq Y_t < \nu_p \} I_{\nu_p} < \nu_p < \nu_p - n^{-a} \eta\}, \\
 I_{t21} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p > Y_t \geq \nu_p \} I_{\nu_p} \leq \nu_p - n^{-a} \eta\} \quad \text{and} \\
 I_{t22} &= E\{Y_t - \nu_p \{I_{\nu_p} \nu_p > Y_t \geq \nu_p \} I_{\nu_p} > \nu_p > \nu_p - n^{-a} \eta\}.
 \end{aligned}$$

Apply the Cauchy-Schwarz inequality for  $k$  and

$$|I_{tk1}| \leq \sqrt{E_{\nu_p} - \nu_p}^2 P_{\nu_p} \{|\nu_p - \nu_p| \geq n^{-a} \eta\}.$$

en Le  $\mathbb{P}$  nd def c  $E_{\nu_p} - \nu_p^2 = O_p(n^{-1})$

$I_{tk1} \rightarrow$  e  $\nu_p$  y f . A

o e  $I_{t12}$  e no e  $|I_{t12}| \leq E\{Y_t - \nu_p \mathbb{1}_{\nu_p \leq Y_t < \nu_p} n^{-a\eta}\}$ .  $\mathbb{P}$  e n

$$I_{t12} \leq \int_{\nu_p}^{\nu_p + n^{-a\eta}} dF(z) - \nu_p f(z) dz = O_p(n^{-2a})$$

n e e c y e p p o c e c n  $I_{t22} = O_p(n^{-2a})$  e e nd A  
 e n y c o n a  $\gamma > \gamma$

$$E W_t = O_p(n^{-1+\kappa})$$

fo n y p o e  $\kappa < \kappa$  n p e

$$E\left[n^{-1} \sum Y_t - \nu_p \mathbb{1}_{\nu_p \leq Y_t < \nu_p} - \mathbb{1}_{Y_t \geq \nu_p}\right] = O_p(n^{-1+\kappa})$$

e no con de  $Var W_i$  o  $a \in \mathbb{R}, /$

$$\begin{aligned} E W_t^2 &= E\left[Y_t - \nu_p \mathbb{1}_{\nu_p \leq Y_t < \nu_p} - \mathbb{1}_{Y_t \geq \nu_p} \mathbb{1}_{Y_t \geq \nu_p}\right] \\ &= E\left[Y_t - \nu_p \mathbb{1}_{\nu_p > Y_t \geq \nu_p} - \mathbb{1}_{\nu_p > Y_t \geq \nu_p}\right] \\ &= E\left[Y_t - \nu_p \mathbb{1}_{\nu_p \leq Y_t < \nu_p} \mathbb{1}_{\nu_p \geq \nu_p - n^{-a\eta}} - \mathbb{1}_{\nu_p < \nu_p - n^{-a\eta}}\right] \\ &= E\left[Y_t - \nu_p \mathbb{1}_{\nu_p > Y_t \geq \nu_p} \mathbb{1}_{\nu_p \geq \nu_p - n^{-a\eta}} - \mathbb{1}_{\nu_p < \nu_p - n^{-a\eta}}\right] \end{aligned}$$

No e  $\mathbb{P}$

$$E\{\mathbb{1}_{\nu_p \leq Y_t < \nu_p} \mathbb{1}_{\nu_p \leq \nu_p - n^{-a\eta}}\} \leq P\{|\nu_p - \nu_p| \geq n^{-a\eta}\} \text{ nd}$$

$$E\{\mathbb{1}_{\nu_p > Y_t \geq \nu_p} \mathbb{1}_{\nu_p > \nu_p - n^{-a\eta}}\} \leq P\{|\nu_p - \nu_p| \geq n^{-a\eta}\}$$

con e e o ze o e  $\nu_p$  y f  $\mathbb{P}$  ed y Le  $\mathbb{P}$  App y n e C c y  
 c z neq y e

$$E\{Y_t - \nu_p \mathbb{1}_{\nu_p \leq Y_t < \nu_p} \mathbb{1}_{\nu_p \leq \nu_p - n^{-a\eta}}\} \text{ nd}$$

$$E\{Y_t - \nu_p \mathbb{1}_{\nu_p > Y_t \geq \nu_p} \mathbb{1}_{\nu_p \geq \nu_p - n^{-a\eta}}\}$$





