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ASYMPTOTIC NONEQUIVALENCE OF GARCH MODELS AND DIFFUSIONS[1]

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Dedicated to the Memory of Lucien Le Cam 1924–2000

This paper investigates the statistical relationship of the GARCH model and its diffusion limit. Regarding the two types of models as two statistical experiments formed by discrete observations from the models, we study their asymptotic equivalence in terms of Le Cam's deficiency distance. To our surprise, we are able to show that the GARCH model and its diffusion limit are asymptotically equivalent only under deterministic volatility. With stochastic volatility, due to the difference between the structure with respect to noise propagation in their conditional variances, their likelihood processes asymptotically behave quite differently, and thus they are not asymptotically equivalent. This stochastic nonequivalence discredits a general belief that the two types of models are asymptotically equivalent in all respects and warns against the common financial practice that applies statistical inferences derived under the GARCH model to its diffusion limit.

1. Introduction. There are two relatively independent strands of financial modeling: continuous-time models typically used in theoretical finance and discrete-time models favored for empirical work. The continuous-time models are dominated by the diffusion approach. Most of the discrete-time models are of the autoregressive conditionally heteroscedastic (ARCH) type. Historically, the two literatures on the discrete-time and continuous-time models have developed quite independently. In the early 1990s researchers started to reconcile the two modeling approaches. Nelson (1990) first established the continuous-time diffusion limit for the discrete-time generalized ARCH (GARCH) model by showing that GARCH processes weakly converge to some bivariate diffusions, as the length of the discrete time intervals goes to zero. Duan (1997) proposed an augmented GARCH model to unify various parametric GARCH models and derived its diffusion limit, among others. The existing theory links the two types of models by weak convergence [Rossi (1996)]. Given that statistical inference is essential for both types of modeling, this paper investigates the statistical relationship between the GARCH model and its diffusion limit.

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Since the GARCH model and its diffusion limit share the same parameters, we naturally treat them as two statistical experiments formed by discrete observations from the two models and study their asymptotic equivalence by Le Cam's deficiency distance. Here "equivalence" means that each statistical procedure for one model has a corresponding equal-performance statistical procedure for another model. Surprisingly, it is shown that the GARCH model and its diffusion limit are asymptotically equivalent under nonstochastic volatility and not otherwise. Stochastic volatility is the essential characteristic of GARCH modeling. The GARCH model with nonstochastic volatility is nothing but a regression model and its diffusion limit is a white noise model. Thus, the stochastic nonequivalence indicates that Nelson's weak convergence result has no analog in Le Cam's paradigm.

The GARCH and diffusion models are of great interest in finance. It is very common to hear researchers invoke Nelson's result to justify the common belief that both models are "more or less equivalent." Our results send a warning against accepting this belief uncritically. The reconciliation of the two modeling approaches in financial econometrics and financial mathematics is in terms of the weak convergence results for the distributions of price processes. The statistical equivalence considered here is essentially determined by the asymptotic behavior of the likelihoods. Due to the difference between distribution and likelihood, weak convergence results like Nelson's do not necessarily imply asymptotic equivalence of the GARCH and diffusion models viewed as statistical experiments.

There is a great volume of statistical literature on comparison of experiments [Basawa and Prakasa Rao (1980), Brown and Low (1996), Jacod and Shiryaev (1987), Le Cam (1986), Le Cam and Yang (1990) and Nussbaum (1996)]. Most of the work on the equivalence of experiments is about diffusions with known fixed diffusion variance but unknown drift. For the inference of diffusion drift, the Cameron–Martin–Girsanov theorem gives an explicit form for the likelihood process of continuous-time observations from a diffusion. Under Le Cam's deficiency distance, the continuous-time observations are asymptotically equivalent to their discretely sampled versions, and they both, in turn, are asymptotically equivalent to observations from the corresponding discrete-time model. However, the inference for diffusion variance is intrinsically different [Florens-Zmirou (1989), Genon-Catalot (1990), Kessler (1997), Prakasa Rao (1988) and Yoshida (1992)]. For example, singularity may occur for the infinite-dimensional distributions of continuous-time observations from a diffusion under different values for the parameters in its diffusion variance, and the diffusion variance can be perfectly recovered from continuous-time observations. Thus, it is impossible to have any statistical equivalence between continuous-time observations and discretely sampled observations.

Our explanation for the unexpected phenomenon is as follows. The GARCH and diffusion models employ quite different mechanisms to propagate noise in their conditional variances. In the GARCH framework, the conditional variance is governed by the squares of past observational errors, so the likelihood involves a triple: normal random errors, their squares and the GARCH conditional variances, where the last two are correlated. While the diffusion model uses an independent, unobservable white noise to govern its conditional variance, and thus its likelihood behaves like the conditional expectation with respect to the unobservable white noise of the GARCH likelihood with the correlated triple replaced by three uncorrelated random components: normal random errors, their squares and the diffusion conditional variances. Hence, with stochastic volatility, the different noise propagation systems in their conditional variances result in quite different asymptotic likelihoods for the two types of models, and that, in turn, causes the nonequivalence. With nonstochastic volatility, the two models are Gaussian and their deterministic conditional variances approach the same limit. Thus, they are asymptotically equivalent.

The stochastic nonequivalence has an important consequence for statistical inference in the GARCH and diffusion models, and in particular provides some theoretical evidence against the practice that applies statistical procedures derived under the GARCH model to its diffusion limit. In a diffusion model, the conditional volatility is not observable, the likelihood is extremely hard to obtain and parameter estimation can be very difficult; while a GARCH model uses past observations to model the conditional variance, the likelihood has an explicit expression, and parameters can easily be estimated. This makes the GARCH approach more attractive for estimation and subsequent statistical inference. With diffusion modeling being favored over GARCH modeling for option pricing, one may be tempted to use a diffusion model with parameters estimated by fitting its corresponding GARCH model, to apply the statistical inference procedures developed under the GARCH model to the diffusion model and to plug the set of estimated parameter values from the GARCH model into formulas for option pricing obtained from the diffusion model. In fact, this naive approach is enthusiastically advocated in the finance literature and widely used in financial practice. The usual justification is that weak convergence results like Nelson's suggest that parameter estimators obtained by fitting a GARCH model can consistently estimate the parameters in its diffusion limit. However, due to the stochastic nonequivalence of the two types of models, estimators and tests derived under the GARCH model may behave asymptotically quite differently from those derived under its diffusion limit and can have inferior performance when being applied to observations coming from its diffusion limit. For modeling stochastic volatility, if a diffusion model is preferred, it is statistically more efficient to fit data directly to the diffusion model and carry out the inference [Aït-Sahalia (1996), Danielsson (1994), Gallant, Hsieh and Tauchen (1997), Gallant and Long (1997), Gallant and Tauchen (1998) and Jacquier, Polson and Rossi (1994)].

Our approach to proving the results is to follow Le Cam's principle to study likelihood processes and derive the limit of the deficiency distance between the two types of models. The rest of the paper is organized as follows. Section 2 introduces ARCH models and relates them to diffusions. Section 3 briefly reviews comparison of experiments and then presents our main results. Sections 4–6 are devoted to proving the results. The likelihood processes for the models are studied in Sections 4 and 5, and theorems are proved in Section 6.

2. GARCH models and diffusions.

2.1. *GARCH models.* Probably the most important innovation in discrete-time modeling of financial time series is the introduction by Engle (1982) of the ARCH model. The model makes the conditional variance of a series of prediction errors equal to some function of lagged errors, time, parameters and predetermined exogenous and lagged endogenous variables. Specifically, the observed time series $x_k,\ k = 1, \dots, n$, is assumed to follow the model

$$x_k = \mu_k + y_k, \qquad y_k = \sigma_k \varepsilon_k, \tag{1}$$

$$\sigma_k^2 = \sigma^2(y_{k-1}, y_{k-2}, \dots, k, A_k, \boldsymbol{\alpha}), \tag{2}$$

where ε_k is a sequence of i.i.d. standard normal random variables, σ_k^2 is the conditional variance of x_k given the information at time k, μ_k is the drift term which may depend on k, σ_k^2 and $x_{k-1}, x_{k-2}, \dots$, $\boldsymbol{\alpha}$ is a vector of parameters, and A_k is a vector of exogenous and lagged endogenous variables. Any model of the form (1) and (2) is referred to as an ARCH model. The existing ARCH models differ in their specification for σ_k^2.

Engle (1982) chose the following function form for σ_k^2:

$$\sigma_k^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j y_{k-j}^2 = \alpha_0 + \sum_{j=1}^{p} \alpha_j \sigma_{k-j}^2 \varepsilon_{k-j}^2, \tag{3}$$

where α_i's are nonnegative constants. The model specified by (3) is often called ARCH(p). The appeal of this model lies in the fact that it can capture the tendency for volatility clustering: large (or small) price changes tend to be followed by other large (or small) price changes, but of unpredictable sign. In other words, a high value of y_k^2 drives up σ_{k+1}^2, which in turn increases the expectation of y_{k+1}^2 and so on.

Bollerslev (1986) and Engle and Bollerslev (1986) generalized ARCH(p) by introducing the following specification:

$$\begin{aligned} \sigma_k^2 &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{k-i}^2 + \sum_{j=1}^{q} \alpha_{p+j} y_{k-j}^2 \\ &= \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{k-i}^2 + \sum_{j=1}^{q} \alpha_{p+j} \sigma_{k-j}^2 \varepsilon_{k-j}^2, \end{aligned} \tag{4}$$

where α_i's are nonnegative constants. This model is referred to as linear GARCH(p, q). For real financial data it often yields a more parsimonious representation for σ_k^2 as a function of lagged values of σ_k^2's and y_k^2's.

Since σ_k^2 is the conditional variance, it clearly must be nonnegative with probability 1. Linear GARCH models guarantee this by making σ_k^2 a positive linear combination of positive random variables. To ensure nonnegativity of σ_k^2, Geweke (1986) and Pantula (1986) adopted the following natural device by making $\log \sigma_k^2$ a linear function of lagged values of $\log \sigma_k^2$'s and $\log y_k^2$'s:

$$\log \sigma_k^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \log \sigma_{k-i}^2 + \sum_{j=1}^{q} \alpha_{p+j} \log \varepsilon_{k-j}^2, \tag{5}$$

where α_i's are constants, and because of $\log \varepsilon_{k-j}^2 = \log y_{k-j}^2 - \log \sigma_{k-j}^2$, the right-hand side of (5) is a linear combination of the lagged values of $\log \sigma_k^2$'s and $\log y_k^2$'s. We refer to this model as multiplicative GARCH(p, q).

Since the GARCH$(1, 1)$ specification has been found to be adequate in most applications, this paper will confine the analysis to the model with the GARCH$(1, 1)$ specification and the common financial parameterization of the drift

$$\mu_k = c_0 + c_1 \sigma_k^2, \tag{6}$$

and leave the generalization to general GARCH(p, q) specifications and other forms of μ_k to readers.

For a GARCH model, by a conditional argument we can easily derive its likelihood function,

$$\prod_{k=1}^{n} [\sigma_k^{-1} \phi(\{x_k - \mu_k\}/\sigma_k)], \tag{7}$$

where ϕ is the density of the standard normal distribution. Because of the relatively simple likelihood function, statistical inference for the GARCH model can be carried out. [See Bollerslev, Chou and Kroner (1992) and Gouriéroux (1997).]

