# Asymptotic inference for a stochastic differential equation with uniformly distributed time delay 

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## Abstract

For the affine stochastic delay differential equation

$$
\mathrm{d} X(t)=a \int_{-1}^{0} X(t+u) \mathrm{d} u \mathrm{~d} t+\mathrm{d} W(t), \quad t \geqslant 0
$$

the local asymptotic properties of the likelihood function are studied. Local asymptotic normality is proved in case of $a \in\left(-\frac{\pi^{2}}{2}, 0\right)$, local asymptotic mixed normality is shown if $a \in(0, \infty)$, periodic local asymptotic mixed normality is valid if $a \in\left(-\infty,-\frac{\pi^{2}}{2}\right)$, and only local asymptotic quadraticity holds at the points $-\frac{\pi^{2}}{2}$ and 0 . Applications to the asymptotic behaviour of the maximum likelihood estimator $\widehat{a}_{T}$ of $a$ based on $(X(t))_{t \in[0, T]}$ are given as $T \rightarrow \infty$.

## 1 Introduction

Assume $(W(t))_{t \in \mathbb{R}_{+}}$is a standard Wiener process, $a \in \mathbb{R}$, and $\left(X^{(a)}(t)\right)_{t \in \mathbb{R}_{+}}$is a solution of the affine stochastic delay differential equation (SDDE)

$$
\begin{cases}\mathrm{d} X(t)=a \int_{-1}^{0} X(t+u) \mathrm{d} u \mathrm{~d} t+\mathrm{d} W(t), & t \in \mathbb{R}_{+}  \tag{1.1}\\ X(t)=X_{0}(t), & t \in[-1,0]\end{cases}
$$

where $\left(X_{0}(t)\right)_{t \in[-1,0]}$ is a continuous stochastic process independent of $(W(t))_{t \in \mathbb{R}_{+}}$. The SDDE (1.1) can also be written in the integral form

$$
\begin{cases}X(t)=X_{0}(0)+a \int_{0}^{t} \int_{-1}^{0} X(s+u) \mathrm{d} u \mathrm{~d} s+W(t), & t \in \mathbb{R}_{+}  \tag{1.2}\\ X(t)=X_{0}(t), & t \in[-1,0]\end{cases}
$$

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Equation (1.1) is a special case of the affine stochastic delay differential equation

$$
\begin{cases}\mathrm{d} X(t)=\int_{-r}^{0} X(t+u) m_{\theta}(\mathrm{d} u) \mathrm{d} t+\mathrm{d} W(t), & t \in \mathbb{R}_{+},  \tag{1.3}\\ X(t)=X_{0}(t), & t \in[-r, 0]\end{cases}
$$

where $r>0$, and for each $\theta \in \Theta, m_{\theta}$ is a finite signed measure on $[-r, 0]$, see Gushchin and Küchler [4]. In that paper local asymptotic normality has been proved for stationary solutions. In Gushchin and Küchler [2], the special case of (1.3) has been studied with $r=1, \Theta=\mathbb{R}^{2}$, and $m_{\theta}=a \delta_{0}+b \delta_{-1}$ for $\theta=(a, b)$, where $\delta_{x}$ denotes the Dirac measure concentrated at $x \in \mathbb{R}$, and they described the local properties of the likelihood function for the whole parameter space $\mathbb{R}^{2}$.

The solution $\left(X^{(a)}(t)\right)_{t \in \mathbb{R}_{+}}$of (1.1) exists, is pathwise uniquely determined and can be represented as

$$
\begin{equation*}
X^{(a)}(t)=x_{0, a}(t) X_{0}(0)+a \int_{-1}^{0} \int_{u}^{0} x_{0, a}(t+u-s) X_{0}(s) \mathrm{d} s \mathrm{~d} u+\int_{0}^{t} x_{0, a}(t-s) \mathrm{d} W(s) \tag{1.4}
\end{equation*}
$$

for $t \in \mathbb{R}_{+}$, where $\left(x_{0, a}(t)\right)_{t \in[-1, \infty)}$ denotes the so-called fundamental solution of the deterministic homogeneous delay differential equation

$$
\begin{cases}x(t)=x_{0}(0)+a \int_{0}^{t} \int_{-1}^{0} x(s+u) \mathrm{d} u \mathrm{~d} s, & t \in \mathbb{R}_{+},  \tag{1.5}\\ x(t)=x_{0}(t), & t \in[-1,0]\end{cases}
$$

with initial function

$$
x_{0}(t):= \begin{cases}0, & t \in[-1,0) \\ 1, & t=0\end{cases}
$$

In the trivial case of $a=0$, we have $x_{0,0}(t)=1, \quad t \in \mathbb{R}_{+}$, and $X^{(0)}(t)=X_{0}(0)+W(t)$, $t \in \mathbb{R}_{+}$. In case of $a \in \mathbb{R} \backslash\{0\}$, the behaviour of $\left(x_{0, a}(t)\right)_{t \in[-1, \infty)}$ is connected with the so-called characteristic function $h_{a}: \mathbb{C} \rightarrow \mathbb{C}$, given by

$$
\begin{equation*}
h_{a}(\lambda):=\lambda-a \int_{-1}^{0} \mathrm{e}^{\lambda u} \mathrm{~d} u, \quad \lambda \in \mathbb{C} \tag{1.6}
\end{equation*}
$$

and the set $\Lambda_{a}$ of the (complex) solutions of the so-called characteristic equation for (1.5),

$$
\begin{equation*}
\lambda-a \int_{-1}^{0} \mathrm{e}^{\lambda u} \mathrm{~d} u=0 \tag{1.7}
\end{equation*}
$$

Applying usual methods (e.g., argument principle in complex analysis and the existence of local inverses of holomorphic functions), one can derive the following properties of the set $\Lambda_{a}$, see, e.g., Reiß [9]. We have $\Lambda(a) \neq \emptyset$, and $\Lambda(a)$ consists of isolated points. Moreover, $\Lambda(a)$ is countably infinite, and for each $c \in \mathbb{R}$, the set $\left\{\lambda \in \Lambda_{a}: \operatorname{Re}(\lambda) \geqslant c\right\}$ is finite. In particular,

$$
v_{0}(a):=\sup \left\{\operatorname{Re}(\lambda): \lambda \in \Lambda_{a}\right\}<\infty .
$$

Put

$$
v_{1}(a):=\sup \left\{\operatorname{Re}(\lambda): \lambda \in \Lambda_{a}, \operatorname{Re}(\lambda)<v_{0}(a)\right\}
$$

where $\sup \emptyset:=-\infty$. We have the following cases:
(i) If $a \in\left(-\frac{\pi^{2}}{2}, 0\right)$ then $v_{0}(a)<0$;
(ii) If $a=-\frac{\pi^{2}}{2}$ then $v_{0}(a)=0$ and $v_{0}(a) \notin \Lambda_{a}$;
(iii) If $a \in\left(-\infty,-\frac{\pi^{2}}{2}\right)$ then $v_{0}(a)>0$ and $v_{0}(a) \notin \Lambda_{a}$;
(iv) If $a \in(0, \infty)$ then $v_{0}(a)>0, v_{0}(a) \in \Lambda_{a}, m\left(v_{0}(a)\right)=1$ (where $m\left(v_{0}(a)\right)$ denotes the multiplicity of $v_{0}(a)$ ), and $v_{1}(a)<0$.

