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MARTINGALE ESTIMATING FUNCTIONS BASED ON EIGENFUNCTIONS FOR DISCRETELY OBSERVED SMALL DIFFUSIONS

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Abstract

We consider asymptotic properties of an estimator of a drift parameter for a one-dimensional diffusion process with small dispersion parameter ε . For discrete data observed at equidistant times k/n , $k = 0, 1, \dots, n$, we study consistency and asymptotic normality of an M-estimator derived from a martingale estimating function based on an eigenfunction as ε tends to 0 and n tends to ∞ simultaneously.

Key Words and Phrases: Diffusion process with small noise, Discrete time observation, Parametric inference.

1. Introduction

We consider statistical inference for a class of one-dimensional diffusion processes defined as solutions of the stochastic differential equations

$$\begin{aligned} dX_t &= b(X_t, \theta)dt + \varepsilon\sigma(X_t)dw_t, \quad t \in [0, 1], \quad \varepsilon \in (0, 1], \\ X_0 &= x_0, \end{aligned} \tag{1}$$

where x_0 and ε are known constants and w is an r -dimensional standard Wiener process. Further, b is an \mathbf{R} -valued function defined on $\mathbf{R} \times \bar{\Theta}$, σ is an \mathbf{R}^r -valued function defined on \mathbf{R} , Θ is an open bounded convex subset of \mathbf{R}^p and $\bar{\Theta}$ denotes the closure of Θ . We assume that the drift b is known apart from the parameter θ . The types of data considered in the present paper are observations of X at n regularly spaced time points: $(X_{t_k})_{0 \leq k \leq n}$ with $t_k = k/n$. The asymptotics we treat is when $\varepsilon \rightarrow 0$ and $n \rightarrow \infty$ simultaneously.

Diffusion processes with small noise have a lot of applications in various fields. Applications to mathematical finance were given in Yoshida (1992c), Kunitomo and Takahashi (2001) and Uchida and Yoshida (2004). The asymptotic theory of parametric inference for diffusion processes with small noise is well developed. For continuous-time observations, see Kutoyants (1984, 1994) and Yoshida (1992a, 2003). For discrete observations, see Genon-Catalot (1990), Laredo (1990), Sørensen (2000), Sørensen and Uchida (2003) and Uchida (2003). Recently, Uchida (2004) derived an explicit estimating function by using the expansion in Florens-Zmirou (1989). His estimating function is asymptotically equivalent to the martingale estimating function proposed by Bibby and

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Sørensen (1995) under $(\varepsilon n^l)^{-1} \rightarrow 0$ for a positive integer l . He also proved that the estimator obtained from the approximate martingale estimating function has asymptotic efficiency under $(\varepsilon n^l)^{-1} \rightarrow 0$ for a positive integer l . However, there is a disadvantage that the estimator may not be obtained explicitly when the approximate martingale estimating function is complicated. In order to overcome this difficulty, Matsuzaki and Uchida (2004) proposed one-step estimators based on the method of Newton-Raphson in numerical analysis. Using an initial estimator, they derived a one-step estimator with asymptotic efficiency. A sufficient condition for the initial estimator is that the initial estimator has asymptotic normality as $\varepsilon \rightarrow 0$ and $n \rightarrow \infty$. Note that the initial estimator does not have to be asymptotically efficient. Therefore, we investigate explicit estimating functions to obtain estimators with asymptotic normality as $\varepsilon \rightarrow 0$ and $n \rightarrow \infty$. The present paper is a contribution in this direction.

Kessler and Sørensen (1999) proposed explicit martingale estimating functions based on eigenfunctions for discretely observed ergodic diffusion processes. Though the estimators obtained from the estimating function may not be asymptotically efficient, they have very good asymptotic properties. We will apply the martingale estimating functions based on eigenfunctions to small diffusion models defined by (1). Another difference between Kessler and Sørensen (1999) and the present paper is asymptotics. Note that the asymptotics in the present paper is when $\varepsilon \rightarrow 0$ and $t_k - t_{k-1} = 1/n \rightarrow 0$ simultaneously, while the asymptotics in Kessler and Sørensen (1999) is when $t_k - t_{k-1} = \Delta$ is fixed and $n\Delta \rightarrow \infty$.

In section 2, we construct the martingale estimating functions based on eigenfunctions. We also present asymptotic properties of M-estimators obtained from the martingale estimating functions. Section 3 gives two examples and simulation studies. Section 4 concludes. In section 5, we prove the results stated in section 2.