2.2. *Diffusion processes.* In contrast to stochastic difference equations used in discrete-time models, stochastic differential equations are widely used to describe continuous-time models in the theoretical finance literature. The stochastic processes characterized by the stochastic differential equations are continuous-time diffusions (also referred to as Itô processes), and continuous-time modeling has made extensive use of Itô stochastic calculus, which provides an elegant means to analyze the diffusions. Specifically, a continuous-time model assumes that a security price S_t obeys the following stochastic differential equation:

$$S_t^{-1} \, dS_t = \nu_t \, dt + \sigma_t \, dW_t, \qquad t \in [0, T], \tag{8}$$

where W_t is a standard Wiener process, ν_t is called (diffusion) drift in probability or instantaneous mean rate of return in finance and σ_t^2 is called diffusion variance in probability or instantaneous conditional variance (or volatility) in finance. The celebrated Black–Scholes model corresponds to (8) with constants ν_t and σ_t [Black and Sholes (1973) and Merton (1973)]. However, many econometric studies have documented that financial time series tend to be highly heteroskedastic. To accommodate this, we allow σ_t^2 to be random and often assume σ_t^2 itself is governed by another stochastic differential equation [see (15) and (17) in Section 2.3 below]. Such σ_t^2 is called a stochastic volatility and the corresponding model is termed a continuous-time stochastic volatility model. For the continuous-time model, the "no arbitrage" condition (the fundamental concept in finance, which is often labeled in plain English as the "no free lunch" condition) can be beautifully characterized by a martingale measure (or risk-neutral measure in finance), that is, a probability law under which S_t is a martingale. Prices of options and derivatives are then the conditional expectation of certain functionals of S under this measure. [A derivative is a financial instrument whose value depends on the values of other, more basic underlying variables such as stocks, interest rates and currency exchange rates. A call (or put) option is a special derivative which gives its holder a right, not obligation, to buy (or sell) a security at certain price by future time. See Hull (1997).] The calculations and derivations can be manipulated by tools such as the Itô lemma and the Girsanov theorem. [(See Dothan (1990), Duffie (1992), Harrison and Kreps (1979), Harrison and Pliska (1981), Hull and White (1987), Ikeda and Watanabe (1989), Karatzas and Shreve (1991), Merton (1990) and Stroock and Varadhan (1979).]

The log price process $X_t = \log S_t$ is often used. By the Itô lemma and from (8) we obtain the diffusion model for X_t,

$$dX_t = (\nu_t + \sigma_t^2/2)\,dt + \sigma_t\,dW_t,$$

where the drift for X_t has a term σ_t^2. GARCH models are used to model statistically the increments of the log price process, so from the diffusion point of view, (6) is also a natural parameterization of the GARCH drift μ_k.

Since the likelihood for discretely sampled observations from a diffusion defined by nonlinear stochastic differential equations is not available, the statistical inference for the diffusion model is usually much harder than that for a GARCH model. Recently some inference methods have been developed for the diffusion model [Aït-Sahalia (1996), Gallant, Hsieh and Tauchen (1997), Gallant and Long (1997) and Gallant and Tauchen (1998)].

2.3. *Diffusion limits of GARCH models.* Divide the time interval $[0, T]$ into n subinterval of length $s_n = T/n$ and set $t_k = ks_n$, $k = 0, 1, \dots, n$. For i.i.d. standard normal random variables $\{\varepsilon_k\}$, let

$$\xi_k = \kappa_1(\log \varepsilon_k^2 - \kappa_0), \qquad \zeta_k = 2^{-1/2}(\varepsilon_k^2 - 1), \tag{9}$$

where the generic constants κ_0 and κ_1 are

$$\kappa_0 = E \log \varepsilon_1^2 \approx -1.27, \qquad \kappa_1 = \{\operatorname{var}(\log \varepsilon_1^2)\}^{-1/2} \approx 0.45. \tag{10}$$

The multiplicative GARCH(1, 1) approximating process is defined as follows. For $k = 1, \ldots, n$, let

$$X_{n,k} - X_{n,k-1} = (\gamma_0 + \gamma_1 \sigma_{n,k}^2) s_n + \sigma_{n,k} s_n^{1/2} \varepsilon_k, \tag{11}$$

$$\log \sigma_{n,k}^2 = \beta_0 s_n + (1 + \beta_1 s_n) \log \sigma_{n,k-1}^2 + \beta_2 s_n^{1/2} \xi_{k-1}. \tag{12}$$

The approximating process $(X_{n,t}, \sigma_{n,t}^2)$, $t \in [0, T]$, is given by

$$X_{n,t} = X_{n,k}, \qquad \sigma_{n,t}^2 = \sigma_{n,k}^2 \qquad \text{for } t \in [t_k, t_{k+1}),\ k = 0, \ldots, n. \tag{13}$$

Nelson (1990) showed that as $n \to \infty$, the normalized partial sum process of (ε_k, ξ_k) weakly converges to a planar Wiener process and thus the process $(X_{n,t}, \sigma_{n,t}^2)$ converges in distribution to the bivariate diffusion process (X_t, σ_t^2) governed by the following stochastic differential equation system:

$$dX_t = (\gamma_0 + \gamma_1 \sigma_t^2)\, dt + \sigma_t\, dW_{1,t}, \tag{14}$$

$$d \log \sigma_t^2 = (\beta_0 + \beta_1 \log \sigma_t^2)\, dt + \beta_2\, dW_{2,t}, \qquad \sigma_0^2 = e^{\beta_3}, \tag{15}$$

where $W_{1,t}$ and $W_{2,t}$ are two independent standard Wiener processes. The diffusion model described by (14) and (15) [or the process (X_t, σ_t^2)] is referred to as the diffusion limit of the multiplicative GARCH model (11) and (12).

For the linear GARCH model, everything is the same except for replacement of (12) and (15), respectively, by

$$\sigma_{n,k}^2 = \beta_0 s_n + \sigma_{n,k-1}^2 (1 + \beta_1 s_n + \beta_2 s_n^{1/2} \zeta_{k-1}), \tag{16}$$

$$d\sigma_t^2 = (\beta_0 + \beta_1 \sigma_t^2)\, dt + \beta_2 \sigma_t^2\, dW_{3,t}, \qquad \sigma_0^2 = e^{\beta_3}, \tag{17}$$

where $W_{3,t}$ is a standard Wiener process, $\operatorname{corr}(W_{2,t}, W_{3,t}) = \operatorname{corr}(\varepsilon_1^2, \log \varepsilon_1^2) \approx 0.64$, and $W_{1,t}$ is independent of $W_{2,t}$ and $W_{3,t}$. [See Duan (1997), Nelson (1990) and Rossi (1996).]

For simplicity, throughout this paper we assume initial values $X_{n,0} = X_0$ and $\sigma_{n,0}^2 = \sigma_0^2 = e^{\beta_3}$.

Note that the diffusion model is for the log price process and the GARCH model is for the increments of the log price process. The increments of the GARCH approximating processes defined by equations (11) and (12) and equations (11) and (16) obey the GARCH structure of Section 2.1. Indeed, in equation (11), the term $(\gamma_0 + \gamma_1 \sigma_{n,k}^2) s_n$ is the drift μ_k [see (1)] of the form specified in (6) with γ_0 and γ_1 the rescaled versions of c_0 and c_1, namely, $c_0 = \gamma_0 s_n$, $c_1 = \gamma_1 s_n$. Using the relationship between (ξ_k, ζ_k) and ε_k^2 given by (9) and (10), we rewrite equations (12) and (16), respectively, as

$$\log \sigma_{n,k}^2 = \alpha_0 + \alpha_1 \log \sigma_{n,k-1}^2 + \alpha_2 \log \varepsilon_{k-1}^2, \tag{18}$$

with

$$\alpha_0 = \beta_0 s_n - \beta_2 s_n^{1/2}\kappa_0\kappa_1, \qquad \alpha_1 = 1 + \beta_1 s_n, \qquad \alpha_2 = \beta_2 s_n^{1/2}\kappa_1$$

and

$$\sigma_{n,k}^2 = \alpha_0 + \alpha_1\sigma_{n,k-1}^2 + \alpha_2\sigma_{n,k-1}^2\varepsilon_{k-1}^2, \tag{19}$$

with

$$\alpha_0 = \beta_0 s_n, \qquad \alpha_1 = 1 + \beta_1 s_n - \beta_2 s_n^{1/2}/2^{1/2}, \qquad \alpha_2 = \beta_2 s_n^{1/2}/2^{1/2}.$$

Comparing (18) and (19) with GARCH specifications (4) and (5), we clearly demonstrate that model (11) and (12) and model (11) and (16) are multiplicative and linear GARCH(1, 1), respectively. The parameters γ_i's and β_i's are, respectively, the rescaled versions of the drift parameters c_i's [in (6)] and local reparameterization of the volatility parameters α_i's [in (4) and (5)] so that the diffusion limits can be obtained. As option pricing depends on security prices, these weak convergence results can be used to show that option pricing formulas for GARCH models agree in the limit with those for their diffusion limits. Also, the results are very useful for the cases where one may find the distributional results are available for continuous-time models that are not available for the GARCH models. [See Duan (1995), Nelson (1990) and Rossi (1996).]

3. Statistical equivalence and nonequivalence.

3.1. *Comparison of experiments.* A statistical problem $\mathbb{E}$ consists of a sample space Ω, a suitable σ-field $\mathcal{F}$, and a family of distributions P_θ indexed by parameter θ which belongs to some parameter space Θ, that is, $\mathbb{E} = (\Omega, \mathcal{F}, (P_\theta, \theta \in \Theta))$. $\mathbb{E}$ is referred to as a statistical experiment. Le Cam's deficiency distance is often used to compare statistical experiments.

Consider two statistical experiments with the same parameter space Θ, $\mathbb{E}_i = (\Omega_i, \mathcal{F}_i, (P_{i,\theta}, \theta \in \Theta))$, $i = 1, 2$. Denote by $\mathcal{A}$ a measurable action space, let $L : \Theta \times \mathcal{A} \to [0, \infty)$ be a loss function, and set $\|L\| = \sup\{L(\theta, a) : \theta \in \Theta,\ a \in \mathcal{A}\}$. In the ith problem, let δ_i be a decision procedure and denote by $R_i(\delta_i, L, \theta)$ the risk from using procedure δ_i when L is the loss function and θ is the true value of the parameter. Le Cam's deficiency distance $\Delta(\mathbb{E}_1, \mathbb{E}_2)$ between $\mathbb{E}_1$ and $\mathbb{E}_2$ is the maximum of $\delta(\mathbb{E}_1, \mathbb{E}_2)$ and $\delta(\mathbb{E}_2, \mathbb{E}_1)$, where

$$\delta(\mathbb{E}_1, \mathbb{E}_2) = \inf_{\delta_1} \sup_{\delta_2} \sup_{\theta \in \Theta} \sup_{L : \|L\| = 1} |R_1(\delta_1, L, \theta) - R_2(\delta_2, L, \theta)|$$

is called the deficiency of $\mathbb{E}_1$ with respect to $\mathbb{E}_2$. Two experiments $\mathbb{E}_1$ and $\mathbb{E}_2$ are called equivalent if $\Delta(\mathbb{E}_1, \mathbb{E}_2) = 0$. Equivalence means that each procedure δ_1 in problem $\mathbb{E}_1$ has a corresponding procedure δ_2 in problem $\mathbb{E}_2$ with the same risk, uniformly over $\theta \in \Theta$ and all L with $\|L\| = 1$, and vice versa. Two sequences of statistical experiments $\mathbb{E}_{n,1}$ and $\mathbb{E}_{n,2}$ are said to be asymptotically equivalent if

$\Delta(\mathbb{E}_{n,1}, \mathbb{E}_{n,2}) \to 0$, as $n \to \infty$. Thus, any sequence of procedures $\delta_{n,1}$ in problem $\mathbb{E}_{n,1}$ has a corresponding sequence of procedures $\delta_{n,2}$ in problem $\mathbb{E}_{n,2}$ with risk differences tending to zero uniformly over $\theta \in \Theta$ and all L with $\|L\| = 1$. The procedures $\delta_{n,1}$ and $\delta_{n,2}$ are said to be asymptotically equivalent. [See Le Cam (1986), Le Cam and Yang (1990) and Strasser (1985).]