For any $\gamma>v_{0}(a)$, we have $x_{0, a}(t)=\mathrm{O}\left(\mathrm{e}^{\gamma t}\right), t \in \mathbb{R}_{+}$. In particular, $\left(x_{0, a}(t)\right)_{t \in \mathbb{R}_{+}}$is square integrable if (and only if, see Gushchin and Küchler [3]) $v_{0}(a)<0$. The Laplace transform of $\left(x_{0, a}(t)\right)_{t \in \mathbb{R}_{+}}$is given by

$$
\int_{0}^{\infty} \mathrm{e}^{-\lambda t} x_{0, a}(t) \mathrm{d} t=\frac{1}{h_{a}(\lambda)}, \quad \lambda \in \mathbb{C}, \quad \operatorname{Re}(\lambda)>v_{0}(a)
$$

Based on the inverse Laplace transform and Cauchy's residue theorem, the following crucial lemma can be shown (see, e.g., Gushchin and Küchler [2, Lemma 1.1]).
1.1 Lemma. For each $a \in \mathbb{R} \backslash\{0\}$ and each $c \in\left(-\infty, v_{0}(a)\right)$, there exists $\gamma \in(-\infty, c)$ such that the fundamental solution $\left(x_{0, a}(t)\right)_{t \in[-1, \infty)}$ of (1.5) can be represented in the form

$$
x_{0, a}(t)=\psi_{0, a}(t) \mathrm{e}^{v_{0}(a) t}+\sum_{\substack{\lambda \in \Lambda_{a} \\ \operatorname{Re}(\lambda) \in\left[c, v_{0}(a)\right)}} c_{a}(\lambda) \mathrm{e}^{\lambda t}+\mathrm{o}\left(\mathrm{e}^{\gamma t}\right), \quad \text { as } t \rightarrow \infty,
$$

with some constants $c_{a}(\lambda), \lambda \in \Lambda_{a}$, and with

$$
\psi_{0, a}(t):= \begin{cases}\frac{v_{0}(a)}{v_{0}(a)^{2}+2 v_{0}(a)-a}, & \text { if } v_{0}(a) \in \Lambda_{a} \quad \text { and } m\left(v_{0}(a)\right)=1 \\ A_{0}(a) \cos \left(\kappa_{0}(a) t\right)+B_{0}(a) \sin \left(\kappa_{0}(a) t\right) & \text { if } v_{0}(a) \notin \Lambda_{a}\end{cases}
$$

with $\kappa_{0}(a):=\left|\operatorname{Im}\left(\lambda_{0}(a)\right)\right|$, where $\lambda_{0}(a) \in \Lambda_{a}$ is given by $\operatorname{Re}\left(\lambda_{0}(a)\right)=v_{0}(a)$, and

$$
\begin{aligned}
& A_{0}(a):=\frac{2\left[\left(v_{0}(a)^{2}-\kappa_{0}(a)^{2}\right)\left(v_{0}(a)-2\right)-a v_{0}(a)\right]}{\left(v_{0}(a)^{2}-\kappa_{0}(a)^{2}+2 v_{0}(a)-a\right)^{2}+4 \kappa_{0}(a)^{2}\left(v_{0}(a)+1\right)^{2}}, \\
& B_{0}(a):=\frac{2\left(v_{0}(a)^{2}+\kappa_{0}(a)^{2}+a\right) \kappa_{0}(a)}{\left(v_{0}(a)^{2}-\kappa_{0}(a)^{2}+2 v_{0}(a)-a\right)^{2}+4 \kappa_{0}(a)^{2}\left(v_{0}(a)+1\right)^{2}} .
\end{aligned}
$$

## 2 Quadratic approximations to likelihood ratios

We recall some definitions and statements concerning quadratic approximations to likelihood ratios based on Jeganathan [6], Le Cam and Yang [7] and van der Vaart [10].

Let $(\Omega, \mathcal{A}, \mathbb{P})$ be a probability space. Let $\Theta \subset \mathbb{R}^{p}$ be an open set. For each $\boldsymbol{\theta} \in \Theta$, let $\left(X^{(\boldsymbol{\theta})}(t)\right)_{t \in[-1, \infty)}$ be a continuous stochastic process on $(\Omega, \mathcal{A}, \mathbb{P})$. For each $T \in \mathbb{R}_{+}$, let $\mathbb{P}_{\boldsymbol{\theta}, T}$ be the probability measure induced by $\left(X^{(\boldsymbol{\theta})}(t)\right)_{t \in[-1, T]}$ on the space $(C([-1, T]), \mathcal{B}(C([-1, T])))$.
2.1 Definition. The family $\left(C([-1, T]), \mathcal{B}(C([-1, T])),\left\{\mathbb{P}_{\boldsymbol{\theta}, T}: \boldsymbol{\theta} \in \Theta\right\}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments is said to have locally asymptotically quadratic (LAQ) likelihood ratios at $\boldsymbol{\theta} \in \Theta$ if there exist (scaling) matrices $\boldsymbol{r}_{\boldsymbol{\theta}, T} \in \mathbb{R}^{p \times p}, T \in \mathbb{R}_{++}$, random vectors $\boldsymbol{\Delta}_{\boldsymbol{\theta}}: \Omega \rightarrow \mathbb{R}^{p}$ and $\boldsymbol{\Delta}_{\boldsymbol{\theta}, T}: \Omega \rightarrow \mathbb{R}^{p}, \quad T \in \mathbb{R}_{++}$, and random matrices $\boldsymbol{J}_{\boldsymbol{\theta}}: \Omega \rightarrow \mathbb{R}^{p \times p}$ and $\boldsymbol{J}_{\boldsymbol{\theta}, T}: \Omega \rightarrow \mathbb{R}^{p \times p}$, $T \in \mathbb{R}_{++}$, such that

$$
\begin{equation*}
\log \frac{\mathrm{d} \mathbb{P}_{\boldsymbol{\theta}+\boldsymbol{r}_{\boldsymbol{\theta}, T} \boldsymbol{h}_{T}, T}}{\mathrm{~d} \mathbb{P}_{\boldsymbol{\theta}, T}}\left(\left.X^{(\boldsymbol{\theta})}\right|_{[-r, T]}\right)=\boldsymbol{h}_{T}^{\top} \boldsymbol{\Delta}_{\boldsymbol{\theta}, T}-\frac{1}{2} \boldsymbol{h}_{T}^{\top} \boldsymbol{J}_{\boldsymbol{\theta}, T} \boldsymbol{h}_{T}+\mathrm{o}_{\mathbb{P}}(1) \quad \text { as } T \rightarrow \infty \tag{2.1}
\end{equation*}
$$

whenever $\boldsymbol{h}_{T} \in \mathbb{R}^{p}$, $T \in \mathbb{R}_{++}$, is a bounded family satisfying $\boldsymbol{\theta}+\boldsymbol{r}_{\boldsymbol{\theta}, T} \boldsymbol{h}_{T} \in \Theta$ for all $T \in \mathbb{R}_{++}$,