2. Martingale estimating functions based on eigenfunctions

We first state notation used in this paper. Let $\theta_0 \in \Theta$ denote the true value of θ . Let X_t^0 be the solution of the ordinary differential equation corresponding to $\varepsilon = 0$, i.e. $dX_t^0 = b(X_t^0, \theta_0)dt$, $X_0^0 = x_0$. For a matrix A , A^* is the transpose of A . We denote by $C_{\uparrow}^{\infty, k}(\mathbf{R} \times \Theta \times (0, 1]; \mathbf{R})$ the space of all functions f satisfying the following two conditions: (i) $f(x, \theta, \varepsilon)$ is an \mathbf{R} -valued function on $\mathbf{R} \times \Theta \times (0, 1]$ that is infinitely differentiable with respect to x and continuously differentiable with respect to θ up to order k , (ii) for $n \geq 0$ and $0 \leq |\nu| \leq k$, there exists $C > 0$ such that $\sup_{\theta \in \Theta} |\delta^\nu \partial_x^n f| \leq C(1 + |x|)^C$ for all x, ε . Here $\partial_x = \partial/\partial x$ and $\nu = (\nu^1, \dots, \nu^p)$ is a multi-index, $|\nu| = \nu^1 + \dots + \nu^p$, $\delta^\nu = \delta_1^{\nu^1} \dots \delta_p^{\nu^p}$, $\delta_j = \partial/\partial \theta^j$, $j = 1, \dots, p$. Likewise, let $C_{\uparrow}^{\infty, k}(\mathbf{R} \times \Theta; \mathbf{R})$ be the space of all functions f satisfying the following two conditions: (i) $f(x, \theta)$ is an \mathbf{R} -valued function on $\mathbf{R} \times \Theta$ that is infinitely differentiable with respect to x and continuously differentiable with respect to θ up to order k , (ii) for $n \geq 0$ and $0 \leq |\nu| \leq k$, there exists $C > 0$ such that $\sup_{\theta \in \Theta} |\delta^\nu \partial_x^n f| \leq C(1 + |x|)^C$ for all x . Let $C_{\uparrow}^{\infty}(\mathbf{R}; \mathbf{R}^r)$ be the set of all functions f of class $C^{\infty}(\mathbf{R}; \mathbf{R}^r)$ such that f and all of its derivatives have polynomial growth. Let $C_b^k(\Theta \times (0, 1]; \mathbf{R})$ be the space of all functions f satisfying the following two conditions: (i) $f(\theta, \varepsilon)$ is an \mathbf{R} -valued function on $\Theta \times (0, 1]$ that is continuously differentiable with respect to θ up to order k , (ii) for $0 \leq |\nu| \leq k$, there exists $C > 0$ such that $|\delta^\nu f| \leq C$ for all θ, ε . We denote by \xrightarrow{p} and \xrightarrow{d} the convergence in probability and the convergence in distribution as $\varepsilon \rightarrow 0$ and $n \rightarrow \infty$, respectively. Let P_θ be the law of the solution of

(1). Let L_θ be the infinitesimal generator of the diffusion (1): For $g \in C^2(\mathbf{R})$,

$$L_\theta g(x) = b(x, \theta) \partial_x g(x) + \frac{1}{2} \varepsilon^2 [\sigma \sigma^*](x) \partial_x^2 g(x).$$

For a twice continuously differentiable function $\phi(x, \theta, \varepsilon)$ with respect to x , $\phi(x, \theta, \varepsilon)$ is called an eigenfunction for L_θ with eigenvalue $\lambda(\theta, \varepsilon)$ if

$$L_\theta \phi(x, \theta, \varepsilon) = -\lambda(\theta, \varepsilon) \phi(x, \theta, \varepsilon)$$

for all x in the state space of X under P_θ . For more details, see Kessler and Sørensen (1999).

In this paper we make the following assumptions.

- A1. For every $\theta \in \bar{\Theta}$, there exists a constant $K_\theta > 0$ such that $b^2(x, \theta) + |\sigma(x)|^2 \leq K_\theta(1 + x^2)$.
- A2. b is Lipschitz on $\mathbf{R} \times \bar{\Theta}$.
- A3. $b(x, \theta) \in C_{\uparrow}^{\infty, 3}(\mathbf{R} \times \bar{\Theta}; \mathbf{R})$, $\sigma(x) \in C_{\uparrow}^{\infty}(\mathbf{R}; \mathbf{R}^r)$.
- A4. There exists an eigenfunction $\phi(x, \theta, \varepsilon) \in C_{\uparrow}^{\infty, 2}(\mathbf{R} \times \bar{\Theta} \times (0, 1]; \mathbf{R})$ with eigenvalue $\lambda(\theta, \varepsilon) \in C_b^2(\bar{\Theta} \times (0, 1]; \mathbf{R})$ such that $L_\theta \phi(x, \theta, \varepsilon) = -\lambda(\theta, \varepsilon) \phi(x, \theta, \varepsilon)$ for all x in the state space of X under P_θ .
- A5. $\inf_x [\sigma \sigma^*](x) > 0$.

REMARK. (i) By a localization argument, the results which will be presented in this paper still hold under mild regularity conditions about b , σ and ϕ in the neighborhood of the path of X_t^0 instead of A3–A5. (ii) By A4, we set $\phi(x, \theta, 0) = \lim_{\varepsilon \rightarrow 0} \phi(x, \theta, \varepsilon)$ and $\lambda(\theta, 0) = \lim_{\varepsilon \rightarrow 0} \lambda(\theta, \varepsilon)$.

Under some regularity conditions, we have

$$E_\theta[\phi(X_{t_k}, \theta, \varepsilon) | X_{t_{k-1}}] = e^{-\lambda(\theta, \varepsilon)/n} \phi(X_{t_{k-1}}, \theta, \varepsilon).$$

For details of the regularity conditions, see section 5 in Kessler and Sørensen (1999). We then obtain the following martingale estimating function: for $i = 1, 2, \dots, p$,

$$\begin{aligned} M_{\varepsilon, n}^i(\theta) &= \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) (\phi(X_{t_k}, \theta, \varepsilon) - E_\theta[\phi(X_{t_k}, \theta, \varepsilon) | X_{t_{k-1}}]) \\ &= \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) \left[\phi(X_{t_k}, \theta, \varepsilon) - e^{-\lambda(\theta, \varepsilon)/n} \phi(X_{t_{k-1}}, \theta, \varepsilon) \right]. \end{aligned}$$