3.2. *Main results on GARCH and diffusion experiments.* Denote by $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \beta_3)$ and $\boldsymbol{\gamma} = (\gamma_0, \gamma_1)$ the vectors of variance (or volatility) parameters and drift parameters in the GARCH and diffusion models defined in Section 2.3, respectively. Let $\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}) = (\beta_0, \beta_1, \beta_2, \beta_3, \gamma_0, \gamma_1)$ be the vector of all six parameters and the parameter space Θ consist of $\boldsymbol{\theta}$ with γ_i and β_i belonging to bounded intervals. Denote by $P_{n,\boldsymbol{\theta}}$ the distribution of the approximating process X_{n,t_k}, $k = 1, \dots, n$, defined by the stochastic difference equations (11) and (12) for the multiplicative GARCH model [or (11) and (16) for the linear GARCH model], and denote by $Q_{n,\boldsymbol{\theta}}$ the distribution of the discrete samples at t_k, $k = 1, \dots, n$, of the diffusion limit X_t governed by the stochastic differential equations (14) and (15) for the multiplicative GARCH case [or (14) and (17) for the linear GARCH case, respectively]. Define the GARCH and diffusion experiments, respectively, by

$$\begin{aligned} \mathbb{E}_{n,1} &= \big(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (P_{n,\boldsymbol{\theta}},\ \boldsymbol{\theta} \in \Theta)\big), \\ \mathbb{E}_{n,2} &= \big(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (Q_{n,\boldsymbol{\theta}}, \boldsymbol{\theta} \in \Theta)\big). \end{aligned} \tag{20}$$

We emphasize that, as in the standard financial setting, volatility processes σ^2's are latent, and processes X's are observable and samples in both GARCH and diffusion experiments are taken from processes X's only. Also as pointed out in Section 1, paragraph 4, the infinite-dimensional distributions of continuous-time observations, $\{X_t, t \in [0, T]\}$, from the diffusion limit under different values for the variance parameter $\boldsymbol{\beta}$ are mutually singular, and the volatility process σ_t^2 can be exactly recoverered by the quadratic variation process of $\{X_t, t \in [0, T]\}$. For these reasons, the diffusion experiment $\mathbb{E}_{n,2}$ considers discretely sampled observations, with $Q_{n,\boldsymbol{\theta}}$ for the finite-dimensional distribution of the discrete samples.

We have the following theorems whose proofs are given in Sections 4–6.

THEOREM 1. *The experiments $\mathbb{E}_{n,1}$ and $\mathbb{E}_{n,2}$ are not asymptotically equivalent.*

As a comparison, we define corresponding experiments with nonstochastic volatility which corresponds to $\beta_2 = 0$. Denote by Θ' the subset of Θ consisting of all $\boldsymbol{\theta}$ with $\beta_2 = 0$. Treating Θ' as the parameter space for $(\beta_0, \beta_1, \beta_3, \gamma_0, \gamma_1)$ in five dimensions, we define

$$\mathbb{E}'_{n,1} = \big(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (P_{n,\boldsymbol{\theta}}, \boldsymbol{\theta} \in \Theta')\big), \qquad \mathbb{E}'_{n,2} = \big(\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (Q_{n,\boldsymbol{\theta}}, \boldsymbol{\theta} \in \Theta')\big).$$

THEOREM 2. *The experiments $\mathbb{E}'_{n,1}$ and $\mathbb{E}'_{n,2}$ are asymptotically equivalent.*

3.3. *Heuristic explanation of the main results.* As we explained in Section 1, paragraph 5, Theorem 1 is due to the different noise propagation systems that the GARCH model and its diffusion limit utilize in their conditional variances. The following heuristic comparison of two simple models offers genuine insight into the phenomenon.

For each GARCH model we discretize its diffusion limit and obtain a corresponding discrete model, which is called a discrete stochastic volatility model in financial econometrics. The multiplicative GARCH(1, 1) model,

$$y_k = \mu + \sigma_k \varepsilon_k, \qquad \log \sigma_k^2 = \alpha_0 + \alpha_1 \log \sigma_{k-1}^2 + \alpha_2 \kappa_1 (\log \varepsilon_{k-1}^2 - \kappa_0), \qquad k = 1, \dots, n, \tag{21}$$

has the following discrete counterpart:

$$y_k = \mu + \sigma_k z_k, \qquad \log \sigma_k^2 = \alpha_0 + \alpha_1 \log \sigma_{k-1}^2 + \alpha_2 \delta_k, \qquad k = 1, \dots, n, \tag{22}$$

where ε_k, z_k and δ_k are independent standard normal random variables, and κ_0 and κ_1 are constants defined in (10). Obviously model (22) has the same diffusion limit as model (21), but unlike the GARCH model, its likelihood also mimics that of the diffusion limit.

For model (21), the distribution of $(y_k, \sigma_k^2)_{k\geq 1}$ is determined by $(\varepsilon_k, \log \varepsilon_k^2)_{k\geq 1}$, while its likelihood function given by (7) depends on $(\varepsilon_k, \log \varepsilon_k^2, \varepsilon_k^2)_{k\geq 1}$. The corresponding distribution and likelihood for model (22) are obtained, respectively, by first replacing $(\varepsilon_k, \log \varepsilon_k^2)_{k\geq 1}$ with $(z_k, \delta_k)_{k\geq 1}$ in the GARCH distribution and substituting $(\varepsilon_k, \log \varepsilon_k^2, \varepsilon_k^2)_{k\geq 1}$ with $(z_k, \delta_k, z_k^2)_{k\geq 1}$ in the GARCH likelihood, and then taking the conditional expectation with respect to δ_k's.

As ε_k^2 and $\log \varepsilon_k^2$ are correlated but both are uncorrelated with ε_k, the normalized partial sum processes for $(\varepsilon_k, \log \varepsilon_k^2, \varepsilon_k^2)$ converge in distribution to three-dimensional Brownian motion $(W_{1,t}, W_{2,t}, W_{3,t})$, where $W_{2,t}$ and $W_{3,t}$ are correlated but both are independent of $W_{1,t}$. With the independence between z_k and δ_k, the weak limit of the normalized partial sum processes for (z_k, δ_k, z_k^2) is three independent Brownian motions $(W_{1,t}, W_{2,t}, W_{4,t})$. Thus for both models, the asymptotic distributions of the partial sum processes for (y_k, σ_k^2) are determined by the same stochastic differential equation system governed by two independent Brownian motions $(W_{1,t}, W_{2,t})$, but the asymptotic likelihoods for models (21) and (22) are related in a similar fashion to three correlated Brownian motions $(W_{1,t}, W_{2,t}, W_{3,t})$ and three independent Brownian motions $(W_{1,t}, W_{2,t}, W_{4,t})$, respectively. As a result, under stochastic volatility, the two models have the same asymptotic distributions but different asymptotic likelihoods, and consequently they are not asymptotically equivalent [Le Cam and Yang (1990), Section 2.2 of Chapter 2, or Le Cam (1986), Proposition 8 and its remark in Section 4 of Chapter 6, pages 93–95]. With nonstochastic volatility, the deterministic conditional variances don't depend on $\log \varepsilon_k^2$ or δ_k, and the two likelihood processes asymptotically depend on only either $(W_{1,t}, W_{3,t})$ or $(W_{1,t}, W_{4,t})$. As

$(W_{1,t}, W_{3,t})$ and $(W_{1,t}, W_{4,t})$ are identically distributed, asymptotically the two models have the same statistical behavior and thus are equivalent.

3.4. *Numerical evidence for the main results.* Empirical work suggests great differences in statistical inference between the GARCH and discrete stochastic volatility models. Hsieh (1991) and Jacquier, Polson and Rossi (1994) reported substantial differences in likelihood, parameter estimation, forecasting and autocorrelation when fitting the two models to simulated data and real financial data. For each model their simulations indicate that the likelihood-based methods can very accurately estimate parameters (with root mean squared error ranging from 0.02 to 0.05 for sample size 2000). Here we conducted a simulation to evaluate the numerical performance of the MLE derived under the linear GARCH model when being fed with data coming from its corresponding discrete stochastic volatility model. In the simulation we took $n = 2000$, $\mu = 0$, $\alpha_0 = 0.5$, $\alpha_1 = 0.3$ and $\alpha_2 = 0.6$. A sample from each model was simulated. Using the Splus GARCH module we calculated the MLE and its estimated asymptotic standard error (a.s.e.) by fitting the GARCH model to the sample generated from the GARCH model and then repeated the calculation by replacing the GARCH sample with data coming from the volatility model. The whole procedure was repeated 100 times. From the 100 repetitions, we calculated the average estimated values and a.s.e., and their standard errors (s.e.). Results for α_1 and α_2 are listed in Table 1.

The simulation results show dramatic differences between the GARCH and volatility samples. When fitting the GARCH model to the GARCH data, the MLE performs extremely well, with negligible bias, small s.e. and a.s.e. close to the actual s.e. While for the volatility samples, the same MLE produces a very poor estimator, with huge bias, large s.e. and a.s.e. far off the target. To rule out the possibility that the bias is caused by the fact that the gradient search algorithm used by Splus in the MLE computation was stuck by local maxima, we have set the true parameter values as initial values and found little difference in the outcome values for the MLE. We have tried to reduce the huge bias by increasing sample size up to 10^5 but failed to achieve even a small amount of reduction. Also we have tested various values for α_i and found out that for volatility samples, the MLE tends to overestimate α_1 and underestimate α_2, and the amounts over and

TABLE 1
The average values of the GARCH MLE of (α_1, α_2) *and its a.s.e., with their s.e.* (*in parentheses*) *for GARCH and volatility data*

	GARCH sample		**Volatility sample**	
Parameter	**Estimate**	**a.s.e.**	**Estimate**	**a.s.e.**
α_1	0.2958 (0.0371)	0.0348 (0.0037)	0.5292 (0.1015)	0.0281 (0.0093)
α_2	0.5998 (0.0475)	0.0476 (0.0028)	0.2837 (0.0782)	0.0200 (0.0049)

under estimated tend to get smaller as α_2 decreases. As α_2 gets close to zero, the bias approaches the level for GARCH data. The numerical findings are very much in agreement with the theoretical results described in Theorems 1 and 2 and reinforce the point in paragraph 6 of Section 1 that the nonequivalence result has an important consequence for the statistical inference of the GARCH and diffusion models.

3.5. *Proofs of the main results.* Our approach to proving the theorems is based on the following principle described in Le Cam (1986), Le Cam and Yang (1990) and Nussbaum (1996). For two experiments $\mathbb{E}_i = (\Omega_i, \mathcal{F}_i, (P_{i,\theta}, \theta \in \Theta))$, $i = 1, 2$, assume there is some $\theta^* \in \Theta$ such that all the $P_{i,\theta}$ are dominated by P_{i,θ^*}, $i = 1, 2$, and form

$$\Lambda_i(\theta) = \frac{dP_{i,\theta}}{dP_{i,\theta^*}}.$$

Treating $\Lambda_i = (\Lambda_i(\theta),\ \theta \in \Theta)$ as stochastic processes indexed by θ given on the probability space $(\Omega_i, \mathcal{F}_i, P_{i,\theta^*})$, we call them the likelihood processes of the experiments $\mathbb{E}_i$. If there are versions Λ_i^* of Λ_i defined on a common probability space $(\Omega, \mathcal{F}, \mathbb{P})$, then on the common probability space Λ_i^* generate equivalent versions of the experiments, and

$$\Delta(\mathbb{E}_1, \mathbb{E}_2) \le \sup_{\theta\in\Theta} E_{\mathbb{P}}|\Lambda_1^* - \Lambda_2^*| \le 2 \sup_{\theta\in\Theta} H\bigl(\Lambda_1^*(\theta), \Lambda_2^*(\theta)\bigr), \tag{23}$$

where $H(\Lambda_1^*(\theta), \Lambda_2^*(\theta)) = E_{\mathbb{P}}([\Lambda_1^*(\theta)]^{1/2} - [\Lambda_2^*(\theta)]^{1/2})^2$ is Hellinger distance. Hellinger distance can easily handle normal distributions and distributions of product forms.

Specifically, Sections 4 and 5 derive likelihood processes for the GARCH model and its diffusion limit and study their asymptotic distributions in a local neighborhood. Section 6 proves nonequivalence under stochastic volatility by showing different limiting distributions for the two likelihood processes and equivalence under nonstochastic volatility by proving the convergence of Hellinger distance to zero.

4. Likelihood processes for GARCH models.

4.1. *Notation and conventions.* To track complex processes under different circumstances and manage long technical arguments, we fix the following notation and conventions.