$$
\begin{equation*}
\left(\boldsymbol{\Delta}_{\boldsymbol{\theta}, T}, \boldsymbol{J}_{\boldsymbol{\theta}, T}\right) \xrightarrow{\mathcal{D}}\left(\boldsymbol{\Delta}_{\boldsymbol{\theta}}, \boldsymbol{J}_{\boldsymbol{\theta}}\right) \quad \text { as } T \rightarrow \infty \tag{2.2}
\end{equation*}
$$

and we have

$$
\begin{equation*}
\mathbb{P}\left(\boldsymbol{J}_{\boldsymbol{\theta}} \text { is symmetric and strictly positive definite }\right)=1 \tag{2.3}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathbb{E}\left(\exp \left\{\boldsymbol{h}^{\top} \boldsymbol{\Delta}_{\boldsymbol{\theta}}-\frac{1}{2} \boldsymbol{h}^{\top} \boldsymbol{J}_{\boldsymbol{\theta}} \boldsymbol{h}\right\}\right)=1, \quad \boldsymbol{h} \in \mathbb{R}^{p} \tag{2.4}
\end{equation*}
$$

2.2 Definition. A family $\left(C([-1, T]), \mathcal{B}(C([-1, T])),\left\{\mathbb{P}_{\boldsymbol{\theta}, T}: \boldsymbol{\theta} \in \Theta\right\}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments is said to have locally asymptotically mixed normal (LAMN) likelihood ratios at $\boldsymbol{\theta} \in \Theta$ if it is $L A Q$ at $\boldsymbol{\theta} \in \Theta$, and the conditional distribution of $\boldsymbol{\Delta}_{\boldsymbol{\theta}}$ given $\boldsymbol{J}_{\boldsymbol{\theta}}$ is $\mathcal{N}_{p}\left(\mathbf{0}, \boldsymbol{J}_{\boldsymbol{\theta}}\right)$, or, equivalently, there exist a random vector $\mathcal{Z}: \Omega \rightarrow \mathbb{R}^{p}$ and a random matrix $\eta_{\boldsymbol{\theta}}: \Omega \rightarrow \mathbb{R}^{p \times p}$, such that they are independent, $\mathcal{Z} \stackrel{\mathcal{D}}{=} \mathcal{N}_{p}\left(\mathbf{0}, \boldsymbol{I}_{p}\right)$, and $\boldsymbol{\Delta}_{\boldsymbol{\theta}}=\eta_{\boldsymbol{\theta}} \mathcal{Z}, \quad \boldsymbol{J}_{\boldsymbol{\theta}}=\eta_{\boldsymbol{\theta}} \eta_{\boldsymbol{\theta}}^{\top}$.
2.3 Definition. The family $\left(C([-1, T]), \mathcal{B}(C([-1, T])),\left\{\mathbb{P}_{\boldsymbol{\theta}, T}: \boldsymbol{\theta} \in \Theta\right\}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments is said to have periodic locally asymptotically mixed normal (PLAMN) likelihood ratios at $\boldsymbol{\theta} \in \Theta$ if there exist $D \in \mathbb{R}_{++}$, (scaling) matrices $\boldsymbol{r}_{\boldsymbol{\theta}, T} \in \mathbb{R}^{p \times p}$, $T \in \mathbb{R}_{++}$, random vectors $\boldsymbol{\Delta}_{\boldsymbol{\theta}}(d): \Omega \rightarrow \mathbb{R}^{p}, d \in[0, D)$, and $\boldsymbol{\Delta}_{\boldsymbol{\theta}, T}: \Omega \rightarrow \mathbb{R}^{p}, T \in \mathbb{R}_{++}$, and random matrices $\boldsymbol{J}_{\boldsymbol{\theta}}(d): \Omega \rightarrow \mathbb{R}^{p \times p}, \quad d \in[0, D)$, and $\boldsymbol{J}_{\boldsymbol{\theta}, T}: \Omega \rightarrow \mathbb{R}^{p \times p}$, $T \in \mathbb{R}_{++}$, such that (2.1) holds whenever $\boldsymbol{h}_{T} \in \mathbb{R}^{p}, \quad T \in \mathbb{R}_{++}$, is a bounded family satisfying $\boldsymbol{\theta}+\boldsymbol{r}_{\boldsymbol{\theta}, T} \boldsymbol{h}_{T} \in \Theta$ for all $T \in \mathbb{R}_{++}$,

$$
\begin{equation*}
\left(\boldsymbol{\Delta}_{\boldsymbol{\theta}, k D+d}, \boldsymbol{J}_{\boldsymbol{\theta}, k D+d}\right) \xrightarrow{\mathcal{D}}\left(\boldsymbol{\Delta}_{\boldsymbol{\theta}}(d), \boldsymbol{J}_{\boldsymbol{\theta}}(d)\right) \quad \text { as } k \rightarrow \infty \tag{2.5}
\end{equation*}
$$

for all $d \in[0, D)$, we have

$$
\begin{equation*}
\mathbb{P}\left(\boldsymbol{J}_{\boldsymbol{\theta}}(d) \text { is symmetric and strictly positive definite }\right)=1, \quad d \in[0, D), \tag{2.6}
\end{equation*}
$$

and for each $d \in[0, D)$, the conditional distribution of $\boldsymbol{\Delta}_{\boldsymbol{\theta}}(d)$ given $\boldsymbol{J}_{\boldsymbol{\theta}}(d)$ is $\mathcal{N}_{p}\left(\mathbf{0}, \boldsymbol{J}_{\boldsymbol{\theta}}(d)\right)$, or, equivalently, there exist a random vector $\mathcal{Z}: \Omega \rightarrow \mathbb{R}^{p}$ and a random matrix $\eta_{\boldsymbol{\theta}}(d)$ : $\Omega \rightarrow \mathbb{R}^{p \times p}$ such that they are independent, $\mathcal{Z} \stackrel{\mathcal{D}}{=} \mathcal{N}_{p}\left(\mathbf{0}, \boldsymbol{I}_{p}\right)$, and $\quad \boldsymbol{\Delta}_{\boldsymbol{\theta}}(d)=\eta_{\boldsymbol{\theta}}(d) \mathcal{Z}, \quad \boldsymbol{J}_{\boldsymbol{\theta}}(d)=$ $\eta_{\boldsymbol{\theta}}(d) \eta_{\boldsymbol{\theta}}^{\top}(d)$.
2.4 Remark. The notion of LAMN is defined in Le Cam and Yang [7] and Jeganathan [6] so that PLAMN in the sense of Definiton 2.3 is LAMN as well.
2.5 Definition. A family $\left(C([-1, T]), \mathcal{B}(C([-1, T])),\left\{\mathbb{P}_{\boldsymbol{\theta}, T}: \boldsymbol{\theta} \in \Theta\right\}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments is said to have locally asymptotically normal (LAN) likelihood ratios at $\boldsymbol{\theta} \in \Theta$ if it is LAMN at $\boldsymbol{\theta} \in \Theta$, and $\boldsymbol{J}_{\boldsymbol{\theta}}$ is deterministic.