For results put later on, we introduce several functions. Let $K_{\varepsilon, n}(\theta) = (K_{\varepsilon, n}^{ij}(\theta))_{1 \leq i, j \leq p}$, where $K_{\varepsilon, n}^{ij}(\theta) = \delta_j M_{\varepsilon, n}^i(\theta)$. Let $K(\theta) = (K^{ij}(\theta))_{1 \leq i, j \leq p}$ and $A(\theta) = (A^{ij}(\theta))_{1 \leq i, j \leq p}$, where

$$K^{ij}(\theta) = \int_0^1 (\delta_j \delta_i b)(X_s^0, \theta) [\sigma \sigma^*]^{-1}(X_s^0) b(X_s^0, \theta_0) \partial_x \phi(X_s^0, \theta, 0) ds$$

$$\begin{aligned}
& + \int_0^1 (\delta_j \delta_i b)(X_s^0, \theta) [\sigma \sigma^*]^{-1}(X_s^0) \lambda(\theta, 0) \phi(X_s^0, \theta, 0) ds \\
& + \int_0^1 (\delta_i b)(X_s^0, \theta) [\sigma \sigma^*]^{-1}(X_s^0) b(X_s^0, \theta_0) \partial_x \delta_j \phi(X_s^0, \theta, 0) ds \\
& + \int_0^1 (\delta_i b)(X_s^0, \theta) [\sigma \sigma^*]^{-1}(X_s^0) \lambda(\theta, 0) \delta_j \phi(X_s^0, \theta, 0) ds \\
& + \int_0^1 (\delta_i b)(X_s^0, \theta) [\sigma \sigma^*]^{-1}(X_s^0) (\delta_j \lambda)(\theta, 0) \phi(X_s^0, \theta, 0) ds,
\end{aligned}$$

and

$$A^{ij}(\theta_0) = \int_0^1 (\delta_i b)(X_s^0, \theta_0) [\sigma \sigma^*]^{-1}(X_s^0) (\partial_x \phi)^2(X_s^0, \theta_0, 0) (\delta_j b)(X_s^0, \theta_0) ds.$$

In order to show asymptotic results of M-estimators, we need the following two lemmas.

LEMMA 2.1. *Under A1–A5, $K_{\varepsilon,n}(\theta) \xrightarrow{p} K(\theta)$ uniformly in $\theta \in \bar{\Theta}$.*

LEMMA 2.2. *Under A1–A5, $\varepsilon^{-1} M_{\varepsilon,n}(\theta_0) \xrightarrow{d} N(0, A(\theta_0))$.*

Let $\hat{\theta}_{\varepsilon,n}$ be an M-estimator defined as a solution of $M_{\varepsilon,n}(\theta) = 0$. The main theorem is as follows.

THEOREM 2.3. *Let $\gamma \in (0, 1)$. Suppose that A1–A5 hold true. Moreover, suppose that there exists an open set $\tilde{\Theta}$ including θ_0 such that*

$$\inf_{\theta_1, \theta_2 \in \tilde{\Theta}, |x|=1} \left| x^* \left(\int_0^1 K(\theta_1 + s(\theta_2 - \theta_1)) ds \right) \right| > 0.$$

Then,

$$P_{\theta_0}[(\exists_1 \hat{\theta}_{\varepsilon,n} \in \tilde{\Theta} \text{ such that } M_{\varepsilon,n}(\hat{\theta}_{\varepsilon,n}) = 0) \text{ and } (|\hat{\theta}_{\varepsilon,n} - \theta_0| \leq \varepsilon^\gamma)] \rightarrow 1$$

and

$$\varepsilon^{-1}(\hat{\theta}_{\varepsilon,n} - \theta_0) \xrightarrow{d} N(0, K(\theta_0)^{-1} A(\theta_0) (K^*(\theta_0))^{-1}).$$

3. Examples

In this section, we consider two kinds of non-linear models and examine the asymptotic behaviour of the estimator proposed in section 2 through simulations. We generate 1000 independent sample paths with $\theta = \theta_0$ (true parameter value) and the initial value x_0 . In order to evaluate the estimator ($\hat{\theta}_{\varepsilon,n}$), we also examine the estimator in corollary 1 of Genon-Catalot (1990) and the estimator in Laredo (1990), which are called the simple estimator ($\hat{\theta}_{\varepsilon,n}^{(S)}$) and Laredo's estimator ($\hat{\theta}_{\varepsilon,n}^{(L)}$) respectively in this section. For each of the three estimators, its mean and standard deviation are computed. The simulations are done for each $\varepsilon = 0.1, 0.05, 0.01$ and $n = 5, 10, 50$, with the Euler-Maruyama scheme, see Kloeden and Platen (1992).