e e o e<sup>n</sup> p o y n e o

By choosing  $r = n^a$  for  $a \in \mathbb{R}$ , and  $k' = n^c$  for  $c \in \mathbb{R}$ ,  $-a < c < 1$ , we have

$$n \xrightarrow{p} n \rightarrow \infty. \quad \square$$

We define  $S_{n,1} = n^{-1/2} \sum_{j=1}^r W_{j,n}$  and

By applying the inequality of Markov and the condition of  $W_{j,n}$  we have

Le  $\eta = E\{p^{-1}Y_t K_{h\nu_p} Y_t - \nu_p\} = p^{-1} \int_{\nu_p} K_{\nu_p} f_{\nu_p} - \nu_p d\nu_p = p^{-1} \nu_p f_{\nu_p} = O_p^2$   
 n'importe quel  $\alpha$  dans l'équation précédente, on a  $E\{np^{-1} \sum Y_t K_{h\nu_p} - Y_t, \nu_{p,h} - \nu_p\} = O_p(n^{-1})$

$$E\{np^{-1} \sum Y_t K_{h\nu_p} - Y_t, \nu_{p,h} - \nu_p\} = \eta E\{\nu_{p,h} - \nu_p\} = O_p(n^{-1})$$

$$- \frac{1}{2} p^{-1} \nu_p f'_{\nu_p} \sigma_K^2 = o_p^3 = O_p(n^{-1})$$

Comme  $A = \sum_{t=1}^n \{Y_t G_{h\nu_p} - Y_t\} - \sum_{t=1}^n \{Y_t K_{h\nu_p} - Y_t, \nu_{p,h} - \nu_p\}$

$$E\{\nu_{p,h} - \nu_p\} = \nu_p - \frac{1}{2} p^{-1} \sigma_K^2 f_{\nu_p} = o_p^2 = O_p(n^{-1})$$

Comme  $\nu_{p,h} - \nu_p = o_p^2$ , on a

le noyau de la fonction de  $\nu_{p,h}$ . Le  $A_1 = np^{-1} \sum_{t=1}^n \{Y_t G_{h\nu_p} - Y_t - Y_t K_{h\nu_p} - Y_t, \nu_{p,h} - \nu_p\}$  est le terme d'ordre 3 de l'expansion

de

$$Var\{A_1\} = Var\{np^{-1} \sum Y_t G_{h\nu_p} - Y_t\} + Var\{\eta, \nu_{p,h} - \nu_p\} - Cov\{np^{-1} \sum Y_t G_{h\nu_p} - Y_t, \eta, \nu_{p,h} - \nu_p\}.$$

et on a

$$Var\{np^{-1} \sum Y_t G_{h\nu_p} - Y_t\} = n^{-1} p^{-2} \left[ Var\{Y_t G_{h\nu_p} - Y_t\} + \sum_{k=1}^{n-1} -k/n Cov\{Y_1 G_{h\nu_p} - Y_1, Y_{k+1} G_{h\nu_p} - Y_{k+1}\} \right].$$

Le  $c_K = \int_{-\infty}^{\infty} \nu K_{\nu} d\nu = \int_{-\infty}^{\infty} K_{\nu} d\nu$  est une constante

$$Var\{Y_t G_{h\nu_p} - Y_t\} = \int z^2 G_{h\nu_p}^2 - z f_{\nu_p} dz - p^2 \nu_p^2 = O_p^2$$

$$= \int_{-\infty}^{\infty} K_{\nu_p} d\nu_p \left[ \int_{-\infty}^u K_{\nu_p} d\nu_p \left\{ \int_{\nu_p}^{\infty} z^2 f_{\nu_p} dz + \int_{\nu_p - h\nu_p}^{\nu_p} z^2 f_{\nu_p} dz \right\} \right.$$

$$\left. - \int_u^{\infty} K_{\nu_p} d\nu_p \left\{ \int_{\nu_p}^{\infty} z^2 f_{\nu_p} dz + \int_{\nu_p - h\nu_p}^{\nu_p} z^2 f_{\nu_p} dz \right\} - p^2 \nu_p^2 \right] = O_p^2$$