## 3 Radon-Nikodym derivatives

From this section, we will consider the SDDE 1.1 with fixed continuous initial process $\left(X_{0}(t)\right)_{t \in[-1,0]}$. Further, for all $T \in \mathbb{R}_{++}$, let $\mathbb{P}_{a, T}$ be the probability measure induced by $\left(X^{(a)}(t)\right)_{t \in[-1, T]}$ on $(C([-1, T]), \mathcal{B}(C([-1, T])))$. We need the following statement, which can be derived from formula (7.139) in Section 7.6.4 of Liptser and Shiryaev [8].
3.1 Lemma. Let $a, \widetilde{a} \in \mathbb{R}$. Then for all $T \in \mathbb{R}_{++}$, the measures $\mathbb{P}_{a, T}$ and $\mathbb{P}_{\tilde{a}, T}$ are absolutely continuous with respect to each other, and

$$
\begin{aligned}
& \log \frac{\mathrm{d} \mathbb{P}_{\widetilde{a}, T}}{\mathrm{dP}_{a, T}}\left(\left.X^{(a)}\right|_{[-1, T]}\right) \\
& =(\widetilde{a}-a) \int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} X^{(a)}(t)-\frac{\widetilde{a}^{2}-a^{2}}{2} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t \\
& =(\widetilde{a}-a) \int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} W(t)-\frac{(\widetilde{a}-a)^{2}}{2} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t .
\end{aligned}
$$

In order to investigate convergence of the family

$$
\begin{equation*}
\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}:=\left(C\left(\mathbb{R}_{+}\right), \mathcal{B}\left(C\left(\mathbb{R}_{+}\right)\right),\left\{\mathbb{P}_{a, T}: a \in \mathbb{R}\right\}\right)_{T \in \mathbb{R}_{++}} \tag{3.1}
\end{equation*}
$$

of statistical experiments, we derive the following corollary.
3.2 Corollary. For each $a \in \mathbb{R}, T \in \mathbb{R}_{++}, r_{a, T} \in \mathbb{R}$ and $h_{T} \in \mathbb{R}$, we have

$$
\log \frac{\mathrm{d} \mathbb{P}_{a+r_{a, T} h_{T}, T}}{\mathrm{~d} \mathbb{P}_{a, T}}\left(\left.X^{(a)}\right|_{[-1, T]}\right)=h_{T} \Delta_{a, T}-\frac{1}{2} h_{T}^{2} J_{a, T},
$$

with

$$
\Delta_{a, T}:=r_{a, T} \int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} W(t), \quad J_{a, T}:=r_{a, T}^{2} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t .
$$

Consequently, the quadratic approximation (2.1) is valid.

## 4 Local asymptotics of likelihood ratios

4.1 Proposition. If $a \in\left(-\frac{\pi^{2}}{2}, 0\right)$ then the family $\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments given in (3.1) is LAN at a with scaling $r_{a, T}=\frac{1}{\sqrt{T}}, T \in \mathbb{R}_{++}$, and with

$$
J_{a}=\int_{0}^{\infty}\left(\int_{-(t \wedge 1)}^{0} x_{0, a}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t
$$

4.2 Proposition. The family $\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments given in (3.1) is $L A Q$ at 0 with scaling $r_{0, T}=\frac{1}{T}, T \in \mathbb{R}_{++}$, and with

$$
\Delta_{0}=\int_{0}^{1} \mathcal{W}(t) \mathrm{d} \mathcal{W}(t), \quad J_{0}=\int_{0}^{1} \mathcal{W}(t)^{2} \mathrm{~d} t
$$

where $(\mathcal{W}(t))_{t \in[0,1]}$ is a standard Wiener process.
4.3 Proposition. The family $\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments given in (3.1) is $L A Q$ at $-\frac{\pi^{2}}{2}$ with scaling $r_{-\frac{\pi}{2}, T}=\frac{1}{T}, T \in \mathbb{R}_{++}$, and with

$$
\begin{gathered}
\Delta_{-\frac{\pi^{2}}{2}}=\frac{4(4-\pi)}{\pi\left(\pi^{2}+16\right)} \int_{0}^{1}\left(\mathcal{W}_{1}(t) \mathrm{d} \mathcal{W}_{2}(t)-\mathcal{W}_{2}(t) \mathrm{d} \mathcal{W}_{1}(t)\right) \\
J_{-\frac{\pi^{2}}{2}}=\frac{16(4-\pi)^{2}}{\pi^{2}\left(\pi^{2}+16\right)^{2}} \int_{0}^{1}\left(\mathcal{W}_{1}(t)^{2}+\mathcal{W}_{2}(t)^{2}\right) \mathrm{d} t
\end{gathered}
$$

where $\left(\mathcal{W}_{1}(t), \mathcal{W}_{2}(t)\right)_{t \in[0,1]}$ is a 2-dimensional standard Wiener process.
4.4 Proposition. If $a \in(0, \infty)$ then the family $\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments given in (3.1) is LAMN at a with scaling $r_{a, T}=\mathrm{e}^{-v_{0}(a) T}, T \in \mathbb{R}_{++}$, and with

$$
\Delta_{a}=Z \sqrt{J_{a}}, \quad J_{a}=\frac{\left(1-\mathrm{e}^{-v_{0}(a)}\right)^{2}}{2 v_{0}(a)\left(v_{0}(a)^{2}+2 v_{0}(a)-a\right)^{2}}\left(U^{(a)}\right)^{2}
$$

with

$$
U^{(a)}=x_{0}(0)+a \int_{-1}^{0} \int_{u}^{0} \mathrm{e}^{-v_{0}(a)(u-s)} \mathrm{d} s \mathrm{~d} u+\int_{0}^{\infty} \mathrm{e}^{-v_{0}(a) s} \mathrm{~d} W(s)
$$

and $Z$ is a standard normally distributed random variable independent of $J_{a}$.
4.5 Proposition. If $a \in\left(-\infty,-\frac{\pi^{2}}{2}\right)$ then the family $\left(\mathcal{E}_{T}\right)_{T \in \mathbb{R}_{++}}$of statistical experiments given in (3.1) is PLAMN at a with period $D=\frac{\pi}{\kappa_{0}(a)}$, with scaling $r_{a, T}=\mathrm{e}^{-v_{0}(a) T}, T \in \mathbb{R}_{++}$, and with

$$
\Delta_{a}(d)=Z \sqrt{J_{a}(d)}, \quad J_{a}(d)=\int_{0}^{\infty} \mathrm{e}^{-v_{0}(a) s}\left(V^{(a)}(d-s)\right)^{2} \mathrm{~d} s, \quad d \in\left[0, \frac{\pi}{\kappa_{0}(a)}\right)
$$

where

$$
\begin{aligned}
V^{(a)}(t):= & X_{0}(0) \varphi_{a}(t)+a \int_{-1}^{0} \int_{u}^{0} \varphi_{a}(t+u-s) \mathrm{e}^{v_{0}(a)(u-s)} X_{0}(s) \mathrm{d} s \mathrm{~d} u \\
& +\int_{0}^{\infty} \varphi_{a}(t-s) \mathrm{e}^{-v_{0}(a) s} \mathrm{~d} W(s), \quad t \in \mathbb{R}_{+}
\end{aligned}
$$

with

$$
\varphi_{a}(t):=A_{0}(a) \cos \left(\kappa_{0}(a) t\right)+B_{0}(a) \sin \left(\kappa_{0}(a) t\right), \quad t \in \mathbb{R}
$$

and $Z$ is a standard normally distributed random variable independent of $J_{a}(d)$.
4.6 Remark. If LAN property holds then one can construct asymptotically optimal tests, see, e.g., Theorem 15.4 and Addendum 15.5 of van der Vaart [10].

