

ESTIMATION OF THE EQUILIBRIUM AND OF THE DEGREE OF VOLATILITY  
OF THE ORNSTEIN-UHLENBECK'S STOCHASTIC PROCESS \*

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**Abstract.** By using the Kolmogorov's strong law of large numbers, the consistent estimates of the equilibrium and of the degree of volatility are constructed in the Ornstein-Uhlenbeck's stochastic model.

**Keywords and phrases:** Ornstein-Uhlenbeck process, Wiener process, stochastic differential equation.

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**1 Introduction.** The Ornstein-Uhlenbeck process,  $x_t$  satisfies the following stochastic differential equation:

$$dx_t = \theta(\mu - x_t)dt + \sigma dW_t, \quad (1)$$

where  $\theta > 0$ ,  $\mu \in R$  and  $\sigma > 0$  are parameters and  $W_t$  denotes the Wiener process.

The solution of the stochastic differential equation (1) has the following form

$$x_t = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t}) + \sigma \int_0^t e^{-\theta(t-s)} dW_s, \quad (2)$$

where  $x_0$  is assumed to be constant.

The parameters in (2) have the following sense:

(i)  $\mu$  represents the equilibrium or mean value supported by fundamentals (in other words, the central location);

(ii)  $\sigma$  is the degree of volatility around it caused by shocks;

(iii)  $\theta$  is the rate by which these shocks dissipate and the variable reverts towards the mean;

(iv)  $x_0$  is the underlying asset price at moment  $t = 0$  ( the underlying asset initial price );

(v)  $x_t$  is the underlying asset price at moment  $t > 0$ .

There are various scientific papers devoted to estimate of parameter  $\mu$ ,  $\sigma$  and  $\theta$ (see, for example [1], [2]). There least-square minimization and maximum likelihood estimation techniques are used for the estimating parameters  $\sigma$  and  $\mu$  which work successfully. The same we can not say concerning the estimating the parameter  $\theta$  (see, for example, [1]).

The purpose of the present paper is to introduce a new approach which by use of values  $(z_k)_{k \in N}$  of corresponding trajectories at a fixed positive moment  $t$ , will allows us

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\*This article is dedecated to the memory of the Tbilisi State University Professor Grigol Sokhadze

to construct a consistent estimate of parameters  $\sigma$  and  $\mu$  of the Ornstein-Uhlenbeck's stochastic process under an assumption that all another parameters are known.

The rest of the present paper is organized as follows.

In Section 2 we consider some auxiliary notions and facts from the theory of stochastic differential equations and mathematical statistics.

In Section 3 we present the constructions of consistent estimates for unknown parameters  $\sigma$  and  $\mu$  in the Ornstein-Uhlenbeck's stochastic model.

**2 Some auxiliary facts from the theory of stochastic differential equations and mathematical statistics.** By use of approaches introduced in [3] one can get the validity of the following Lemmas

**Lemma 1.** *Let's consider an Ornstein-Uhlenbeck process  $x_t$  satisfies the following stochastic differential equation:*

$$dx_t = \theta(\mu - x_t)dt + \sigma dW_t \quad (3)$$

where  $\theta > 0$ ,  $\mu$  and  $\sigma > 0$  are parameters and  $W_t$  denotes the Wiener process. Then the solution of this stochastic differential equation (3) is given by

$$x_t = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t}) + \sigma \int_0^t e^{-\theta(t-s)} dW_s,$$

where  $x_0$  is assumed to be constant.

**Lemma 2.** *Under conditions of Lemma 1, the following equalities*

- (i)  $E(x_t) = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t});$
  - (ii)  $cov(x_s, x_t) = \frac{\sigma^2}{2\theta} (e^{-\theta(t-s)} - e^{-\theta(t+s)});$
  - (iii)  $var(x_s) = \frac{\sigma^2}{2\theta} (1 - e^{-2\theta s});$
- hold true.

**Lemma 3.** *(Kolmogorov's strong law of large numbers [4]) Let  $X_1, X_2, \dots$  be a sequence of independent identically distributed random variables defined on the probability space  $(\Omega, \mathcal{F}, P)$ . If these random variables have a finite expectation  $m$  (i.e.,  $E(X_1) = E(X_2) = \dots = m < \infty$ ), then the following condition*

$$P(\{\omega : \lim_{n \rightarrow \infty} n^{-1} \sum_{k=1}^n X_k(\omega) = m\}) = 1$$

holds.

**3 Main results.** We begin this section by the following definition.

**Definition.** A Borel measurable function  $T_n : R^n \rightarrow R$  ( $n \in N$ ) is called a consistent estimator of a parameter  $\theta$  (in the sense of almost everywhere convergence) for the family  $(\mu_\theta^N)_{\theta \in R}$  if the following condition

$$\mu_\theta^N(\{(x_k)_{k \in N} : (x_k)_{k \in N} \in R^N \ \& \ \lim_{n \rightarrow \infty} T_n(x_1, \dots, x_n) = \theta\}) = 1$$

holds true for each  $\theta \in R$ .

By the use of Kolmogorov's Strong Law of Large numbers the validity of the following assertion is obtained.