CONVENTION 1. It is often necessary to put processes and random variables on some common probability spaces. At such occasions, we often automatically change probability spaces and consider versions of the processes and the random variables on new probability spaces, without altering notation. Because of this convention and Skorohod's theorem, we often switch between "convergence in probability" and "convergence in distribution." Also because of the convention, when no confusion occurs, we try to use the same notation for random variables or processes with identical distribution. For the sake of simplicity, we take $T = 1$ and $s_n = 1/n$. All O's and o's hold uniformly over $t \in [0, 1]$.

NOTATION 2. For a fixed $\boldsymbol{\beta}^*$, let $\boldsymbol{\theta}^* = (\boldsymbol{\beta}^*, 0)$ and define a local neighborhood around $\boldsymbol{\theta}^*$,

$$\Theta_{n,c}(\boldsymbol{\beta}^*) = \{\boldsymbol{\theta} = (\boldsymbol{\beta}, \boldsymbol{\gamma}) \in \Theta : \boldsymbol{\beta} = \boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}, |\boldsymbol{\varphi}| \le c\} \subset \Theta, \tag{24}$$

and the corresponding local experiments

$$\begin{aligned} \mathbb{E}_{n,1}(\boldsymbol{\beta}^*) &= (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (P_{n,\boldsymbol{\theta}}, \boldsymbol{\theta} \in \Theta_{n,c})), \\ \mathbb{E}_{n,2}(\boldsymbol{\beta}^*) &= (\mathbb{R}^n, \mathcal{B}(\mathbb{R}^n), (Q_{n,\boldsymbol{\theta}}, \boldsymbol{\theta} \in \Theta_{n,c})). \end{aligned} \tag{25}$$

Also introduce notation $\boldsymbol{\theta}^+ = (\boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}, \mathbf{0})$ to denote parameter $\boldsymbol{\theta} \in \Theta_{n,c}(\boldsymbol{\beta}^*)$ with drift component $\boldsymbol{\gamma} = \mathbf{0}$.

The shrinking in $\Theta_{n,c}$ is only for $\boldsymbol{\beta}$, because $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are the drift and variance parameters, respectively. As discussed in paragraph 4 of Section 1, for drift, the likelihood processes have nondegenerate limiting distributions over all $\boldsymbol{\gamma}$; while for variance, we need to localize $\boldsymbol{\beta}$ in a $n^{-1/2}$-shrinking neighborhood and derive nondegenerate limiting distributions for the likelihood processes.

CONVENTION 3. For $\boldsymbol{\theta} = (\boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}, \boldsymbol{\gamma}) \in \Theta_{n,c}(\boldsymbol{\beta}^*)$, define $\boldsymbol{\vartheta} = (\boldsymbol{\varphi}, \boldsymbol{\gamma})$. Then there is a one-to-one correspondence between $\boldsymbol{\theta}$ and $\boldsymbol{\vartheta}$. When no confusion occurs, for convenience we use $\boldsymbol{\vartheta}$ to index $\Theta_{n,c}(\boldsymbol{\beta}^*)$ and write $\Theta_{n,c}(\boldsymbol{\beta}^*)$ as $\Theta_{n,c}$ for short. For example, under this convention, $\boldsymbol{\vartheta}^* = (\mathbf{0}, \mathbf{0})$ and $\boldsymbol{\vartheta}^+ = (\boldsymbol{\varphi}, \mathbf{0})$ correspond to $\boldsymbol{\theta}^*$ and $\boldsymbol{\theta}^+$, respectively.

CONVENTION 4. Our notation must keep track of three distinct kinds of processes defined in Section 2.3 under two circumstances:

1. the sequence of the discrete-time processes $X_{n,k}$ and $\sigma_{n,k}^2$ that depend both on n and on the discrete time index k, $k = 0, \dots, n$;
2. the sequence of the continuous-time processes $X_{n,t}$ and $\sigma_{n,t}^2$ formed as random step functions from the discrete time processes in (1) using equation (13);
3. the limiting diffusion process (X_t, σ_t^2) with initial values $X_{n,0} = X_0$ and $\sigma_{n,0}^2 = \sigma_0^2$, and as $n \to \infty$, $(X_{n,t}, \sigma_{n,t}^2) \Rightarrow (X_t, \sigma_t^2)$.

Each kind of process occurs under two circumstances, that the parameter $\boldsymbol{\vartheta} = (\boldsymbol{\varphi}, \boldsymbol{\gamma})$ [or $\boldsymbol{\theta} = (\boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}, \boldsymbol{\gamma})$] and $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^* \equiv (\mathbf{0}, \mathbf{0})$ [or $\boldsymbol{\theta} = \boldsymbol{\theta}^* \equiv (\boldsymbol{\beta}^*, \mathbf{0})$]. To distinguish the latter from the former, we add a subscript "0" to the processes to denote that they are under the condition $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^*$. For example,

$\sigma_{n,t}^2$ and $\sigma_{n,t,0}^2$ denote the GARCH volatility process under the conditions that $\vartheta = (\boldsymbol{\varphi}, \boldsymbol{\gamma})$ and $\vartheta = \vartheta^*$, respectively, and $\sigma_{t,0}^2$ denotes the diffusion volatility process with $\vartheta = \vartheta^*$.

NOTATION 5. Define

$$V_{n,t} = n^{1/2}\left(1 - \frac{\sigma_{n,t,0}^2}{\sigma_{n,t}^2}\right), \qquad H_{n,t} = n\left(1 + \log\frac{\sigma_{n,t,0}^2}{\sigma_{n,t}^2} - \frac{\sigma_{n,t,0}^2}{\sigma_{n,t}^2}\right), \tag{26}$$

$$V_t = \sum_{i=0}^{3} \varphi_i \frac{\partial \log \sigma_{t,0}^2}{\partial \beta_i^*}. \tag{27}$$

All processes depend on the parameter ϑ and the dependence is not often explicitly given in process notation. For example, we may write V_t as $V_t(\vartheta)$ to mark the dependence clearly.

NOTATION 6. Define partial sum processes

$$W_{1,t}^{(n)} = n^{-1/2}\sum_{j=1}^{[nt]} \varepsilon_j, \qquad W_{2,t}^{(n)} = n^{-1/2}\sum_{j=1}^{[nt]} \xi_j, \qquad W_{3,t}^{(n)} = n^{-1/2}\sum_{j=1}^{[nt]} \zeta_j, \tag{28}$$

where ε_j are standard normal random errors, and ξ_j and ζ_j are defined in (9). From the modulus of continuity of Wiener process [Karatzas and Shreve (1991), Chapter 2] and strong approximation [Komlós, Major and Tusnády (1975) and Tusnády (1977)] we have that on some probability spaces there exist three standard Wiener processes $W_{1,t}, W_{2,t}, W_{3,t}$ with $W_{1,t}$ independent of $W_{2,t}$ and $W_{3,t}$, and $\operatorname{corr}(W_{2,t}, W_{3,t}) = \operatorname{corr}(\varepsilon_1^2, \log \varepsilon_1^2) \approx 0.64$ (see also Section 2.3), such that

$$\sup_{0 \le t \le 1} \{|W_{1,t}^{(n)} - W_{1,t}| + |W_{2,t}^{(n)} - W_{2,t}| + |W_{3,t}^{(n)} - W_{3,t}|\} = O_p(n^{-1/2}\log^2 n). \tag{29}$$

4.2. *Asymptotics of likelihood processes.* Denote by $L_{n,1}(\vartheta)$ the likelihood function of the GARCH approximating process X_{n,t_k} and let $\Lambda_{n,1}(\vartheta) = L_{n,1}(\vartheta)/L_{n,1}(\vartheta^*)$ be its likelihood process under P_{n,ϑ^*}. We will show below that $\Lambda_{n,1}(\vartheta)$ has a limit $\Lambda_1(\vartheta)$ defined by

$$\begin{aligned}\log \Lambda_1(\vartheta) = {} & \frac{1}{\sqrt{2}}\int_0^1 V_t \, dW_{3,t} - \frac{1}{4}\int_0^1 V_t^2 \, dt + \int_0^1 \sigma_{t,0}^{-1}(\gamma_0 + \gamma_1 \sigma_{t,0}^2) \, dW_{1,t} \\ & - \frac{1}{2}\int_0^1 \sigma_{t,0}^{-2}(\gamma_0 + \gamma_1\sigma_{t,0}^2)^2 \, dt.\end{aligned} \tag{30}$$

From (6), (7), (11), (12), (13) and (16), we obtain that

$$\begin{aligned}\log L_{n,1}(\vartheta) = {} & -\sum_{j=1}^{n}\bigl(X_{n,t_j} - X_{n,t_{j-1}} - s_n\bigl(\gamma_0 + \gamma_1\sigma_{n,t_j}^2\bigr)\bigr)^2\bigl(2s_n\sigma_{n,t_j}^2\bigr)^{-1} \\ & - \sum_{j=1}^{n} \log \sigma_{n,t_j} - (n/2)\log(2\pi s_n)\end{aligned}$$

and thus

$$
\begin{aligned}
\log \Lambda_{n,1}(\vartheta) = {} & \sum_{j=1}^{n} (\log \sigma_{n,t_j,0} - \log \sigma_{n,t_j}) \\
& + (2s_n)^{-1} \sum_{j=1}^{n} \sigma_{n,t_j,0}^{-2} \big(X_{n,t_j,0} - X_{n,t_{j-1},0}\big)^2 \\
& - (2s_n)^{-1} \sum_{j=1}^{n} \sigma_{n,t_j}^{-2} \big\{X_{n,t_j,0} - X_{n,t_{j-1},0} - s_n\big(\gamma_0 + \gamma_1 \sigma_{n,t_j}^2\big)\big\}^2 \\
= {} & \frac{1}{2} \sum_{j=1}^{n} \left(1 - \frac{\sigma_{n,t_j,0}^2}{\sigma_{n,t_j}^2}\right)(\varepsilon_j^2 - 1) \\
& + \frac{1}{2} \sum_{j=1}^{n} \left(1 + \log \frac{\sigma_{n,t_j,0}^2}{\sigma_{n,t_j}^2} - \frac{\sigma_{n,t_j,0}^2}{\sigma_{n,t_j}^2}\right) \\
& + s_n^{1/2} \sum_{j=1}^{n} (\gamma_0 + \gamma_1 \sigma_{n,t_j}^2) \sigma_{n,t_j,0} \sigma_{n,t_j}^{-2} \varepsilon_j \\
& - \frac{s_n}{2} \sum_{j=1}^{n} (\gamma_0 + \gamma_1 \sigma_{n,t_j}^2)^2 \sigma_{n,t_j}^{-2} \\
= {} & \frac{1}{\sqrt{2}} \int_0^1 V_{n,t}\, dW_{3,t}^{(n)} + \frac{1}{2} \int_0^1 H_{n,t}\, dt \\
& + \int_0^1 (\gamma_0 + \gamma_1 \sigma_{n,t}^2) \sigma_{n,t,0} \sigma_{n,t}^{-2}\, dW_{1,t}^{(n)} \\
& - \frac{1}{2} \int_0^1 (\gamma_0 + \gamma_1 \sigma_{n,t}^2)^2 \sigma_{n,t}^{-2}\, dt,
\end{aligned} \tag{31}
$$

where the second equality is from (11), and the third equality is due to the definitions of $V_{n,t}$ and $H_{n,t}$ in (26), and the piecewiseness of $\sigma_{n,t}^2$ and $W_{i,t}^{(n)}$ defined in (13) and (28), respectively.

PROPOSITION 1.

$$V_{n,t} = V_t + O_p(n^{-1/2} \log^2 n),$$

where $V_{n,t}$ *and* V_t *are defined in* (26) *and* (27), *respectively*.

Proposition 1 will be proved in Sections 4.3 and 4.4 where Lemmas 1 and 4 indicate that V_t smoothly depends on $W_{2,t}$ or $W_{3,t}$.

PROPOSITION 2.

$$H_{n,t} = -V_t^2/2 + O_p(n^{-1/2}\log^2 n),$$

where $H_{n,t}$ *and* V_t *are defined in* (26) *and* (27), *respectively*.