## 5 Maximum likelihood estimates

For fixed $T \in \mathbb{R}_{++}$, maximizing $\log \frac{\mathrm{dP}_{0, T}}{\mathrm{PP}_{a, T}}\left(\left.X^{(a)}\right|_{[-1, T]}\right)$ in $a \in \mathbb{R}$ gives the MLE of $a$ based on the observations $(X(t))_{t \in[-1, T]}$ having the form

$$
\widehat{a}_{T}=\frac{\int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} X^{(a)}(t)}{\int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t}
$$

provided that $\int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t>0$. Using the SDDE (1.1), one can check that

$$
\widehat{a}_{T}-a=\frac{\int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} W(t)}{\int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t}
$$

hence

$$
r_{a, T}^{-1}\left(\widehat{a}_{T}-a\right)=\frac{\Delta_{a, T}}{J_{a, T}}
$$

Using the results of Section 4 and the continuous mapping theorem, we obtain the following result.
5.1 Proposition. If $a \in\left(-\frac{\pi^{2}}{2}, 0\right)$ then

$$
\sqrt{T}\left(\widehat{a}_{T}-a\right) \xrightarrow{\mathcal{D}} \mathcal{N}\left(0, J_{a}^{-1}\right) \quad \text { as } T \rightarrow \infty
$$

where $J_{a}$ is given in Proposition 4.1.

$$
\text { If } a=0 \quad \text { then }
$$

$$
T\left(\widehat{a}_{T}-a\right)=T \widehat{a}_{T} \xrightarrow{\mathcal{D}} \frac{\int_{0}^{1} \mathcal{W}(t) \mathrm{d} \mathcal{W}(t)}{\int_{0}^{1} \mathcal{W}(t)^{2} \mathrm{~d} t} \quad \text { as } T \rightarrow \infty
$$

where $(\mathcal{W}(t))_{t \in[0,1]}$ is a standard Wiener process.

$$
\begin{aligned}
& \text { If } a=-\frac{\pi^{2}}{2} \text { then } \\
& \qquad T\left(\widehat{a}_{T}-a\right)=T\left(\widehat{a}_{T}+\frac{\pi^{2}}{2}\right) \xrightarrow{\mathcal{D}} \frac{\int_{0}^{1}\left(\mathcal{W}_{1}(t) \mathrm{d} \mathcal{W}_{2}(t)-\mathcal{W}_{2}(t) \mathrm{d} \mathcal{W}_{1}(t)\right)}{\int_{0}^{1}\left(\mathcal{W}_{1}(t)^{2}+\mathcal{W}_{2}(t)^{2}\right) \mathrm{d} t} \quad \text { as } T \rightarrow \infty
\end{aligned}
$$

where $\left(\mathcal{W}_{1}(t), \mathcal{W}_{2}(t)\right)_{t \in[0,1]}$ is a 2-dimensional standard Wiener process.

$$
\text { If } a \in(0, \infty) \text { then }
$$

$$
\mathrm{e}^{v_{0}(a) T}\left(\widehat{a}_{T}-a\right) \xrightarrow{\mathcal{D}} \frac{Z}{\sqrt{J_{a}}} \quad \text { as } T \rightarrow \infty,
$$

where $J_{a}$ is given in Proposition 4.4.

$$
\begin{aligned}
& \text { If } a \in\left(-\infty,-\frac{\pi^{2}}{2}\right) \text { then for each } d \in\left[0, \frac{\pi}{\kappa_{0}(a)}\right) \\
& \qquad \mathrm{e}^{v_{0}(a)\left(k \frac{\pi}{\kappa_{0}(a)}+d\right)}\left(\widehat{a}_{k_{\frac{\pi}{k_{0}(a)}}+d}-a\right) \xrightarrow{\mathcal{D}} \frac{Z}{\sqrt{J_{a}(d)}} \quad \text { as } T \rightarrow \infty,
\end{aligned}
$$

where $J_{a}(d)$ is given in Proposition 4.5.
If LAMN property holds then we have local asymptotic minimax bound for arbitrary estimators, see, e.g., Le Cam and Yang [7, 6.6, Theorem 1]. Maximum likelihood estimators attain this bound for bounded loss function, see, e.g., Le Cam and Yang [7, 6.6, Remark 11]. Moreover, maximum likelihood estimators are asymptotically efficient in Hájek's convolution theorem sense (see, for example, Le Cam and Yang [7, 6.6, Theorem 3 and Remark 13] or Jeganathan [6]).

## 6 Proofs

In some cases the proofs are omitted or condensed, however in these cases we always refer to our ArXiv preprint Benke and Pap [1] for a detailed discussion.

By Fubini's theorem and the Cauchy-Schwarz inequality, one obtains the following estimate.
6.1 Lemma. Let $(y(t))_{t \in[-1, \infty)}$ be a deterministic continuous function. Put

$$
Z(t):=\int_{-1}^{0} \int_{u}^{0} y(t+u-s) X_{0}(s) \mathrm{d} s \mathrm{~d} u, \quad t \in \mathbb{R}_{+}
$$

Then for each $T \in \mathbb{R}_{+}$,

$$
\int_{0}^{T} Z(t)^{2} \mathrm{~d} t \leqslant \int_{-1}^{0} X_{0}(s)^{2} \mathrm{~d} s \int_{-1}^{T} y(v)^{2} \mathrm{~d} v
$$

For each $a \in \mathbb{R}$ and each deterministic continuous function $(y(t))_{t \in[-1, \infty)}$, consider the continuous stochastic process $\left(Y^{(a)}(t)\right)_{t \in \mathbb{R}_{+}}$given by

$$
\begin{equation*}
Y^{(a)}(t):=y(t) X_{0}(0)+a \int_{-1}^{0} \int_{u}^{0} y(t+u-s) X_{0}(s) \mathrm{d} s \mathrm{~d} u+\int_{0}^{t} y(t-s) \mathrm{d} W(s) \tag{6.1}
\end{equation*}
$$

for $t \in \mathbb{R}_{+}$. The following statements are analogues of Lemmas 4.3, 4.5, 4.6, 4.8 and 4.9 of Gushchin and Küchler [2].
6.2 Lemma. Let $(y(t))_{t \in[-1, \infty)}$ be a deterministic continuous function with $\int_{0}^{\infty} y(t)^{2} \mathrm{~d} t<\infty$. Then for each $a \in \mathbb{R}$,

$$
\begin{gathered}
\frac{1}{T} \int_{0}^{T} Y^{(a)}(t) \mathrm{d} t \xrightarrow{\mathbb{P}} 0 \quad \text { as } T \rightarrow \infty \\
\frac{1}{T} \int_{0}^{T} Y^{(a)}(t)^{2} \mathrm{~d} t \xrightarrow{\mathbb{P}} \int_{0}^{\infty} y(t)^{2} \mathrm{~d} t \quad \text { as } T \rightarrow \infty .
\end{gathered}
$$