3.1. Non-linear model

Consider a non-linear model defined by the following stochastic differential equation

$$\begin{aligned} dX_t &= -\theta \tan X_t dt + \varepsilon dw_t, \\ X_0 &= x_0, \end{aligned}$$

where x_0 and ε are known constants and θ is an unknown parameter. Here we assume that $X_t \neq m\pi/2$ ($m = 0, 1, \dots$). The non-trivial eigenfunction is $\phi(x, \theta, \varepsilon) = \sin(x)$ and its eigenvalue is $\lambda(\theta, \varepsilon) = \theta + \varepsilon^2/2$. The martingale estimating function based on an eigenfunction is given by

$$M_{\varepsilon,n}(\theta) = -\sum_{k=1}^n \tan X_{t_{k-1}} \left[\sin X_{t_k} - \exp \left\{ -\frac{1}{n} \left(\theta + \frac{\varepsilon^2}{2} \right) \right\} \sin X_{t_{k-1}} \right],$$

and one has the estimator

$$\hat{\theta}_{\varepsilon,n} = n \left\{ \log \left(\sum_{k=1}^n \tan X_{t_{k-1}} \sin X_{t_k} \right) - \log \left(\sum_{k=1}^n \tan X_{t_{k-1}} \sin X_{t_{k-1}} \right) \right\} - \frac{\varepsilon^2}{2}.$$

By Theorem 2.3, the asymptotic variance of $\varepsilon^{-1}(\hat{\theta}_{\varepsilon,n} - \theta_0)$ is as follows.

$$K(\theta_0)^{-1} A(\theta_0) (K^*(\theta_0))^{-1} = \frac{\int_0^1 \sin^2 X_s^0 ds}{\left(\int_0^1 \frac{\sin X_s^0}{\cos X_s^0} ds \right)^2},$$

where X_s^0 is a solution of the ordinary differential equation: $dX_s^0 = -\theta_0 \tan X_s^0 ds$.

Table 1 shows the means and standard deviations of simulated values. We set $\theta = 2$ and $x_0 = 1/2$. When $n \leq 10$, $\hat{\theta}_{\varepsilon,n}^{(S)}$ has a considerable bias and $\hat{\theta}_{\varepsilon,n}^{(L)}$ has a little small bias, while $\hat{\theta}_{\varepsilon,n}$ is better than the others. Compared with those of $\hat{\theta}_{\varepsilon,n}^{(S)}$ and $\hat{\theta}_{\varepsilon,n}^{(L)}$, the standard deviations of $\hat{\theta}_{\varepsilon,n}$ get a little greater because $\hat{\theta}_{\varepsilon,n}$ is not asymptotically efficient. However, $\hat{\theta}_{\varepsilon,n}$ gives satisfactory approximation in all cases.

3.2. The radial Ornstein-Uhlenbeck process

We consider another non-linear model defined by the stochastic differential equation

$$\begin{aligned} dX_t &= \left(\frac{\theta}{X_t} - X_t \right) dt + \varepsilon dw_t, \\ X_0 &= x_0, \end{aligned}$$

where x_0 and ε are known constants and θ is an unknown parameter. Here we assume that the state space is the positive real line. This model is called the radial Ornstein-Uhlenbeck process. The eigenfunctions are $\phi_i(x, \theta, \varepsilon) = L_i^{(\theta/\varepsilon^2 - 1/2)}(x^2/\varepsilon^2)$, where $L_i^{(\nu)}$ is the i th-order Laguerre polynomial with parameter ν , and the associated eigenvalues are $\{2i : i = 1, 2, \dots\}$ (Karlin and Taylor (1981), p.333). The first non-trivial eigenfunction is $\phi(x, \theta, \varepsilon) = (\theta + \varepsilon^2/2) - x^2$ with eigenvalue $\lambda(\theta, \varepsilon) = 2$. We obtain the following martingale estimating function.

$$M_{\varepsilon,n}(\theta) = \sum_{k=1}^n \frac{1}{X_{t_{k-1}}} \left[\left(\theta + \frac{\varepsilon^2}{2} \right) - X_{t_k}^2 - e^{-\frac{2}{n}} \left\{ \left(\theta + \frac{\varepsilon^2}{2} \right) - X_{t_{k-1}}^2 \right\} \right].$$

Table 1: (Non-linear model) The mean and standard deviation (s.d.) of the three estimators determined from 1000 independent simulated sample paths for $\theta = 2$, $x_0 = 1/2$.

n	ε	$\hat{\theta}_{\varepsilon,n}^{(S)}$		$\hat{\theta}_{\varepsilon,n}^{(L)}$		$\hat{\theta}_{\varepsilon,n}$	
		mean	s.d.	mean	s.d.	mean	s.d.
5	0.10	1.619732	0.244242	1.916941	0.350186	2.046181	0.399759
5	0.05	1.604015	0.122962	1.927802	0.176971	2.009593	0.196568
5	0.01	1.601109	0.024705	1.934346	0.035514	2.001343	0.039226
10	0.10	1.820309	0.306519	1.963445	0.373302	2.050758	0.393158
10	0.05	1.793241	0.153053	1.976303	0.188003	2.011086	0.193620
10	0.01	1.786957	0.030637	1.983474	0.037636	2.001493	0.038591
50	0.10	2.005406	0.368952	1.974965	0.377853	2.053692	0.388012
50	0.05	1.965942	0.183091	1.991505	0.190903	2.011772	0.191976
50	0.01	1.956236	0.036568	2.000019	0.038265	2.001479	0.038305

We then have the estimator,

$$\hat{\theta}_{\varepsilon,n} = \frac{\sum_{k=1}^n X_{t_k}^2 X_{t_{k-1}}^{-1} - e^{-\frac{2}{n}} \sum_{k=1}^n X_{t_{k-1}}}{(1 - e^{-\frac{2}{n}}) \sum_{k=1}^n X_{t_{k-1}}^{-1}} - \frac{\varepsilon^2}{2}.$$

The asymptotic variance of $\varepsilon^{-1}(\hat{\theta}_{\varepsilon,n} - \theta_0)$ is given by

$$K(\theta_0)^{-1} A(\theta_0) (K^*(\theta_0))^{-1} = \left(\int_0^1 \frac{1}{X_s^0} ds \right)^{-2},$$

where X_s^0 is a solution of the ordinary differential equation, $dX_t^0 = (\theta_0/X_t^0 - X_t^0) dt$.