PROOF. Note that $H_{n,t} = n\{n^{-1/2}V_{n,t} + \log(1 - n^{-1/2}V_{n,t})\}$ and as $x \to 0$, $x + \log(1-x) = -x^2/2 + O(x^3)$. In view of Proposition 1, we have that

$$H_{n,t} = n\{-(n^{-1/2}V_{n,t})^2/2 + O_p(n^{-3/2})\} = -V_t^2/2 + O_p(n^{-1/2}\log^2 n). \quad \square$$

PROPOSITION 3.

$$\Lambda_{n,1}(\vartheta) = \Lambda_1(\vartheta) + O_p(n^{-1/2}\log^2 n),$$

where $\Lambda_1(\vartheta)$ *is defined in* (30).

PROOF. Comparing Lemma 3 (or Lemma 6) with Lemma 1 (or Lemma 4, respectively) in Sections 4.3 and 4.4 below and using the strong approximation (29) we easily conclude that both $\sigma_{n,t}^2$ and $\sigma_{n,t,0}^2$ converge in probability to $\sigma_{t,0}^2$ with error rate $n^{-1/2}\log^2 n$. Then by (26), (27), the strong approximation (29) and Propositions 1 and 2, we can show that the integrals in $\Lambda_{n,1}(\vartheta)$ given by (31) converge in probability to the corresponding integrals in $\Lambda_1(\vartheta)$ defined in (30) with errors of order $n^{-1/2}\log^2 n$. This completes the proof. $\square$

PROPOSITION 4. *Assume that* $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^+ \equiv (\boldsymbol{\varphi}, \mathbf{0})$ (*i.e.*, $\boldsymbol{\gamma} = 0$) *and Novikov's condition* [*i.e.*, $E\exp\{\frac{1}{4}\int_0^1 V_t^2\,dt\} < \infty$] *is satisfied. Then as* $n \to \infty$, $E|\Lambda_{n,1}(\boldsymbol{\vartheta}^+) - \Lambda_1(\boldsymbol{\vartheta}^+)| \to 0$.

PROOF. Since $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^+$ means that the drift parameter $\boldsymbol{\gamma} = 0$, substituting $\boldsymbol{\gamma}$ by zero in $\Lambda_1(\boldsymbol{\vartheta})$ defined in (30), we obtain that Novikov's condition ensures $E\Lambda_1(\boldsymbol{\vartheta}^+) = 1$ and thus $E[\Lambda_1(\boldsymbol{\vartheta}^+)|W_{2,u}, W_{3,u}, u \le t] = \exp\{\frac{1}{\sqrt{2}}\int_0^t V_s\,dW_{3,s} - \frac{1}{4}\int_0^t V_s^2\,ds\}$ is a martingale [Ikeda and Watanabe (1989) and Karatzas and Shreve (1991), Section 3.5]. As $1 - \sigma_{n,j,0}^2/\sigma_{n,j}^2 < 1$, it is easy to check that as a likelihood process, $E\Lambda_{n,1}(\boldsymbol{\vartheta}^+) = 1$. Now the proposition is a consequence of Proposition 3 and the Scheffé theorem. $\square$

REMARK 4.1. Since V_t^2 is of order $W_{2,t}^2$ or $W_{3,t}^2$, we can show that there exists a constant $\delta > 0$ depending only on time interval [0, 1] such that Novikov's condition holds for all $\boldsymbol{\varphi}$ with $\varphi_2^2 \le \delta$. For example, for the multiplicative GARCH case with $\beta_0^* = \beta_1^* = 0$, $V_t = \varphi_2 W_{2,t}$. The Karhunen–Loève expansion of $W_{2,t}$, $t \in [0, 1]$, is given by

$$W_{2,t} = \sum_{j=0}^{\infty} 2^{1/2}\pi^{-1}(j + 1/2)^{-1}\sin\{\pi(j + 1/2)t\}z_j,$$

where z_j are i.i.d. standard normal random variables. Then we have $\int_0^1 W_{2,t}^2\,dt = \sum_{j=0}^{\infty} \pi^{-2}(j+1/2)^{-2} z_j^2$, and for $\varphi_2^2 < \delta = \pi^2/4$,

$$\begin{aligned} E\exp\left(\frac{1}{4}\int_0^1 V_t^2\,dt\right) &= \prod_{j=0}^{\infty} E\exp\{\pi^{-2}\varphi_2^2(2j+1)^{-2}z_j^2\} \\ &= \prod_{j=0}^{\infty}\{1-2\pi^{-2}\varphi_2^2(2j+1)^{-2}\}^{-1/2} \\ &\sim \exp\left\{\pi^{-2}\varphi_2^2\sum_{j=0}^{\infty}(2j+1)^{-2}\right\} < \infty. \end{aligned}$$

4.3. *Proof of Proposition* 1 *for the multiplicative* GARCH *model.*

LEMMA 1. *The solution of* (15) *is given by*

$$\log\sigma_t^2 = e^{\beta_1 t}\left\{\beta_3 + \beta_2\int_0^t e^{-\beta_1 s}\,dW_{2,s} + \beta_0\int_0^t e^{-\beta_1 s}\,ds\right\}.$$

PROOF. Applying the Itô lemma [Ikeda and Watanabe (1989) and Karatzas and Shreve (1991)] to the process given by the lemma, we have

$$\begin{aligned} d\log\sigma_t^2 &= \beta_1 e^{\beta_1 t}\,dt e^{-\beta_1 t}\log\sigma_t^2 + e^{\beta_1 t}\{\beta_2 e^{-\beta_1 t}\,dW_{2,t} + \beta_0 e^{-\beta_1 t}\,dt\} \\ &= (\beta_0 + \beta_1\log\sigma_t^2)\,dt + \beta_2\,dW_{2,t}. \end{aligned}$$ □

LEMMA 2. *The process defined in* (12) *has the expression*

$$\log\sigma_{n,k}^2 = \alpha_1^{k-1}\log\sigma_0^2 + (\alpha_2/\alpha_1)\sum_{j=1}^{k-1}\alpha_1^{k-j}\xi_j + (\alpha_0/\alpha_1)\sum_{j=1}^{k-1}\alpha_1^{k-j},$$

with $\log\sigma_0^2 = \beta_3$, $\alpha_0 = s_n\beta_0$, $\alpha_1 = 1 + s_n\beta_1$ *and* $\alpha_2 = s_n^{1/2}\beta_2$.

The lemma is easily proved by applying (12) recursively.

LEMMA 3.

$$\log\sigma_{n,t}^2 = e^{\beta_1 t}\left\{\beta_3 + \beta_2\int_0^t e^{-\beta_1 s}\,dW_{2,s}^{(n)} + \beta_0\int_0^t e^{-\beta_1 s}\,ds\right\} + O_p(n^{-1}).$$

REMARK 4.2. As $V_{n,t}$ relates to V_t through the $n^{-1/2}$ order term in the expansion of $\log\sigma_{n,t}^2 - \log\sigma_{n,t,0}^2$, in order to prove Proposition 1 we need to keep the approximation to be of order higher than $n^{-1/2}$. Since the strong approximation has error of order lower than $n^{-1/2}$, we can not replace $W_2^{(n)}$ by W_2 at this point.

PROOF OF LEMMA 3. First note that uniformly for $k = 1, \dots, n$,

$$(1 + \beta_1/n)^k = \exp\{k \log(1 + \beta_1/n)\} = \exp\{k[\beta_1/n + O(n^{-2})]\}$$
$$= e^{\beta_1 k/n} + O(n^{-1}).$$

Now Lemma 2 implies that

$$\begin{aligned}\log \sigma_{n,k}^2 &= (1 + \beta_1/n)^{k-1}\beta_3 \\ &\quad + \beta_2(1 + \beta_1/n)^{-1} \sum_{j=1}^{k-1} (1 + \beta_1/n)^{k-j} \big[W_{2,j/n}^{(n)} - W_{2,(j-1)/n}^{(n)}\big] \\ &\quad + \beta_0(1 + \beta_1/n)^{-1} \sum_{j=1}^{k-1} (1 + \beta_1/n)^{k-j}/n \\ &= e^{\beta_1 k/n}\beta_3 + \beta_2 \int_0^{k/n} e^{\beta_1(k/n - s)}\, dW_{2,s}^{(n)} + \beta_0 \int_0^{k/n} e^{\beta_1(k/n-s)}\, ds + O_p(n^{-1}).\end{aligned}$$

The lemma is easily proved by combining the above result with (13). □

PROOF OF PROPOSITION 1. Note from Convention 4 in Section 4.1 that for $\sigma_{n,t}^2$ and σ_t^2, $\boldsymbol{\beta} = \boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}$, $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, \beta_2^*, \beta_3^*)$ and $\boldsymbol{\varphi} = (\varphi_0, \varphi_1, \varphi_2, \varphi_3)$; and for $\sigma_{n,t,0}^2$ and $\sigma_{t,0}^2$, $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. Then by Lemmas 1 and 3 we obtain

$$\begin{aligned}\log \frac{\sigma_{n,t}^2}{\sigma_{n,t,0}^2} &= n^{-1/2}\varphi_3 e^{\beta_1^* t} + n^{-1/2}\varphi_1 t e^{\beta_1^* t}\beta_3^* \\ &\quad + n^{-1/2} \int_0^t e^{\beta_1^*(t-s)}\{\varphi_2 + \varphi_1\beta_2^*(t-s)\}\, dW_{2,s}^{(n)} \\ &\quad + n^{-1/2} \int_0^t e^{\beta_1^*(t-s)}\{\varphi_0 + \beta_0^*\varphi_1(t-s)\}\, ds + O_p(n^{-1}) \\ &= n^{-1/2} V_t + O_p(n^{-1}\log^2 n)\end{aligned}$$

and thus

$$\begin{aligned}V_{n,t} &= n^{1/2}\{1 - \exp(-n^{-1/2}V_t + O_p(n^{-1}\log^2 n))\} \\ &= V_t + O_p(n^{-1/2}\log^2 n).\end{aligned}$$

□

4.4. *Proof of Proposition* 1 *for the linear GARCH model.*

LEMMA 4. *The solution of* (17) *is given by*

$$\begin{aligned}\sigma_t^2 &= \exp\{\beta_1 t + \beta_2 W_{3,t} - \beta_2^2 t/2\} \\ &\quad \times \left\{\exp(\beta_3) + \beta_0 \int_0^t \exp(-\beta_1 s - \beta_2 W_{3,s} + \beta_2^2 s/2)\, ds\right\}.\end{aligned}$$

PROOF. Applying the Itô lemma to the process given by the lemma, we have

$$\begin{aligned} d\sigma_t^2 &= \sigma_t^2\, d(\beta_1 t + \beta_2 W_{3,t} - \beta_2^2 t/2) + (\beta_2^2/2)\sigma_t^2\, dt + \beta_0\, dt \\ &= (\beta_0 + \beta_1\sigma_t^2)\, dt + \beta_2\sigma_t^2\, dW_{3,t}. \end{aligned} \qquad \square$$

LEMMA 5. *The process defined by* (16) *has the expression*

$$\sigma_{n,k}^2 = \prod_{j=1}^{k-1}(\alpha_1 + \alpha_2\zeta_j)\left\{\sigma_0^2 + \alpha_0 \sum_{i=1}^{k-1}\prod_{j=1}^{i-1}(\alpha_1+\alpha_2\zeta_j)^{-1}\right\},$$

with $\sigma_0^2 = e^{\beta_3}$, $\alpha_0 = s_n\beta_0$, $\alpha_1 = 1 + s_n\beta_1$ *and* $\alpha_2 = s_n^{1/2}\beta_2$.

The lemma is proved by using (16) recursively.

LEMMA 6.

$$\begin{aligned} \sigma_{n,t}^2 &= \exp\left\{\beta_1 t + \beta_2 W_{3,t}^{(n)} - \frac{\beta_2^2 t}{2}\right\} \\ &\quad \times \left\{\exp(\beta_3) + \beta_0 \int_0^t \exp\left(-\beta_1 s - \beta_2 W_{3,s}^{(n)} + \frac{\beta_2^2 s}{2}\right) ds\right\} + O_p(n^{-1}). \end{aligned}$$

REMARK 4.3. For the reason discussed in Remark 4.2, we cannot substitute $W_3^{(n)}$ by W_3 now.