6.3 Lemma. Let $w \in \mathbb{R}_{++}$and $y(t):=\mathrm{e}^{w t}, \quad t \in[-1, \infty)$. Then for each $a \in \mathbb{R}$,

$$
\begin{gathered}
\mathrm{e}^{-w t} Y^{(a)}(t) \xrightarrow{\text { a.s. }} U_{w}^{(a)}, \quad \text { as } t \rightarrow \infty, \\
\mathrm{e}^{-2 w T} \int_{0}^{T}\left(Y^{(a)}(t)\right)^{2} \mathrm{~d} t \xrightarrow{\text { a.s. }} \frac{1}{2 w}\left(U_{w}^{(a)}\right)^{2}, \quad \text { as } T \rightarrow \infty,
\end{gathered}
$$

with

$$
U_{w}^{(a)}:=X_{0}(0)+a \int_{-1}^{0} \int_{u}^{0} \mathrm{e}^{w(u-s)} X_{0}(s) \mathrm{d} s \mathrm{~d} u+\int_{0}^{\infty} \mathrm{e}^{-w s} \mathrm{~d} W(s)
$$

6.4 Lemma. Let $w \in \mathbb{R}_{++}, \kappa \in \mathbb{R}$, and $y(t):=\varphi(t) \mathrm{e}^{w t}, t \in[-1, \infty)$, with $\varphi(t)=\cos (\kappa t)$, $t \in[-1, \infty)$, or $\varphi(t)=\sin (\kappa t), \quad t \in[-1, \infty)$. Then for each $a \in \mathbb{R}$,

$$
\begin{gathered}
\mathrm{e}^{-w t} Y^{(a)}(t)-V_{w}^{(a)}(t) \xrightarrow{\text { a.s. }} 0, \quad \text { as } t \rightarrow \infty, \\
\mathrm{e}^{-2 w T} \int_{0}^{T}\left(Y^{(a)}(t)\right)^{2} \mathrm{~d} t-\int_{0}^{\infty} \mathrm{e}^{-2 w t}\left(V_{w}^{(a)}(T-t)\right)^{2} \mathrm{~d} t \xrightarrow{\mathbb{P}} 0, \quad \text { as } T \rightarrow \infty,
\end{gathered}
$$

with

$$
V_{w}^{(a)}(t):=X_{0}(0) \varphi(t)+a \int_{-1}^{0} \int_{u}^{0} \varphi(t+u-s) \mathrm{e}^{w(u-s)} X_{0}(s) \mathrm{d} s \mathrm{~d} u+\int_{0}^{\infty} \varphi(t-s) \mathrm{e}^{-w s} \mathrm{~d} W(s)
$$

for $t \in \mathbb{R}$.
Proof of Proposition 4.1. Observe that the process $\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)_{t \in \mathbb{R}_{+}}$has a representation (6.1) with

$$
y(t)=\int_{-(t \wedge 1)}^{0} x_{0, a}(t+u) \mathrm{d} u, \quad t \in[-1, \infty)
$$

Assumption $a \in\left(-\frac{\pi^{2}}{2}, 0\right)$ implies $v_{0}(a)<0$, and hence $\int_{0}^{\infty} x_{0, a}(t)^{2} \mathrm{~d} t<\infty$ holds. Thus

$$
\int_{0}^{\infty} y(t)^{2} \mathrm{~d} t=\int_{-1}^{0} \int_{-1}^{0} \int_{-(u \wedge v)}^{0} x_{0, a}(t+u) x_{0, a}(t+v) \mathrm{d} t \mathrm{~d} u \mathrm{~d} v \leqslant \int_{0}^{\infty} x_{0, a}(t)^{2} \mathrm{~d} t<\infty
$$

Hence we can apply Lemma 6.2 to obtain

$$
J_{a, T}=\frac{1}{T} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t \xrightarrow{\mathbb{P}} \int_{0}^{\infty}\left(\int_{-(t \wedge 1)}^{0} x_{0, a}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t=J_{a}
$$

as $T \rightarrow \infty$. Moreover, the process

$$
M^{(a)}(T):=\int_{0}^{T} \int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u \mathrm{~d} W(t), \quad T \in \mathbb{R}_{+}
$$

is a continuous martingale with $M^{(a)}(0)=0$ and with quadratic variation

$$
\left\langle M^{(a)}\right\rangle(T)=\int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t
$$

hence, Theorem VIII.5.42 of Jacod and Shiryaev [5] yields the statement.
Proof of Proposition 4.2. We have

$$
\Delta_{0, T}=\frac{1}{T} \int_{0}^{T} \int_{-1}^{0} X^{(0)}(t+u) \mathrm{d} u \mathrm{~d} W(t) \quad T \in \mathbb{R}_{++}
$$

As in the proof of Proposition 4.1, for each $t \in[1, \infty)$, we obtain

$$
\int_{-1}^{0} X^{(0)}(t+u) \mathrm{d} u=X_{0}(0) \int_{-1}^{0} x_{0,0}(t+u) \mathrm{d} u+\int_{0}^{t} \int_{-1}^{0} x_{0,0}(t+u-s) \mathrm{d} u \mathrm{~d} W(s)
$$

Here we have

$$
\int_{-1}^{0} x_{0,0}(t+u) \mathrm{d} u=1, \quad \int_{-1}^{0} x_{0,0}(t+u-s) \mathrm{d} u= \begin{cases}1, & \text { for } s \in[0, t-1] \\ t-s, & \text { for } s \in[t-1, t]\end{cases}
$$

hence

$$
\int_{-1}^{0} X^{(0)}(t+u) \mathrm{d} u=X_{0}(0)+W(t)+\int_{t-1}^{t}(t-s-1) \mathrm{d} W(s)=W(t)+\bar{X}(t)
$$

where $\mathbb{E}\left(T^{-2} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t\right) \rightarrow 0$ as $T \rightarrow \infty$. For each $T \in \mathbb{R}_{++}$, consider the process

$$
W^{T}(s):=\frac{1}{\sqrt{T}} W(T s), \quad s \in[0,1]
$$

Then we have

$$
\begin{aligned}
\Delta_{0, T} & =\int_{0}^{1} W^{T}(t) \mathrm{d} W^{T}(t)+\frac{1}{T} \int_{0}^{T} \bar{X}(t) \mathrm{d} W(t) \\
J_{0, T} & =\int_{0}^{1} W^{T}(t)^{2} \mathrm{~d} t+\frac{2}{T^{2}} \int_{0}^{T} W(t) \bar{X}(t) \mathrm{d} t+\frac{1}{T^{2}} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t
\end{aligned}
$$