The results with $\theta = 10$ and $x_0 = 3$ are given in Table 2. Even if $n = 5$, both $\hat{\theta}_{\varepsilon,n}^{(L)}$ and $\hat{\theta}_{\varepsilon,n}$ are unbiased, while $\hat{\theta}_{\varepsilon,n}^{(S)}$ has a small bias. Although $\hat{\theta}_{\varepsilon,n}$ has a little greater standard deviation than the others, as the theory shows, it gives as good an approximation as $\hat{\theta}_{\varepsilon,n}^{(L)}$. When $n = 50$, there seems no difference between the three estimators.

4. Conclusions

This paper has proposed a martingale estimating function based on an eigenfunction for a small diffusion process using the same technique as in Kessler and Sørensen (1999). Moreover, it has been shown that an estimator obtained from the estimating function has consistency and asymptotic normality. As seen from the assumption A4, in order to obtain the martingale estimating function, it is important to get an eigenfunction $\phi(x, \theta, \varepsilon)$ with an eigenvalue $\lambda(\theta, \varepsilon)$ such that $L_\theta \phi(x, \theta, \varepsilon) = -\lambda(\theta, \varepsilon) \phi(x, \theta, \varepsilon)$. Since this is the second order differential equation, in general, it is not easy to solve this equation. However, for several diffusion models, we can refer section 13 of chapter 15 in Karlin and Taylor (1981). See also Kessler and Sørensen (1999). From the viewpoint of theory, an extension of this paper to multivariate case is straightforward. In practice,

Table 2: (The radial Ornstein-Uhlenbeck process) The mean and standard deviation (s.d.) of the three estimators determined from 1000 independent simulated sample paths for $\theta = 10$, $x_0 = 3$.

n	ε	$\hat{\theta}_{\varepsilon,n}^{(S)}$		$\hat{\theta}_{\varepsilon,n}^{(L)}$		$\hat{\theta}_{\varepsilon,n}$	
		mean	s.d.	mean	s.d.	mean	s.d.
5	0.10	9.915631	0.271403	10.003568	0.299242	10.010793	0.301986
5	0.05	9.908870	0.135665	9.998501	0.149627	10.005073	0.150860
5	0.01	9.904811	0.027127	9.994905	0.029927	10.001282	0.030152
10	0.10	9.966824	0.286189	10.008460	0.300001	10.011606	0.301243
10	0.05	9.959136	0.143081	10.003445	0.150052	10.005410	0.150511
10	0.01	9.954612	0.028614	9.999736	0.030019	10.001342	0.030086
50	0.10	10.005790	0.298375	10.010167	0.300978	10.012232	0.301648
50	0.05	9.997270	0.149186	10.005154	0.150546	10.005693	0.150739
50	0.01	9.992323	0.029837	10.001322	0.030118	10.001394	0.030135

however, it can be difficult to obtain an eigenfunction with an eigenvalue satisfying the multivariate version of the assumption A4. For a multivariate diffusion process with a small noise, we will need to consider a more convenient procedure.

5. Proofs

Let R be a function $\bar{\Theta} \times (0, 1] \times \mathbf{R} \rightarrow \mathbf{R}$ for which there exists a constant $C > 0$ such that $|R(\theta, a, x)| \leq aC(1 + |x|)^C$ for all θ, a, x . We define $\mathcal{G}_k^n = \sigma(w_s; s \leq t_k)$. Let $\tilde{C}_{\uparrow}^{1,1}(\mathbf{R} \times \Theta; \mathbf{R})$ be the space of all functions $f : \mathbf{R} \times \Theta \rightarrow \mathbf{R}$ such that (i) f is continuously differentiable with respect to x and θ , (ii) f and its derivatives are of polynomial growth in x uniformly in θ . Let $Q(x, \theta) = \phi(x, \theta, \varepsilon) - \phi(X_{t_{k-1}}, \theta, \varepsilon)$. In order to prove Lemmas 2.1 and 2.2, we will use the following two lemmas.

LEMMA 5.1. *Suppose that A1–A4 hold true. Then, for $i = 1, \dots, p$,*

$$\begin{aligned} E_{\theta_0}[Q(X_{t_k}, \theta) | \mathcal{G}_{k-1}^n] &= \frac{1}{n} b(X_{t_{k-1}}, \theta_0) \partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon) \\ &\quad + R\left(\theta, \frac{\varepsilon^2}{n}, X_{t_{k-1}}\right) + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right), \end{aligned} \quad (2)$$

$$\begin{aligned} E_{\theta_0}[\delta_i Q(X_{t_k}, \theta) | \mathcal{G}_{k-1}^n] &= \frac{1}{n} b(X_{t_{k-1}}, \theta_0) \partial_x \delta_i \phi(X_{t_{k-1}}, \theta, \varepsilon) \\ &\quad + R\left(\theta, \frac{\varepsilon^2}{n}, X_{t_{k-1}}\right) + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right), \end{aligned} \quad (3)$$

$$\begin{aligned} E_{\theta_0}[(Q(X_{t_k}, \theta))^2 | \mathcal{G}_{k-1}^n] &= \frac{\varepsilon^2}{n} [\sigma \sigma^*](X_{t_{k-1}}) (\partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon))^2 \\ &\quad + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right), \end{aligned} \quad (4)$$