PROOF OF LEMMA 6. An application of the Doléans–Dade formula [Jacod and Shiryaev (1987)] implies that $\prod_{j=1}^{[nt]}(\alpha_1 + \alpha_2\zeta_j)$ is an exponential semimartingale, which converges weakly to the exponential semimartingale $\exp\{\beta_1 t + \beta_2 W_{3,t} - \beta_2^2 t/2\}$. Moreover,

$$\begin{aligned} \prod_{j=1}^{[nt]}(\alpha_1 + \alpha_2\zeta_j) &= \exp\left\{\sum_{j=1}^{[nt]} \log(1 + s_n\beta_1 + s_n^{1/2}\beta_2\zeta_j)\right\} \\ &= \exp\bigl(\beta_1 t + \beta_2 W_{3,t}^{(n)} - \beta_2^2 t/2\bigr) + O_p(n^{-1}), \end{aligned}$$

and hence

$$\begin{aligned} &\alpha_0 \sum_{i=1}^{[nt]}\prod_{j=1}^{i-1}(\alpha_1 + \alpha_2\zeta_j)^{-1} \\ &\quad = s_n\beta_0 \sum_{i=1}^{[nt]} \exp\bigl\{-\beta_1(i-1)/n - \beta_2 W_{3,(i-1)/n}^{(n)} + \beta_2^2(i-1)/(2n)\bigr\} + O_p(n^{-1}) \\ &\quad = \int_0^t \exp\bigl(-\beta_1 s - \beta_2 W_{3,s}^{(n)} + \beta_2^2 s/2\bigr)\, ds + O_p(n^{-1}). \end{aligned}$$

Now the lemma is a consequence of Lemmas 4 and 5. $\square$

PROOF OF PROPOSITION 1. Note from Convention 4 in Section 4.1 that for $\sigma_{n,t}^2$ and σ_t^2, $\boldsymbol{\beta} = \boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}$, $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, \beta_2^*, \beta_3^*)$ and $\boldsymbol{\varphi} = (\varphi_0, \varphi_1, \varphi_2, \varphi_3)$, and for $\sigma_{n,t,0}^2$ and $\sigma_{t,0}^2$, $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. By Lemmas 4 and 6 we obtain $\sigma_{n,t}^2 - \sigma_{n,t,0}^2 = D_1 + D_2$, where

$$\begin{aligned} D_1 &= n^{-1/2} \exp\{\beta_3^* + \beta_1^* t + \beta_2^* W_{3,t}^{(n)} - (\beta_2^*)^2 t/2\}\{\varphi_3 + \varphi_1 t + \varphi_2 W_{3,t}^{(n)} - \varphi_2 \beta_2^* t\} \\ &\quad + O_p(n^{-1}) \\ &= n^{-1/2} \exp\{\beta_3^* + \beta_1^* t + \beta_2^* W_{3,t} - (\beta_2^*)^2 t/2\}\{\varphi_3 + \varphi_1 t + \varphi_2 W_{3,t} - \varphi_2 \beta_2^* t\} \\ &\quad + O_p(n^{-1}\log^2 n), \\ D_2 &= n^{-1/2} \int_0^t \exp\{\beta_1^*(t-s) + \beta_2^*(W_{3,t}^{(n)} - W_{3,s}^{(n)}) - (\beta_2^*)^2 (t-s)/2\} \\ &\qquad \times \{\varphi_0 + \varphi_1 \beta_0^*(t-s) + \varphi_2 \beta_0^*(W_{3,t}^{(n)} - W_{3,s}^{(n)}) - \varphi_2 \beta_0^* \beta_2^*(t-s)\}\, ds \\ &\quad + O_p(n^{-1}) \\ &= n^{-1/2} \int_0^t \exp\{\beta_1^*(t-s) + \beta_2^*(W_{3,t} - W_{3,s}) - (\beta_2^*)^2 (t-s)/2\} \\ &\qquad \times \{\varphi_0 + \varphi_1 \beta_0^*(t-s) + \varphi_2 \beta_0^*(W_{3,t} - W_{3,s}) - \varphi_2 \beta_0^* \beta_2^*(t-s)\}\, ds \\ &\quad + O_p(n^{-1}\log^2 n). \end{aligned}$$

Finally,

$$\begin{aligned} V_{n,t} &= n^{1/2}\{1 - (\sigma_{n,t,0}^2 + D_1 + D_2)^{-1}\sigma_{n,t,0}^2\} \\ &= n^{1/2}(D_1 + D_2)\sigma_{t,0}^{-2} + O_p(n^{-1/2}\log^2 n) = V_t + O_p(n^{-1/2}\log^2 n). \quad \square \end{aligned}$$

5. Likelihood process for diffusion models. For discrete observations X_{t_k} from (14), $k = 1, \dots, n$, we have

$$\begin{aligned} X_{t_k} - X_{t_{k-1}} &= \int_{t_{k-1}}^{t_k} (\gamma_0 + \gamma_1 \sigma_s^2)\, ds + \int_{t_{k-1}}^{t_k} \sigma_u \, dW_{1,u} \\ &= \gamma_0 s_n + \gamma_1 s_n \bar{\sigma}_{n,t_k}^2 + \{s_n \bar{\sigma}_{n,t_k}^2\}^{1/2} z_k, \end{aligned} \tag{32}$$

where

$$\bar{\sigma}_{n,t}^2 = s_n^{-1} \int_{t-s_n}^t \sigma_u^2 \, du, \qquad z_k = \{s_n \bar{\sigma}_{n,t_k}^2\}^{-1/2} \int_{t_{k-1}}^{t_k} \sigma_u \, dW_{1,u}. \tag{33}$$

From (14), (15) and (17), we have that conditioning on W_2 and W_3, $\int_{t_{k-1}}^{t_k} \sigma_u \, dW_{1,u}$ are independent and follow normal distributions with mean zero and variances $s_n \bar{\sigma}_{n,t_k}^2$, and thus z_k are i.i.d. standard random variables.

Keep in mind the notation and conventions specified in Section 4.1. In particular, use $\boldsymbol{\vartheta} = (\boldsymbol{\varphi}, \boldsymbol{\gamma})$ for $\boldsymbol{\theta} = (\boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}, \boldsymbol{\gamma}) \in \Theta_{n,c}(\boldsymbol{\beta}^*)$ and denote the processes X and σ^2 under $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^*$ by adding a subscript "0" to the processes.

Denote by $E_{W_{23}}$ the expectation taken with respect to W_2 and W_3. Conditioning on $\bar{\sigma}^2_{n,t_j}$ we obtain the joint conditional density of $X_{t_1}, \dots, X_{t_n}$,

$$\prod_{j=1}^n [(s_n \bar{\sigma}^2_{n,t_j})^{-1/2} \phi(\{X_{t_j} - X_{t_{j-1}} - s_n(\gamma_0 + \gamma_1 \bar{\sigma}^2_{n,t_j})\}(s_n^{1/2}\bar{\sigma}_{n,t_j})^{-1})],$$

where ϕ is the density of the standard normal distribution. Averaging out $\bar{\sigma}^2_{n,t_k}$, $k = 1, \dots, n$, in the conditional density, we get the joint density function and have the likelihood

$$\begin{aligned} L_{n,2}(\boldsymbol{\vartheta}) = E_{W_{23}} \exp\Biggl(& -\sum_{j=1}^n (2 s_n \bar{\sigma}^2_{n,t_j})^{-1} \{X_{t_j} - X_{t_{j-1}} - s_n(\gamma_0 + \gamma_1 \bar{\sigma}^2_{n,t_j})\}^2 \\ & - \sum_{j=1}^n \log \bar{\sigma}_{n,t_j} - (n/2)\log(2\pi s_n)\Biggr), \end{aligned}$$

and thus the likelihood process under $Q_{n,\boldsymbol{\vartheta}^*}$,

$$\begin{aligned} \Lambda_{n,2}(\boldsymbol{\vartheta}) &= L_{n,2}(\boldsymbol{\vartheta})/L_{n,2}(\boldsymbol{\vartheta}^*) \\ &= E_{W_{23}} \exp\Biggl(-\sum_{j=1}^n (2 s_n \bar{\sigma}^2_{n,t_j})^{-1} \{X_{t_j,0} - X_{t_{j-1},0} - s_n(\gamma_0 + \gamma_1 \bar{\sigma}^2_{n,t_j})\}^2 \\ &\qquad - \sum_{j=1}^n \log \bar{\sigma}_{n,t_j}\Biggr) \\ &\quad \times \Biggl\{E_{W_{23}} \exp\Biggl(-\sum_{j=1}^n (2 s_n \bar{\sigma}^2_{n,t_j,0})^{-1} (X_{t_j,0} - X_{t_{j-1},0})^2 \\ &\qquad - \sum_{j=1}^n \log \bar{\sigma}_{n,t_j,0}\Biggr)\Biggr\}^{-1} \\ &= E_{W_{23}}\Biggl[B_n \exp\Biggl\{\frac{1}{2}\sum_{j=1}^n \biggl(1 - \frac{\bar{\sigma}^2_{n,t_j,0}}{\bar{\sigma}^2_{n,t_j}}\biggr)(z_j^2 - 1) \\ &\qquad + \frac{1}{2}\sum_{j=1}^n \biggl(1 + \log \frac{\bar{\sigma}^2_{n,t_j,0}}{\bar{\sigma}^2_{n,t_j}} - \frac{\bar{\sigma}^2_{n,t_j,0}}{\bar{\sigma}^2_{n,t_j}}\biggr) \\ &\qquad + s_n^{1/2} \sum_{j=1}^n (\gamma_0 + \gamma_1 \bar{\sigma}^2_{n,t_j}) \bar{\sigma}_{n,t_j,0} \bar{\sigma}^{-2}_{n,t_j} z_j \\ &\qquad - \frac{s_n}{2}\sum_{j=1}^n (\gamma_0 + \gamma_1 \bar{\sigma}^2_{n,t_j})^2 \bar{\sigma}^{-2}_{n,t_j}\Biggr\}\Biggr] \end{aligned} \tag{34}$$

$$= E_{W_{23}}\Bigg[B_n \exp\Bigg\{\frac{1}{\sqrt{2}}\int_0^1 \overline{V}_{n,t}\,dW_{4,t}^{(n)} + \frac{1}{2}\sum_{j=1}^{n}\overline{H}_{n,t}/n + \int_0^1 (\gamma_0+\gamma_1\bar{\sigma}_{n,t}^2)\bar{\sigma}_{n,t,0}\bar{\sigma}_{n,t}^{-2}\,dW_{1,t}^{(n)} - \frac{s_n}{2}\sum_{j=1}^{n}(\gamma_0+\gamma_1\bar{\sigma}_{n,t_j}^2)^2\,\bar{\sigma}_{n,t_j}^{-2}\Bigg\}\Bigg],$$

where the third equation is due to (32),

$$B_n = \Bigg\{E_{W_{23}}\exp\Bigg(-\sum_{j=1}^{n}\log\bar{\sigma}_{n,t_j,0}\Bigg)\Bigg\}^{-1}\exp\Bigg(-\sum_{j=1}^{n}\log\bar{\sigma}_{n,t_j,0}\Bigg), \tag{35}$$

$$\overline{V}_{n,t} = n^{1/2}\bigg(1-\frac{\bar{\sigma}_{n,t,0}^2}{\bar{\sigma}_{n,t}^2}\bigg), \qquad \overline{H}_{n,t} = n\bigg(1+\log\frac{\bar{\sigma}_{n,t_j,0}^2}{\bar{\sigma}_{n,t_j}^2}-\frac{\bar{\sigma}_{n,t_j,0}^2}{\bar{\sigma}_{n,t_j}^2}\bigg) \tag{36}$$

and

$$W_{1,t}^{(n)} = n^{-1/2}\sum_{k=1}^{[nt]} z_k, \qquad W_{4,t}^{(n)} = (2n)^{-1/2}\sum_{k=1}^{[nt]}(z_k^2-1). \tag{37}$$

Note that by Convention 1 in Section 4.1 we use the same notation $W_{1,t}^{(n)}$ here for normalized partial sum processes z_k (in the diffusion model) as that for ε_k [in the GARCH model; see (28)], because they have the same distribution, are uncorrelated with other processes and play an identical role in the corresponding likelihood processes. However, a notation $W_{4,t}^{(n)}$ different from $W_{3,t}^{(n)}$ is introduced to denote the normalized partial sum process for z_k^2. This is because, unlike the GARCH case where ε_k^2's are correlated with the conditional variances $\sigma_{n,t}^2$, in the diffusion model z_k^2's are independent of the conditional variances $\bar{\sigma}_{n,t}^2$, and thus jointly $(\varepsilon_k^2, \sigma_{n,t}^2)$ and $(z_k^2, \bar{\sigma}_{n,t}^2)$ are not identically distributed, although marginally ε_k^2's and z_k^2's are. In fact, this is a key point for the difference between the two likelihoods.