Here

$$
\frac{1}{T} \int_{0}^{T} \bar{X}(t) \mathrm{d} W(t) \xrightarrow{\mathbb{P}} 0, \quad \frac{1}{T^{2}} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t \xrightarrow{\mathbb{P}} 0
$$

as $T \rightarrow \infty$, since

$$
\mathbb{E}\left[\left(\frac{1}{T} \int_{0}^{T} \bar{X}(t) \mathrm{d} W(t)\right)^{2}\right]=\frac{1}{T^{2}} \int_{0}^{T} \mathbb{E}\left(\bar{X}(t)^{2}\right) \mathrm{d} t \rightarrow 0
$$

By the functional central limit theorem,

$$
W^{T} \xrightarrow{\mathcal{D}} \mathcal{W} \quad \text { as } T \rightarrow \infty,
$$

hence

$$
\left|\frac{1}{T^{2}} \int_{0}^{T} W(t) \bar{X}(t) \mathrm{d} t\right| \leqslant \sqrt{\left(\int_{0}^{1} W^{T}(t)^{2} \mathrm{~d} t\right)\left(\frac{1}{T^{2}} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t\right)} \xrightarrow{\mathbb{P}} 0 \quad \text { as } T \rightarrow \infty
$$

and the claim follows from Corollary 4.12 in Gushchin and Küchler [2].
Proof of Proposition 4.3. We have

$$
\Delta_{-\frac{\pi^{2}}{2}, T}=\frac{1}{T} \int_{0}^{T} \int_{-1}^{0} X^{\left(-\pi^{2} / 2\right)}(t+u) \mathrm{d} u \mathrm{~d} W(t) \quad T \in \mathbb{R}_{++}
$$

As in the proof of Proposition 4.1. for each $t \in[1, \infty)$, we have

$$
\begin{aligned}
\int_{-1}^{0} X^{\left(-\pi^{2} / 2\right)}(t+u) \mathrm{d} u= & X_{0}(0) \int_{-1}^{0} x_{0,-\frac{\pi^{2}}{2}}(t+u) \mathrm{d} u+\int_{0}^{t} \int_{-1}^{0} x_{0,-\frac{\pi^{2}}{2}}(t+u-s) \mathrm{d} u \mathrm{~d} W(s) \\
& -\frac{\pi^{2}}{2} \int_{-1}^{0} \int_{v}^{0} X_{0}(s) \int_{-1}^{0} x_{0,-\frac{\pi^{2}}{2}}(t+u+v-s) \mathrm{d} u \mathrm{~d} s \mathrm{~d} v .
\end{aligned}
$$

We have $v_{0}\left(-\frac{\pi^{2}}{2}\right)=0$ and $\kappa_{0}\left(-\frac{\pi^{2}}{2}\right)=\pi$, hence $A_{0}\left(-\frac{\pi^{2}}{2}\right)=\frac{16}{\pi^{2}+16}$ and $B_{0}\left(-\frac{\pi^{2}}{2}\right)=\frac{4 \pi}{\pi^{2}+16}$. Consequently, by Lemma 1.1, there exists $\gamma \in(-\infty, 0)$ such that

$$
x_{0,-\frac{\pi^{2}}{2}}(t)=\frac{16 \cos (\pi t)+4 \pi \sin (\pi t)}{\pi^{2}+16}+\mathrm{o}\left(\mathrm{e}^{\gamma t}\right), \quad \text { as } t \rightarrow \infty
$$

and hence

$$
\begin{aligned}
\int_{-1}^{0} X^{\left(-\pi^{2} / 2\right)}(t+u) \mathrm{d} u & =\int_{0}^{t} \int_{-1}^{0} \frac{16 \cos (\pi(t+u-s))+4 \pi \sin (\pi(t+u-s))}{\pi^{2}+16} \mathrm{~d} u \mathrm{~d} W(s)+\bar{X}(t) \\
& =\frac{8(4-\pi)}{\pi\left(\pi^{2}+16\right)} \int_{0}^{t} \sin (\pi(t-s)) \mathrm{d} W(s)+\bar{X}(t)
\end{aligned}
$$

where $T^{-2} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t \xrightarrow{\mathbb{P}} 0$ as $T \rightarrow \infty$. Introducing

$$
X_{1}(t):=\int_{0}^{t} \cos (\pi s) \mathrm{d} W(s), \quad X_{2}(t):=\int_{0}^{t} \sin (\pi s) \mathrm{d} W(s), \quad t \in \mathbb{R}_{+}
$$

we obtain

$$
\int_{-1}^{0} X^{\left(-\pi^{2} / 2\right)}(t+u) \mathrm{d} u=\frac{8(4-\pi)}{\pi\left(\pi^{2}+16\right)}\left(X_{1}(t) \sin (\pi t)-X_{2}(t) \cos (\pi t)\right)+\bar{X}(t)
$$

and hence

$$
\begin{aligned}
\Delta_{-\frac{\pi^{2}}{2}, T}= & \frac{8(4-\pi)}{\pi\left(\pi^{2}+16\right)} \frac{1}{T} \int_{0}^{T}\left(X_{1}(t) \sin (\pi t)-X_{2}(t) \cos (\pi t)\right) \mathrm{d} W(t)+I_{1}(T) \\
J_{-\frac{\pi^{2}}{2}, T}= & \frac{64(4-\pi)^{2}}{\pi^{2}\left(\pi^{2}+16\right)^{2}} \frac{1}{T^{2}} \int_{0}^{T}\left(X_{1}(t) \sin (\pi t)-X_{2}(t) \cos (\pi t)\right)^{2} \mathrm{~d} t \\
& +\frac{16(4-\pi)}{\pi\left(\pi^{2}+16\right)} I_{2}(T)+I_{3}(T)
\end{aligned}
$$

with

$$
\begin{aligned}
I_{1}(T) & :=\frac{1}{T} \int_{0}^{T} \bar{X}(t) \mathrm{d} W(t), \quad I_{3}(T):=\frac{1}{T^{2}} \int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t \\
I_{2}(T) & :=\frac{1}{T^{2}} \int_{0}^{T}\left(X_{1}(t) \sin (\pi t)-X_{2}(t) \cos (\pi t)\right) \bar{X}(t) \mathrm{d} t
\end{aligned}
$$

For each $T \in \mathbb{R}_{++}$, consider the following processes on $[0,1]$ :

$$
\begin{gathered}
W^{T}(s):=\frac{1}{\sqrt{T}} W(T s), \quad X_{1}^{T}(s):=\frac{1}{\sqrt{T}} X_{1}(T s), \quad X_{2}^{T}(s):=\frac{1}{\sqrt{T}} X_{2}(T s) \\
X^{T}(s):=X_{1}^{T}(s) \sin (\pi T s)-X_{2}^{T}(s) \cos (\pi T s)
\end{gathered}
$$

Then we have

$$
\begin{aligned}
\Delta_{-\frac{\pi^{2}}{2}, T} & =\frac{8(4-\pi)}{\pi\left(\pi^{2}+16\right)} \int_{0}^{1} X^{T}(s) \mathrm{d} W^{T}(s)+I_{1}(T) \\
J_{-\frac{\pi^{2}}{2}, T} & =\frac{64(4-\pi)^{2}}{\pi^{2}\left(\pi^{2}+16\right)^{2}} \int_{0}^{1} X^{T}(s)^{2} \mathrm{~d} s+\frac{16(4-\pi)}{\pi\left(\pi^{2}+16\right)} I_{2}(T)+I_{3}(T) .
\end{aligned}
$$