**Theorem 1.** For  $t > 0$ ,  $x_0 \in R$ ,  $\theta > 0$ ,  $\mu \in R$  and  $\sigma > 0$ , let's  $\gamma_{(t,x_0,\theta,\mu,\sigma)}$  be a Gaussian probability measure in  $R$  with the mean  $m_t = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t})$  and the variance  $\sigma_t^2 = \frac{\sigma^2}{2\theta} (1 - e^{-2\theta t})$ . Assuming that parameters  $x_0$ ,  $t$ ,  $\theta$  and  $\sigma$  are fixed, for  $\mu \in R$  let's denote by  $\gamma_\mu$  the measure  $\gamma_{(t,x_0,\theta,\mu,\sigma)}$ . Let us define the estimate  $T_n^* : R^n \rightarrow R$  by the following formula

$$T_n^*((z_k)_{1 \leq k \leq n}) = \left( \frac{\sum_{k=1}^n z_k}{n} - x_0 e^{-\theta t} \right) / (1 - e^{-\theta t}).$$

Then we get

$$\gamma_\mu^\infty \{ (z_k)_{k \in N} : (z_k)_{k \in N} \in R^\infty \ \& \ \lim_{N \rightarrow \infty} T_n((z_k)_{1 \leq k \leq n}) = x_0 \} = 1,$$

provided that  $T_n$  is a consistent estimator of the equilibrium  $\mu \in R$  in the sense of almost everywhere convergence for the family of probability measures  $(\gamma_\mu^\infty)_{\mu \in R}$ .

**Proof.** Let's consider probability space  $(\Omega, \mathcal{F}, P)$ , where  $\Omega = R^\infty$ ,  $\mathcal{F} = B(R^\infty)$ ,  $P = \gamma_\mu^\infty$ .

For  $k \in N$  we consider  $k$ -th projection  $Pr_k$  defined on  $R^\infty$  by

$$Pr_k((x_i)_{i \in N}) = x_k$$

for  $(x_i)_{i \in N} \in R^\infty$ .

It is obvious that  $(Pr_k)_{k \in N}$  is a sequence of independent Gaussian random variables with the mean  $m_t = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t})$  and the variance  $\sigma_t^2 = \frac{\sigma^2}{2\theta} (1 - e^{-2\theta t})$ . By the use of Kolmogorov's Strong Law of Large numbers we get

$$\gamma_\mu^\infty \{ (z_k)_{k \in N} \in R^\infty \ \& \ \lim_{n \rightarrow \infty} \frac{\sum_{k=1}^n Pr_k((z_k)_{k \in N})}{n} = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t}) \} = 1,$$

which implies

$$\begin{aligned} & \gamma_\mu^\infty \{ (z_k)_{k \in N} \in R^\infty \ \& \ \lim_{n \rightarrow \infty} \left( \frac{\sum_{k=1}^n z_k}{n} - x_0 e^{-\theta t} \right) / (1 - e^{-\theta t}) = \mu \} \\ & = \gamma_\mu^\infty \{ (z_k)_{k \in N} \in R^\infty \ \& \ \lim_{n \rightarrow \infty} T_n^*((z_k)_{1 \leq k \leq n}) = \mu \} = 1. \end{aligned}$$

By the scheme used in the proof of Theorem 1, one can get the validity of the following theorem.

**Theorem 2.** For  $t > 0$ ,  $x_0 \in R$ ,  $\theta > 0$ ,  $\mu \in R$  and  $\sigma > 0$ , let  $\gamma_{(t,x_0,\theta,\mu,\sigma)}$  be a Gaussian probability measure in  $R$  with the mean  $m_t = x_0 e^{-\theta t} + \mu(1 - e^{-\theta t})$  and the variance  $\sigma_t^2 = \frac{\sigma^2}{2\theta} (1 - e^{-2\theta t})$ . Assuming that parameters  $x_0$ ,  $t$ ,  $\mu$  and  $\theta$  are fixed. For  $\sigma^2 > 0$ , let's denote by  $\gamma_{\sigma^2}$  the measure  $\gamma_{(t,x_0,\theta,\mu,\sigma)}$ . Let us define the estimate  $T_n^{***} : R^n \rightarrow R$  by the following formula

$$T_n^{***}((z_k)_{1 \leq k \leq n}) = \frac{2\theta \sum_{k=1}^n (z_k - x_0 e^{-\theta t} - \mu(1 - e^{-\theta t}))^2}{n(1 - e^{-2\theta t})}.$$

Then we get

$$\gamma_{\sigma^2}^{\infty} \{ (z_k)_{k \in N} : (z_k)_{k \in N} \in R^{\infty} \ \& \ \lim_{N \rightarrow \infty} T_n^{***}((z_k)_{1 \leq k \leq n}) = \sigma^2 \} = 1,$$

provided that  $T_n^{***}$  is a consistent estimator of the square of the degree of volatility  $\sigma$  around it caused by shocks in the sense of almost everywhere convergence for the family of probability measures  $(\gamma_{\sigma^2}^{\infty})_{\sigma^2 > 0}$ .

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