By strong approximation [Komlós, Major and Tusnády (1975)] there exists a standard Brownian motion $W_{4,t}$ independent of $W_{1,t}$, $W_{2,t}$, $W_{3,t}$ such that

$$\sup_{0\le t\le T}\big\{|W_{1,t}^{(n)}-W_{1,t}| + |W_{4,t}^{(n)}-W_{4,t}|\big\} = O_p(n^{-1/2}\log n). \tag{38}$$

LEMMA 7. *For the average volatility process $\bar{\sigma}_{n,t}^2$ defined in* (33), *we have*

$$\bar{\sigma}_{n,t}^2 = \sigma_t^2\int_0^1 \exp\bigg(-\beta_2 s_n^{1/2}\int_0^u e^{\beta_1 v}\,d\widetilde{W}_{2,v}\bigg)\,du + O_p(n^{-1})$$

for the multiplicative GARCH case, *and*

$$\bar{\sigma}_{n,t}^2 = \sigma_t^2 \int_0^1 \exp(-\beta_2 s_n^{1/2} \widetilde{W}_{3,u})\, du + O_p(n^{-1})$$

for the linear GARCH case, *where* $\widetilde{W}_{i,u} = s_n^{-1/2}(W_{i,t} - W_{i,t-s_n u})$ *are rescaled Brownian motions*.

REMARK 5.1. Because of stationarity and the rescaling property of Brownian motions W_i, $\widetilde{W}_i$ are Brownian motions whose distributions are independent of t. Because of Convention 1 in Section 4.1, we do not keep track of t. Also both $\int_0^1 \exp(-\beta_2 s_n^{1/2} \int_0^u e^{\beta_1 v}\, d\widetilde{W}_{2,v})\, du$ and $\int_0^1 \exp(-s_n^{1/2}\beta_2 \widetilde{W}_{3,u})\, du$ are of order $1 + O_p(n^{-1/2})$. For the reason discussed in Remark 4.2, we can not replace them by 1 here.

PROOF OF LEMMA 7. For the multiplicative GARCH case, from the definition of $\bar{\sigma}^2$ in (33) and Lemma 1 we have

$$\begin{aligned}
\bar{\sigma}_{n,t}^2 &= \int_0^1 \exp\biggl(e^{-\beta_1 s_n u} \log \sigma_t^2 \\
&\qquad\qquad - e^{\beta_1(t-s_n u)} \biggl\{\beta_2 \int_{t-s_n u}^t e^{-\beta_1 h}\, dW_{2,h} + \beta_0 \int_{t-s_n u}^t e^{-\beta_1 h}\, dh\biggr\}\biggr)\, du \\
&= \sigma_t^2 \int_0^1 \exp\biggl(-\beta_2 s_n^{1/2} \int_0^u e^{\beta_1 v}\, d\widetilde{W}_{2,v}\biggr)\, du + O_p(s_n).
\end{aligned}$$

Similarly, for the linear GARCH case, by Lemma 4 we get

$$\begin{aligned}
\bar{\sigma}_{n,t}^2 &= \sigma_t^2 \int_0^1 \exp\{-s_n(\beta_1 - \beta_2^2/2)u - s_n^{1/2}\beta_2 \widetilde{W}_{3,u}\}\, du \\
&\quad - \beta_0 \int_0^1 du \int_{t-s_n u}^t \exp\{(\beta_1 - \beta_2^2/2)(t - s_n u - h) \\
&\qquad\qquad + \beta_2(W_{3,t-s_n u} - W_{3,h})\}\, dh \\
&= \sigma_t^2 \int_0^1 \exp(-s_n^{1/2}\beta_2 \widetilde{W}_{3,u})\, du + O_p(s_n). \qquad \square
\end{aligned}$$

LEMMA 8.

$$\overline{V}_{n,t} = V_t + O_p(n^{-1/2}),$$

where V_t *and* $\overline{V}_{n,t}$ *are defined in* (27) *and* (36), *respectively*.

PROOF. Thanks to Lemma 7, we can now easily show that for both multiplicative and linear GARCH cases,

$$\frac{\bar{\sigma}_{n,t,0}^2}{\bar{\sigma}_{n,t}^2} = \frac{\sigma_{t,0}^2}{\sigma_t^2} + O_p(n^{-1}). \tag{39}$$

Because of similarity, we prove (39) only for the multiplicative GARCH case. Note from Convention 4 in Section 4.1 that for σ_t^2, $\boldsymbol{\beta} = \boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}$, $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, \beta_2^*, \beta_3^*)$ and $\boldsymbol{\varphi} = (\varphi_0, \varphi_1, \varphi_2, \varphi_3)$; and for $\sigma_{t,0}^2$, $\boldsymbol{\beta} = \boldsymbol{\beta}^*$. By Lemma 7 we can derive

$$\begin{aligned}\bar{\sigma}_{n,t}^2 &= \sigma_t^2 \int_0^1 \exp\biggl(-\beta_2^* s_n^{1/2} \int_0^u e^{\beta_1^* v}\, d\widetilde{W}_v\biggr)\, du + O_p(n^{-1})\\ &= \bar{\sigma}_{n,t,0}^2 (\sigma_t/\sigma_{t,0})^2 + O_p(n^{-1}),\end{aligned}$$

which proves (39).

From Lemmas 1 and 4 we get that σ_t^2 depends on $\boldsymbol{\beta}$ smoothly. Expanding σ_t^2 at $\boldsymbol{\beta}^*$ and using the definition of V_t we get

$$\log \sigma_t^2 = \log \sigma_{t,0}^2 + n^{-1/2} V_t + O_p(n^{-1}).$$

Finally, combining the above equation with (39) we arrive at

$$\overline{V}_{n,t} = n^{1/2}\{1 - \exp(-n^{-1/2} V_t) + O_p(n^{-1})\} = V_t + O_p(n^{-1/2}). \qquad \square$$

LEMMA 9.

$$\overline{H}_{n,t} = -V_t^2/2 + O_p(n^{-1/2}),$$

where V_t and $\overline{H}_{n,t}$ are defined in (27) *and* (36), *respectively*.

PROOF. The lemma is easily proved by Lemma 8 and the same argument for proving Proposition 2. $\square$

There is great difficulty in handling $\Lambda_{n,2}(\boldsymbol{\vartheta})$. First, it is generally impossible to derive an explicit and tractable form for $\Lambda_{n,2}(\boldsymbol{\vartheta})$. Second, the factor B_n in $\Lambda_{n,2}(\boldsymbol{\vartheta})$ converges in probability to zero but it is unbounded, because $EB_n = 1$, and its first factor [see (35)] has an exponent of order $n^2 \operatorname{var}(\int_0^1 \log \sigma_t^2\, dt)/8$. Thus we cannot do the usual asymptotics by exchanging the limit "$n \to \infty$" and the expectation $E_{W_{23}}$. To get around this difficulty and prove the theorems, we consider the likelihood process in a local neighborhood around $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, \beta_2^*, \beta_3^*)$ with $\beta_2^* = 0$. In this case $\bar{\sigma}_{n,t,0}^2$ is deterministic but both $\bar{\sigma}_{n,t}^2$ and V_t are stochastic, since $\boldsymbol{\beta} = \boldsymbol{\beta}^* + n^{-1/2}\boldsymbol{\varphi}$. Also for simplicity, we take $\boldsymbol{\gamma} = 0$. Thus, $\boldsymbol{\theta}^* = (\boldsymbol{\beta}^*, \mathbf{0})$ and $\boldsymbol{\theta} = (\boldsymbol{\beta}, \mathbf{0})$, or equivalently by Convention 3 in Section 4.1, $\boldsymbol{\vartheta}^* = (\mathbf{0}, \mathbf{0})$ and $\boldsymbol{\vartheta} = \boldsymbol{\vartheta}^+ = (\boldsymbol{\varphi}, \mathbf{0})$.

PROPOSITION 5. *Suppose $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, 0, \beta_3^*)$ and define*

$$\Lambda_2(\boldsymbol{\vartheta}^+) = E_{W_{23}} \exp\biggl\{\frac{1}{\sqrt{2}} \int_0^1 V_t\, dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\, dt\biggr\}, \tag{40}$$

where V_t and $W_{4,t}$ are given by (27) *and* (38), *respectively*. *Then as $n \to \infty$, $E|\Lambda_{n,2}(\boldsymbol{\vartheta}^+) - \Lambda_2(\boldsymbol{\vartheta}^+)| \to 0$.*

PROOF. Since $\beta_2^* = 0$, $\sigma_{t,0}^2$ is deterministic, and then (35) implies $B_n = 1$. Taking $B_n = 1$ and $\boldsymbol{\gamma} = 0$ in (34) we get

$$\Lambda_{n,2}(\boldsymbol{\vartheta}^+) = E_{W_{23}} \exp\left\{\frac{1}{2}\int_0^1 \overline{V}_{n,t}\, dW_{4,t}^{(n)} + \frac{1}{2}\sum_{j=1}^n \overline{H}_{n,t}/n\right\}. \tag{41}$$

It is easy to check that as a likelihood process, $E\Lambda_{n,2}(\boldsymbol{\vartheta}^+) = 1$.

The process V_t is a continuous functional of W_2 or W_3 and has a.s. continuous sample paths, so conditional on W_2 and W_3, $\int_0^1 V_t^2\, dt$ is a.s. finite. As $W_{1,t}$, $\{W_{2,t}, W_{3,t}\}$, $W_{4,t}$ are independent but $W_{2,t}$ and $W_{3,t}$ are correlated, we have that conditioning on W_2 and W_3, Novikov's condition (i.e., $E[\exp\{\int_0^1 V_t^2\, dt/4\}|W_2, W_3] < \infty$) holds, and thus the exponential martingale $\exp\{\frac{1}{\sqrt{2}}\int_0^t V_s\, dW_{4,s} - \frac{1}{4}\int_0^t V_s^2\, ds\}$ is indeed a martingale, and $E[\exp\{\frac{1}{\sqrt{2}}\int_0^1 V_t\, dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\, dt\}|W_2, W_3] = 1$. [See Ikeda and Watanabe (1989) and Karatzas and Shreve (1991), Section 3.5.] Therefore,

$$\begin{aligned} E\Lambda_2(\boldsymbol{\vartheta}^+) &= E_{W_4} E_{W_{23}} \exp\left\{\frac{1}{\sqrt{2}}\int_0^1 V_t\, dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\, dt\right\} \\ &= E_{W_{23}} E\left[\exp\left\{\frac{1}{\sqrt{2}}\int_0^1 V_t\, dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\, dt\right\}\Big| W_2, W_3\right] = 1. \end{aligned}$$