$$E_{\theta_0}[(\delta_i Q(X_{t_k}, \theta))^2 | \mathcal{G}_{k-1}^n] = \frac{\varepsilon^2}{n} [\sigma \sigma^*](X_{t_{k-1}}) (\partial_x \delta_i \phi(X_{t_{k-1}}, \theta, \varepsilon))^2 \quad (5)$$

$$+R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right).$$

LEMMA 5.2. Let $f \in \tilde{C}_\uparrow^{1,1}(\mathbf{R} \times \bar{\Theta}; \mathbf{R})$. Assume A1–A4. Then, uniformly in $\theta \in \bar{\Theta}$,

$$(i) \quad \frac{1}{n} \sum_{k=1}^n f(X_{t_{k-1}}, \theta) \xrightarrow{p} \int_0^1 f(X_s^0, \theta) ds,$$

$$(ii) \quad \sum_{k=1}^n f(X_{t_{k-1}}, \theta) Q(X_{t_k}, \theta) \xrightarrow{p} \int_0^1 f(X_s^0, \theta) b(X_s^0, \theta_0) \partial_x \phi(X_s^0, \theta, 0) ds,$$

(iii) for $i = 1, \dots, p$,

$$\sum_{k=1}^n f(X_{t_{k-1}}, \theta) (\delta_i Q)(X_{t_k}, \theta) \xrightarrow{p} \int_0^1 f(X_s^0, \theta) b(X_s^0, \theta_0) \partial_x \delta_i \phi(X_s^0, \theta, 0) ds.$$

Proof of Lemma 5.1. By the same method as the proof of Lemma 7 in Kessler (1997), we prove Lemma 5.1. An easy computation enables us to get

$$\begin{aligned} L_{\theta_0} Q(x, \theta) &= b(x, \theta_0) \partial_x Q(x, \theta) + \frac{1}{2} \varepsilon^2 [\sigma \sigma^*](x) \partial_x^2 Q(x, \theta) \\ &= b(x, \theta_0) \partial_x \phi(x, \theta, \varepsilon) + \frac{1}{2} \varepsilon^2 [\sigma \sigma^*](x) \partial_x^2 \phi(x, \theta, \varepsilon). \end{aligned}$$

It then follows that

$$\begin{aligned} E_{\theta_0}[Q(X_{t_k}, \theta) | \mathcal{G}_{k-1}^n] &= Q(X_{t_{k-1}}, \theta) + \frac{1}{n} L_{\theta_0} Q(X_{t_{k-1}}, \theta) \\ &\quad + \int_0^{\frac{1}{n}} \int_0^{u_1} E_{\theta_0}[L_{\theta_0}^2 Q(X_{t_{k-1}+u_2}, \theta) | \mathcal{G}_{k-1}^n] du_2 du_1 \\ &= \frac{1}{n} b(X_{t_{k-1}}, \theta_0) \partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon) \\ &\quad + R\left(\theta, \frac{\varepsilon^2}{n}, X_{t_{k-1}}\right) + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right). \end{aligned}$$

This completes the proof of (2). Similarly, we can prove (3). \square

Next, we see that

$$\begin{aligned} &E_{\theta_0}[(Q(X_{t_k}, \theta))^2 | \mathcal{G}_{k-1}^n] \\ &= (Q(X_{t_{k-1}}, \theta))^2 + \frac{1}{n} L_{\theta_0}(Q(X_{t_{k-1}}, \theta))^2 \\ &\quad + \int_0^{\frac{1}{n}} \int_0^{u_1} E_{\theta_0}[L_{\theta_0}^2 (Q(X_{t_{k-1}+u_2}, \theta))^2 | \mathcal{G}_{k-1}^n] du_2 du_1 \\ &= \frac{\varepsilon^2}{n} [\sigma \sigma^*](X_{t_{k-1}}) (\partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon))^2 + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right). \end{aligned}$$

This completes the proof of (4). Similarly, (5) can be proved. \square

Proof of Lemma 5.2. (i) In the same way as in the proof of Lemma 8 in Kessler (1997), we can prove (i). See also Lemma 4-(i) in Uchida (2004). \square

(ii) Let $\xi_k(\theta) = f(X_{t_{k-1}}, \theta) \{Q(X_{t_k}, \theta) - b(X_{t_{k-1}}, \theta_0) \partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon)/n\}$. It follows from Lemmas 5.1 and 5.2-(i) that

$$\sum_{k=1}^n E[\xi_k(\theta) | \mathcal{G}_{k-1}^n] = \sum_{k=1}^n \left\{ R\left(\theta, \frac{\varepsilon^2}{n}, X_{t_{k-1}}\right) + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right) \right\} \xrightarrow{p} 0,$$

$$\sum_{k=1}^n E[(\xi_k(\theta))^2 | \mathcal{G}_{k-1}^n] = \sum_{k=1}^n \left\{ R\left(\theta, \frac{\varepsilon^2}{n}, X_{t_{k-1}}\right) + R\left(\theta, \frac{1}{n^2}, X_{t_{k-1}}\right) \right\} \xrightarrow{p} 0.$$