$$Var\{Y_t I_{\nu_p} \geq \nu_p\} = \nu_p^2 f_{\nu_p} c_K = O_p^2.$$

q'importe quel  $\alpha$  dans l'équation précédente, on a

$$Var\{np^{-1} \sum Y_t G_{h\nu_p} - Y_t\} = p^{-2} Var\{\phi_{\nu_p}\} = n^{-1} \nu_p^2 f_{\nu_p} c_K = o_p(n^{-1}).$$

we conclude on the standard deviation of  $\hat{\eta}$

$$\begin{aligned} & \text{Var}\{\hat{\eta}_{p,h} - \nu_p\} = \hat{\eta} - \eta_{p,h} - \nu_p \\ & \eta^2 \text{Var}\{\hat{\nu}_{p,h}\} = \eta \text{Cov}\{\hat{\nu}_{p,h}, \hat{\eta} - \eta_{p,h} - \nu_p\} + \text{Var}\{\hat{\eta} - \eta_{p,h} - \nu_p\}. \end{aligned}$$

By the Cauchy-Schwarz inequality  $\eta^{-1} p^{-1} \nu_p f_{p,h} = O_p(n^{-2})$

$$\eta^2 \text{Var}\{\hat{\nu}_{p,h}\} = p^{-2} \nu_p^2 \text{Var}\{n^{-1} \sum_{t=1}^n I_{p,h}(Y_t) > \nu_p\} - p^{-2} n^{-1} b \nu_p^2 f_{p,h} c_K = o_p(n^{-1}). \quad \square$$

of the inequality given in the proof of Lemma 5.1 for  $\alpha = n^{-1}$  since

$$E\{\hat{\nu}_{p,h} - \nu_p\}^4 \leq Cn^{-2} \quad \text{and} \quad E\{\hat{\eta} - \eta\}^4 = O_p(n^{-2-3}).$$

Applying the Cauchy-Schwarz inequality and Lemma 5.1

$$\text{Var}\{\hat{\eta} - \eta_{p,h} - \nu_p\} = O_p(n^{-2-3/2}) = o_p(n^{-1}) \quad \text{and} \quad \square$$

$$\text{Cov}\{\hat{\nu}_{p,h} - \nu_p, p^{-1} \hat{\eta} - \eta_{p,h} - \nu_p\} = o_p(n^{-1}). \quad \square$$

Consequently  $\square$  and  $\square$

$$\text{Var}\{\hat{\eta}_{p,h} - \nu_p\} = p^{-2} \nu_p^2 \text{Var}\{\phi_{p,h}\} - p^{-2} n^{-1} \nu_p^2 f_{p,h} c_K = o_p(n^{-1}). \quad \square$$

of Lemma 5.1 we conclude on the standard deviation of  $\hat{\eta}$

$$\begin{aligned} & \text{Cov}\{np^{-1} \sum_{t=1}^n Y_t G_{h,p} - Y_t, \hat{\eta}_{p,h} - \nu_p\} \\ & \text{Cov}\{np^{-1} \sum_{t=1}^n Y_t G_{h,p} - Y_t, \eta f_{p,h}^{-1} n^{-1} \sum_{t=1}^n G_{h,p} - Y_t\} = o_p(n^{-1}) \\ & np^{2-1} \nu_p \left[ \text{Cov}\{Y_t G_{h,p} - Y_t, G_{h,p} - Y_t\} \right. \\ & \quad \left. + \sum_{k=1}^{n-1} -k/n \text{Cov}\{Y_1 G_{h,p} - Y_1, G_{h,p} - Y_{k+1}\} \right] = o_p(n^{-1}) \end{aligned}$$

since  $\text{Cov}\{Y_t G_{h,p} - Y_t, G_{h,p} - Y_t\} = p - p \nu_p - \nu_p f_{p,h} c_K = o_p(n^{-1})$

$$\begin{aligned} & \text{Cov}\{np^{-1} \sum_{t=1}^n Y_t G_{h,p} - Y_t, np^{-1} \sum_{i=1}^n Y_i K_{h,p} - Y_t\} = o_p(n^{-1}) \\ & n^{-1} p^{-2} \nu_p \text{Cov}\{\phi_{1,p}, \phi_{2,p}\} - n^{-1} p^{-2} \nu_p^2 f_{p,h} c_K = o_p(n^{-1}). \end{aligned} \quad \square$$

$O_p(n^{-1})$  convergence of the estimator and the efficiency of

$$\text{Var}_{\nu_p}(\hat{\theta}_p) = p^{-1}n^{-1}\sigma_{\theta}^2(p, n) + o_p(n^{-1}),$$

where  $\nu_p$  is the probability measure induced by  $\nu_{p,h}$  on the sample space.