Introducing the process

$$
Y(t):=\int_{0}^{t} X^{T}(s) \mathrm{d} W^{T}(s), \quad t \in \mathbb{R}_{+}
$$

we have

$$
\int_{0}^{t} X^{T}(s)^{2} \mathrm{~d} s=[Y, Y]_{t}, \quad t \in \mathbb{R}_{+}
$$

where $\left([U, V]_{t}\right)_{t \in \mathbb{R}_{+}}$denotes the quadratic covariation process of the processes $\left(U_{t}\right)_{t \in \mathbb{R}_{+}}$and $\left(V_{t}\right)_{t \in \mathbb{R}_{+}}$. Moreover,

$$
Y(t)=\int_{0}^{t}\left(X_{1}^{T}(s) \mathrm{d} X_{2}^{T}(s)-X_{2}^{T}(s) \mathrm{d} X_{1}^{T}(s)\right), \quad t \in \mathbb{R}_{+}
$$

By the functional central limit theorem,

$$
\left(X_{1}^{T}, X_{2}^{T}\right) \xrightarrow{\mathcal{D}} \frac{1}{\sqrt{2}}\left(\mathcal{W}_{1}, \mathcal{W}_{2}\right) \quad \text { as } T \rightarrow \infty
$$

hence

$$
Y \xrightarrow{\mathcal{D}} \mathcal{Y} \quad \text { as } \quad T \rightarrow \infty
$$

with

$$
\mathcal{Y}(t):=\frac{1}{2} \int_{0}^{t}\left(\mathcal{W}_{1}(s) \mathrm{d} \mathcal{W}_{2}(s)-\mathcal{W}_{2}(s) \mathrm{d} \mathcal{W}_{1}(s)\right), \quad t \in \mathbb{R}_{+},
$$

see, e.g., Lemma 4.1 in Gushchin and Küchler [2]. Further, by Corollary 4.12 in Gushchin and Küchler [2],

$$
\left(Y(1),[Y, Y]_{1}\right) \xrightarrow{\mathcal{D}}\left(\mathcal{Y}(1),[\mathcal{Y}, \mathcal{Y}]_{1}\right) \quad \text { as } \quad T \rightarrow \infty
$$

Here we have

$$
[\mathcal{Y}, \mathcal{Y}]_{1}=\frac{1}{4} \int_{0}^{t}\left(\mathcal{W}_{1}(s)^{2}+\mathcal{W}_{2}(s)^{2}\right) \mathrm{d} s
$$

Recall that $I_{3}(T) \xrightarrow{\mathbb{P}} 0$ as $T \rightarrow \infty$. Further, $I_{1}(T) \xrightarrow{\mathbb{P}} 0$ as $T \rightarrow \infty$, since $\mathbb{E}\left(I_{1}(T)^{2}\right)=$ $T^{-2} \int_{0}^{T} \mathbb{E}\left(\bar{X}(t)^{2}\right) \mathrm{d} t \rightarrow 0$ as $T \rightarrow \infty$. Finally,

$$
\left|I_{2}(T)\right| \leqslant \sqrt{\left(\int_{0}^{1} X^{T}(s)^{2} \mathrm{~d} s\right) \frac{1}{T^{2}}\left(\int_{0}^{T} \bar{X}(t)^{2} \mathrm{~d} t\right)} \stackrel{\mathbb{P}}{\longrightarrow} 0 \quad \text { as } T \rightarrow \infty
$$

and the claim follows.
Proof of Proposition 4.4. We have

$$
J_{a, T}=\mathrm{e}^{-2 v_{0}(a) T} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t \quad T \in \mathbb{R}_{+}
$$

The process $\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)_{t \in[1, \infty)}$ has a representation (6.1) with $y(t)=\int_{-1}^{0} x_{0, a}(t+u) \mathrm{d} u$, $t \in \mathbb{R}_{+}$, see the proof of Proposition 4.1. The assumption $a \in(0, \infty)$ implies $v_{0}(a)>0$ and $v_{1}(a)<0$, hence by Lemma 1.1, there exists $\gamma \in\left(v_{1}(a), 0\right)$ such that

$$
x_{0, a}(t)=\frac{v_{0}(a)}{v_{0}(a)^{2}+2 v_{0}(a)-a} \mathrm{e}^{v_{0}(a) t}+\mathrm{o}\left(\mathrm{e}^{\gamma t}\right), \quad \text { as } t \rightarrow \infty
$$

Consequently,

$$
\int_{-1}^{0} x_{0, a}(t+u) \mathrm{d} u=\frac{1-\mathrm{e}^{-v_{0}(a)}}{v_{0}(a)^{2}+2 v_{0}(a)-a} \mathrm{e}^{v_{0}(a) t}+\mathrm{o}\left(\mathrm{e}^{\gamma t}\right), \quad \text { as } t \rightarrow \infty
$$

and we obtain

$$
J_{a, T} \xrightarrow{\mathbb{P}} \frac{1}{2 v_{0}(a)}\left(\frac{1-\mathrm{e}^{-v_{0}(a)}}{v_{0}(a)^{2}+2 v_{0}(a)-a}\right)^{2}\left(U^{(a)}\right)^{2}=J_{a} \quad \text { as } \quad T \rightarrow \infty .
$$

Theorem VIII.5.42 of Jacod and Shiryaev [5] yields the statement.
Proof of Proposition 4.5. We have again

$$
J_{a, T}=\mathrm{e}^{-2 v_{0}(a) T} \int_{0}^{T}\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)^{2} \mathrm{~d} t \quad T \in \mathbb{R}_{+}
$$

and the process $\left(\int_{-1}^{0} X^{(a)}(t+u) \mathrm{d} u\right)_{t \in[1, \infty)}$ has a representation 6.1) with $y(t)=\int_{-1}^{0} x_{0, a}(t+$ u) $\mathrm{d} u, \quad t \in \mathbb{R}_{+}$, see the proof of Proposition 4.1. The assumption $a \in\left(-\infty,-\frac{\pi^{2}}{2}\right)$ implies $v_{0}(a)>0$ and $v_{0}(a) \notin \Lambda_{a}$, hence by Lemma 1.1, there exists $\gamma \in\left(0, v_{0}(a)\right)$ such that

$$
x_{0, a}(t)=\varphi_{a}(t) \mathrm{e}^{v_{0}(a) t}+\mathrm{o}\left(\mathrm{e}^{\gamma t}\right), \quad \text { as } t \rightarrow \infty .
$$

Applying Lemma 6.4, we obtain

$$
J_{a, T}-J_{a}(T) \xrightarrow{\mathbb{P}} 0, \quad \text { as } \quad T \rightarrow \infty .
$$

The process $\left(J_{a}(t)\right)_{t \in \mathbb{R}_{+}}$is periodic with period $D=\frac{\pi}{\kappa_{0}(a)}$.

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