By Lemma 9 in Genon-Catalot and Jacod (1993), it can be proved that $\sum_{k=1}^n \xi_{k,\varepsilon}(\theta) \xrightarrow{p} 0$. In order to show the tightness of $\sum_{k=1}^n \xi_{k,\varepsilon}(\cdot)$, it suffices to prove the following inequalities (cf. Theorem 20 in Appendix I in Ibragimov and Has'minskii (1981) or Lemma 3.1 in Yoshida (1990)): there exists a constant m such that $m > p/2$, and for any $\theta, \theta_1, \theta_2 \in \bar{\Theta}$,

$$E_{\theta_0} \left[\left(\sum_{k=1}^n \xi_{k,\varepsilon}(\theta) \right)^{2m} \right] \leq C, \quad (6)$$

$$E_{\theta_0} \left[\left(\sum_{k=1}^n \xi_{k,\varepsilon}(\theta_2) - \sum_{k=1}^n \xi_{k,\varepsilon}(\theta_1) \right)^{2m} \right] \leq C |\theta_2 - \theta_1|^{2m}, \quad (7)$$

where C is a constant independent of $\theta, \theta_1, \theta_2, \varepsilon$ and n . By Ito's formula, one has

$$\begin{aligned} \xi_k(\theta) &= f(X_{t_{k-1}}, \theta) \int_{t_{k-1}}^{t_k} L_{\theta_0} \phi(X_{t_k}, \theta, \varepsilon) ds \\ &\quad + \varepsilon f(X_{t_{k-1}}, \theta) \int_{t_{k-1}}^{t_k} \sum_{j=1}^r (\partial_x \phi)(X_s, \theta, \varepsilon) \sigma^j(X_s) dw_s^j \\ &\quad - \frac{1}{n} f(X_{t_{k-1}}, \theta) b(X_{t_{k-1}}, \theta_0) \partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon) \\ &=: A_{k,1}(\theta) + A_{k,2}(\theta) - A_{k,3}(\theta) \quad (\text{say}). \end{aligned}$$

In the same way as the proof of Lemma 1 in Yoshida (1992b), we will estimate $A_{k,1}(\theta)$, $A_{k,2}(\theta)$ and $A_{k,3}(\theta)$. By Lemma 6 in Kessler (1997),

$$\begin{aligned} &E_{\theta_0} \left[\left| \sum_{k=1}^n A_{k,1}(\theta) \right|^{2m} \right] \\ &\leq n^{2m-1} \sum_{k=1}^n E_{\theta_0} \left[\left(\int_{t_{k-1}}^{t_k} |f(X_{t_{k-1}}, \theta) L_{\theta_0} \phi(X_{t_k}, \theta, \varepsilon)| ds \right)^{2m} \right] \\ &\leq \sum_{k=1}^n \int_{t_{k-1}}^{t_k} E_{\theta_0} [|f(X_{t_{k-1}}, \theta)|^{2m} E_{\theta_0} [|L_{\theta_0} \phi(X_{t_k}, \theta, \varepsilon)|^{2m} | \mathcal{G}_{k-1}^n]] ds \\ &\leq n \cdot \frac{1}{n} \cdot C. \end{aligned}$$

It follows from the Burkholder-Davis-Gundy inequality that

$$\begin{aligned}
& E_{\theta_0} \left[\left| \sum_{k=1}^n A_{k,2}(\theta) \right|^{2m} \right] \\
& \leq C_{2m} \varepsilon^{2m} E_{\theta_0} \left[\left(\sum_{k=1}^n \int_{t_{k-1}}^{t_k} f(X_{t_{k-1}}, \theta)^2 (\partial_x \phi)(X_s, \theta, \varepsilon) [\sigma \sigma^*](X_s) ds \right)^m \right] \\
& \leq C_{2m} \varepsilon^{2m} \sum_{k=1}^n \int_{t_{k-1}}^{t_k} E_{\theta_0} [f(X_{t_{k-1}}, \theta)^{2m} E_{\theta_0} [((\partial_x \phi)(X_s, \theta, \varepsilon) [\sigma \sigma^*](X_s))^m | \mathcal{G}_{k-1}^n]] ds \\
& \leq C_{2m} \varepsilon^{2m} C,
\end{aligned}$$

where C_m denotes a constant which depends on an integer m . Moreover, we see that

$$\begin{aligned}
E_{\theta_0} \left[\left| \sum_{k=1}^n A_{k,3}(\theta) \right|^{2m} \right] & \leq \frac{1}{n} \sum_{k=1}^n E_{\theta_0} \left[|f(X_{t_{k-1}}, \theta) b(X_{t_{k-1}}, \theta_0) \partial_x \phi(X_{t_{k-1}}, \theta, \varepsilon)|^{2m} \right] \\
& \leq C.
\end{aligned}$$

Consequently, we obtain the inequality (6) and similarly the inequality (7) can be proved. This completes the proof of (ii). By the same fashion, we can prove (iii). \square

Proof of Lemma 2.1. It follows from an easy computation that

$$\begin{aligned}
K_{\varepsilon, n, l}^{ij}(\theta) &= \sum_{k=1}^n (\delta_j \delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) [\phi(X_{t_k}, \theta, \varepsilon) - \phi(X_{t_{k-1}}, \theta, \varepsilon)] \\
&+ \sum_{k=1}^n (\delta_j \delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) (1 - e^{-\lambda(\theta, \varepsilon)/n}) \phi(X_{t_{k-1}}, \theta, \varepsilon) \\
&+ \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) [\delta_j \phi(X_{t_k}, \theta, \varepsilon) - \delta_j \phi(X_{t_{k-1}}, \theta, \varepsilon)] \\
&+ \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) (1 - e^{-\lambda(\theta, \varepsilon)/n}) \delta_j \phi(X_{t_{k-1}}, \theta, \varepsilon) \\
&+ \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta) [\sigma \sigma^*]^{-1}(X_{t_{k-1}}) \frac{(\delta_j \lambda)(\theta, \varepsilon)}{n} e^{-\lambda(\theta, \varepsilon)/n} \phi(X_{t_{k-1}}, \theta, \varepsilon).
\end{aligned}$$