NC

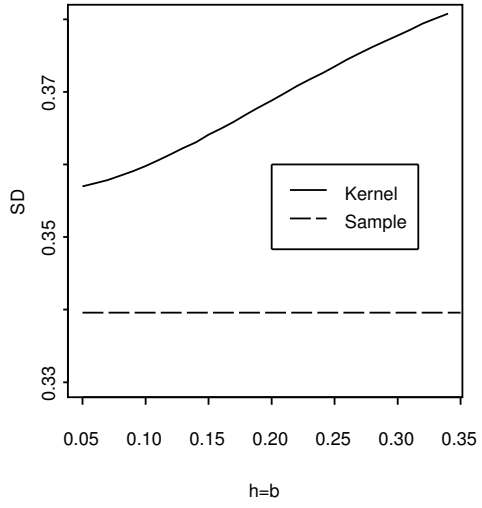
Theorem 9.1 (Manderson, 1994) *Consistency of the*  
*Method of Moments*  
 Let  $\theta$  be a scalar parameter and  $\nu_p$  a probability measure on the sample space. Suppose that

(i)  $E_{\nu_p}(\hat{\theta}_p) = \theta + o_p(n^{-1})$   
 (ii)  $\text{Var}_{\nu_p}(\hat{\theta}_p) = p^{-1}n^{-1}\sigma_{\theta}^2(p, n) + o_p(n^{-1})$

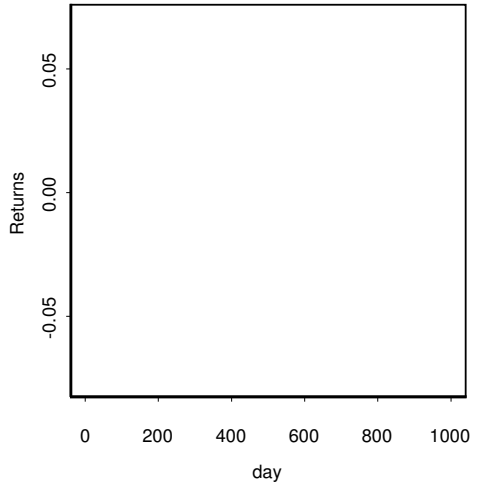
Then  $\hat{\theta}_p \xrightarrow{p} \theta$  in probability.



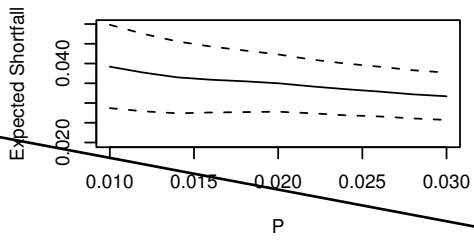
(a) ES Estimates



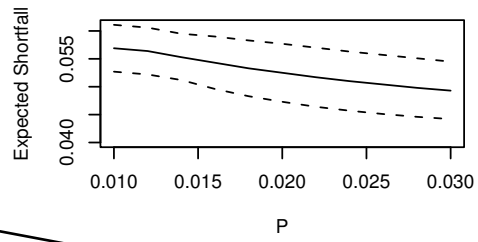




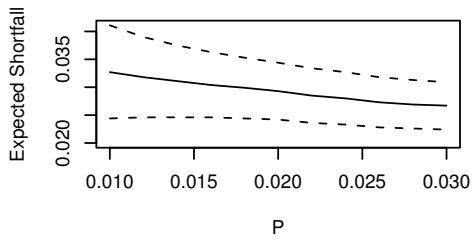
DO ON  $\lambda^2$   $1^2$



CAC  $2^2$   $1^2$



DO ON  $\lambda^2$   $2^2$



$T_{\alpha}^*$  Estimates for  $\nu_{0.01}$ ,  $\mu_{0.01}$  and Standard Errors (S.E)

Ye	CAC		Doone	
	$\nu_{0.01}$	$\mu_p$	$\nu_{0.01}$	$\mu_p$
		$\delta$	$\delta$	
				$\delta$
		$\delta$	$\delta$	