By Lemma 5.2, we complete the proof. \square

Proof of Lemma 2.2. The predictable quadratic variation of the martingale $\varepsilon^{-1} M_{\varepsilon, n}(\theta_0)$ is

$$\begin{aligned}
& \varepsilon^{-2} \langle M^i(\theta_0), M^j(\theta_0) \rangle_n \\
&= \varepsilon^{-2} \sum_{k=1}^n (\delta_i b)(X_{t_{k-1}}, \theta_0) [\sigma \sigma^*]^{-2}(X_{t_{k-1}}) v(X_{t_{k-1}}, \theta_0) (\delta_j b)(X_{t_{k-1}}, \theta_0),
\end{aligned}$$

where $v(X_{t_{k-1}}, \theta_0) = E_{\theta_0}[(\phi(X_{t_k}, \theta_0, \varepsilon) - e^{-\lambda(\theta_0, \varepsilon)/n} \phi(X_{t_{k-1}}, \theta_0, \varepsilon))^2 | X_{t_{k-1}}]$. Note that

$$L_{\theta_0}(\phi(x, \theta_0, \varepsilon))^2 = 2(-\lambda(\theta_0, \varepsilon))(\phi(x, \theta_0, \varepsilon))^2 + \varepsilon^2[\sigma\sigma^*](x)(\partial_x \phi)^2(x, \theta_0, \varepsilon),$$

and that for $l \geq 2$,

$$\begin{aligned} L_{\theta_0}^l(Q(x, \theta_0))^2 &= 2(-\lambda(\theta_0, \varepsilon))^l \phi(x, \theta_0, \varepsilon) Q(x, \theta_0) + (2^l - 2)(-\lambda(\theta_0, \varepsilon))^l (\phi(x, \theta_0, \varepsilon))^2 \\ &\quad + R(\theta_0, \varepsilon^2, x). \end{aligned}$$

By using the same method as the proof of Lemma 5.1, it follows that for any $m \geq 1$,

$$\begin{aligned} v(X_{t_{k-1}}, \theta_0) &= E_{\theta_0}[(Q(X_{t_k}, \theta_0) + (1 - e^{-\lambda(\theta_0, \varepsilon)/n})\phi(X_{t_{k-1}}, \theta_0, \varepsilon))^2 | X_{t_{k-1}}] \\ &= E_{\theta_0}[(Q(X_{t_k}, \theta_0))^2 | X_{t_{k-1}}] - ((1 - e^{-\lambda(\theta_0, \varepsilon)/n})\phi(X_{t_{k-1}}, \theta_0, \varepsilon))^2 \\ &= \sum_{l=1}^{2m} \frac{1}{l!n^l} L_{\theta_0}^l(Q(X_{t_{k-1}}, \theta_0))^2 \\ &\quad - (1 - 2e^{-\lambda(\theta_0, \varepsilon)/n} + e^{-2\lambda(\theta_0, \varepsilon)/n})(\phi(X_{t_{k-1}}, \theta_0, \varepsilon))^2 \\ &\quad + R\left(\theta_0, \frac{1}{n^{2m+1}}, X_{t_{k-1}}\right) \\ &= \frac{\varepsilon^2}{n} [\sigma\sigma^*](X_{t_{k-1}})(\partial_x \phi)^2(X_{t_{k-1}}, \theta_0, \varepsilon) + \sum_{l=2}^{2m} \frac{1}{l!n^l} L_{\theta_0}^l(Q(X_{t_{k-1}}, \theta_0))^2 \\ &\quad - \sum_{l=2}^{2m} \frac{(2^l - 2)(-\lambda(\theta_0, \varepsilon))^l}{l!n^l} (\phi(X_{t_{k-1}}, \theta_0, \varepsilon))^2 + R\left(\theta_0, \frac{1}{n^{2m+1}}, X_{t_{k-1}}\right) \\ &= \frac{\varepsilon^2}{n} [\sigma\sigma^*](X_{t_{k-1}})(\partial_x \phi)^2(X_{t_{k-1}}, \theta_0, \varepsilon) \\ &\quad + R\left(\theta_0, \frac{\varepsilon^2}{n^2}, X_{t_{k-1}}\right) + R\left(\theta_0, \frac{1}{n^{2m+1}}, X_{t_{k-1}}\right). \end{aligned}$$

Therefore, $\varepsilon^{-2} < M^i, M^j >_n \xrightarrow{p} A^{ij}(\theta_0)$. By the central limit theorem for martingales, one has that $\varepsilon^{-1}M_{\varepsilon,n}(\theta_0) \xrightarrow{d} N(0, A(\theta_0))$. This completes the proof. \square

Proof of Theorem 2.3. Now that Lemmas 2.1 and 2.2 have been already proved, it is not difficult to prove Theorem 2.3. Using the same method as the proof of Theorem 6.1 in Sakamoto and Yoshida (1999, 2004), we can show the existence, the uniqueness and the consistency of $\hat{\theta}_{\varepsilon,n}$. For the asymptotic normality of $\hat{\theta}_{\varepsilon,n}$, we can prove it along the same lines as the proof of Theorem 1 in Uchida (2004). This completes the proof. \square

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