As in Section 4.2, by strong approximation (38) and Lemmas 8 and 9 we obtain that the process inside $E_{W_{23}}$ in the expression (41) of $\Lambda_{n,2}(\boldsymbol{\vartheta}^+)$

$$\exp\left\{\frac{1}{\sqrt{2}}\int_0^1 \overline{V}_{n,t}\, dW_{4,t}^{(n)} + \frac{1}{2}\sum_{j=1}^n \overline{H}_{n,t}/n\right\}, \tag{42}$$

converges in probability to

$$\exp\left\{\frac{1}{\sqrt{2}}\int_0^1 V_t\, dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\, dt\right\}, \tag{43}$$

which is the process inside $E_{W_{23}}$ in the expression (40) of $\Lambda_2(\boldsymbol{\vartheta}^+)$. Both processes are nonnegative and have expectation 1, so applying the Scheffé theorem, we have that the expectation of the absolute difference between (42) and (43) converges to zero. That in turn implies $E|\Lambda_{n,2}(\boldsymbol{\vartheta}^+) - \Lambda_2(\boldsymbol{\vartheta}^+)| \to 0$. $\square$

REMARK 5.2. As we mentioned in Section 2.2 and discussed before the proposition, the likelihood process for a diffusion model is generally not available. Even for the limit of the multiplicative GARCH model (40) with $\beta_0^* = \beta_1^* = 0$, we will show that its explicit form is too complicated to be useful. In this case, as shown in Remark 4.1, we have $V_t = \varphi_2 W_{2,t}$, and the Karhunen–Loève expansion of $W_{2,t}$,

$$W_{2,t} = \sum_{j=0}^\infty 2^{1/2}\pi^{-1}(j+1/2)^{-1}\sin\{\pi(j+1/2)t\} z_j,$$

where z_j are i.i.d. standard normal random variables. Then

$$\int_0^1 W_{2,t}\,dW_{4,t} = \sum_{j=0}^{\infty} \pi^{-1}(j+1/2)^{-1} w_j z_j,$$

$$\int_0^1 W_{2,t}^2\,dt = \sum_{j=0}^{\infty} \pi^{-2}(j+1/2)^{-2} z_j^2,$$

where the Fourier coefficients $w_j = \int_0^1 \sqrt{2}\sin\{(j+1/2)\pi t\}\,dW_{4,t}$ are i.i.d. standard normal random variables and independent of z_j. Finally,

$$\begin{aligned}\Lambda_2(\vartheta^+) &= \prod_{j=0}^{\infty} E_{z_j} \exp\left\{\frac{\varphi_2 w_j z_j}{\sqrt{2}\pi(j+1/2)} - \frac{\varphi_2^2 z_j^2}{4\pi^2(j+1/2)^2}\right\}\\ &= \exp\left\{\sum_{j=0}^{\infty} \frac{\varphi_2^2 w_j^2}{2\pi^2(j+1/2)^2+\varphi_2^2}\right\} \prod_{j=0}^{\infty}\left\{\frac{\varphi_2^2}{2\pi^2(j+1/2)^2}+1\right\}^{-1/2}.\end{aligned}$$

The nonrandom product series converges, and the exponent of the random part is a positive linear combination of the squared Fourier coefficients of $W_{4,t}$.

6. Proof of Theorems.

6.1. *Proof of Theorem* 1: *nonequivalence under stochastic volatility.* If $\Delta(\mathbb{E}_{n,1}, \mathbb{E}_{n,2}) \to 0$, as $n \to \infty$, Propositions 4 and 5 imply that with $\boldsymbol{\beta}^* = (\beta_0^*, \beta_1^*, 0, \beta_3^*)$, for all $\vartheta^+ = (\boldsymbol{\varphi}, \mathbf{0})$, $\Lambda_1(\vartheta^+)$ and $\Lambda_2(\vartheta^+)$ must have the same distribution [Le Cam (1986), Proposition 8 and its remark in Section 4 of Chapter 6, pages 93–95; Le Cam and Yang (1990), Section 2.2 of Chapter 2]. However, $W_{1,t}$, $\{W_{2,t}, W_{3,t}\}$, $W_{4,t}$ are independent but $W_{2,t}$ and $W_{3,t}$ are correlated, and from (27), Lemmas 1 and 4, we can see that V_t strongly depends on $W_{2,t}$ or $W_{3,t}$, so V_t is correlated with $W_{3,t}$ and independent of $W_{4,t}$. Thus, $\int_0^1 V_t\,dW_{3,t}$ and $\int_0^1 V_t\,dW_{4,t}$ can not have the same distribution. With $\boldsymbol{\beta}^*$ and ϑ^+ given above, from (30) and (40), we get the following expressions for $\Lambda_i(\vartheta^+)$:

$$\Lambda_1(\vartheta^+) = \exp\left\{\frac{1}{\sqrt{2}}\int_0^1 V_t\,dW_{3,t} - \frac{1}{4}\int_0^1 V_t^2\,dt\right\},$$

$$\Lambda_2(\vartheta^+) = E_{W_{23}} \exp\left\{\frac{1}{\sqrt{2}}\int_0^1 V_t\,dW_{4,t} - \frac{1}{4}\int_0^1 V_t^2\,dt\right\}.$$

We now easily conclude the contradiction that $\Lambda_1(\vartheta^+)$ and $\Lambda_2(\vartheta^+)$ can not be identically distributed. Indeed, for example, for the multiplicative GARCH case, from (27), (30) and Lemma 1 we obtain

$$V_t\big|_{\boldsymbol{\varphi}=\mathbf{0}} = 0, \qquad \Lambda_1(\vartheta^+)\big|_{\boldsymbol{\varphi}=\mathbf{0}} = 1$$

and

$$\frac{\partial V_t}{\partial \varphi_2}\bigg|_{\boldsymbol{\varphi}=\mathbf{0}} = \frac{\partial \log \sigma_{t,0}^2}{\partial \beta_2^*} = \exp(\beta_1^* t)\int_0^t \exp(-\beta_1^* s)\, dW_{2,s}.$$

Thus,

$$\begin{aligned}\frac{\partial \Lambda_1(\boldsymbol{\vartheta}^+)}{\partial \varphi_2}\bigg|_{\boldsymbol{\varphi}=\mathbf{0}} &= \frac{1}{\sqrt{2}}\int_0^1 \frac{\partial V_t}{\partial \varphi_2}\bigg|_{\boldsymbol{\varphi}=\mathbf{0}} dW_{3,t}\\ &= \frac{1}{\sqrt{2}}\int_0^1 \exp(\beta_1^* t)\int_0^t \exp(-\beta_1^* s)\, dW_{2,s}\, dW_{3,t},\end{aligned}$$

which is a double Itô integral and has mean zero and variance

$$\begin{aligned}&\tfrac{1}{2}\int_0^1 \exp(2\beta_1^* t)\int_0^t \exp(-2\beta_1^* s)\, ds\, dt\\ &\quad = \{\exp(2\beta_1^*) - 2\beta_1^* - 1\}\{8(\beta_1^*)^2\}^{-1} \geq 1/4.\end{aligned}$$

However, because of the independence of W_2 and W_4, a similar calculation leads to

$$\begin{aligned}\frac{\partial \Lambda_2(\boldsymbol{\vartheta}^+)}{\partial \varphi_2}\bigg|_{\boldsymbol{\varphi}=\mathbf{0}} &= E_{W_{23}}\int_0^1 \frac{\partial V_t}{\partial \varphi_2}\bigg|_{\boldsymbol{\varphi}=\mathbf{0}} dW_{4,t}\\ &= \frac{1}{\sqrt{2}}\int_0^1 \exp(\beta_1^* t) E_{W_{23}}\left\{\int_0^t \exp(-\beta_1^* s)\, dW_{2,s}\right\} dW_{4,t} = 0.\end{aligned}$$

Therefore, $\Lambda_1(\boldsymbol{\vartheta}^+)$ and $\Lambda_2(\boldsymbol{\vartheta}^+)$ cannot be identically distributed. □

6.2. *Proof of Theorem* 2: *equivalence under nonstochastic volatility.* Because of similarity, we give the arguments only for the multiplicative GARCH case. With deterministic volatility, the two models become a regression model with independent normal errors and the white noise model. Both the GARCH observations X_{n,t_k} [defined in (11)] and the discrete diffusion observations X_{t_k} [given by (32)] have independent increments, and both increments $X_{n,t_k} - X_{n,t_{k-1}}$ and $X_{t_k} - X_{t_{k-1}}$ follow normal distributions with means $\nu_{1,n,k} = (\gamma_0 + \gamma_1 \sigma_{n,t_k}^2) s_n$ and $\nu_{2,n,k} = (\gamma_0 + \gamma_1 \bar{\sigma}_{n,t_k}^2) s_n$, and variances $\tau_{1,n,k}^2 = \sigma_{n,t_k}^2 s_n$ and $\tau_{2,n,k}^2 = \bar{\sigma}_{n,t_k}^2 s_n$, respectively. Therefore, we calculate the Hellinger distance, $H(P_{n,\theta}, Q_{n,\theta})$, between the distribution $P_{n,\theta}$ of X_{n,t_k}, $k = 0, \ldots, n$, and the distribution $Q_{n,\theta}$ of X_{t_k}, $k = 0, \ldots, n$, as follows:

$$\begin{aligned}&H^2(P_{n,\theta}, Q_{n,\theta})\\ &\quad = H^2\left(\prod_{k=1}^n N(\nu_{1,n,k}, \tau_{1,n,k}^2), \prod_{k=1}^n N(\nu_{2,n,k}, \tau_{2,n,k}^2)\right)\\ &\quad = 2 - 2\prod_{k=1}^n \{1 - H^2(N(\nu_{1,n,k}, \tau_{1,n,k}^2), N(\nu_{2,n,k}, \tau_{2,n,k}^2))/2\} \qquad (44)\end{aligned}$$

$$= 2 - 2\prod_{k=1}^{n}\left(\left\{\frac{2\tau_{1,n,k}\tau_{2,n,k}}{\tau_{1,n,k}^2+\tau_{2,n,k}^2}\right\}^{1/2}\exp\left\{-\frac{(\nu_{1,n,k}-\nu_{2,n,k})^2}{\tau_{1,n,k}^2+\tau_{2,n,k}^2}\right\}\right)$$

$$= 2 - 2\prod_{k=1}^{n}\left\{\frac{2\sigma_{n,t_k}\bar{\sigma}_{n,t_k}}{\sigma_{n,t_k}^2+\bar{\sigma}_{n,t_k}^2}\right\}^{1/2}\exp\left\{-\sum_{k=1}^{n}\frac{\gamma_1^2 s_n(\sigma_{n,t_k}^2-\bar{\sigma}_{n,t_k}^2)^2}{\sigma_{n,t_k}^2+\bar{\sigma}_{n,t_k}^2}\right\}$$

$$= 2 - 2\prod_{k=1}^{n}\left\{1-\frac{(\sigma_{n,t_k}-\bar{\sigma}_{n,t_k})^2}{\sigma_{n,t_k}^2+\bar{\sigma}_{n,t_k}^2}\right\}^{1/2}\exp\left\{-\sum_{k=1}^{n}\frac{\gamma_1^2 s_n(\sigma_{n,t_k}^2-\bar{\sigma}_{n,t_k}^2)^2}{\sigma_{n,t_k}^2+\bar{\sigma}_{n,t_k}^2}\right\},$$

where the second equality is by the Hellinger distance property for independent distributions [Le Cam (1986), Chapter 4; Le Cam and Yang (1990), Section 3.2], the third equality is from the expression for Hellinger distance between two univariate normal distributions obtained by direct calculations [see also Brown and Low (1996), equation (3.7)] and the fourth equality is because of substitutions of ν's and τ^2's by σ^2's.

Since $\beta_2 = 0$, Lemma 1 shows that for the deterministic diffusion volatility process σ_t^2,

$$\log\sigma_t^2 = e^{\beta_1 t}\left\{\beta_3 + \beta_0\int_0^t e^{-\beta_1 u}\,du\right\}. \tag{45}$$

Taking $\beta_2 = 0$ and dropping all random terms in Lemmas 2 and 3, we obtain that for the deterministic GARCH volatility process $\sigma_{n,t}^2$,

$$\begin{aligned}\log\sigma_{n,t}^2 &= (1+s_n\beta_1)^{[nt]-1}\beta_3 + (s_n\beta_0)/(1+s_n\beta_1)\sum_{j=1}^{[nt]-1}(1+s_n\beta_1)^{[nt]-j}\\ &= e^{\beta_1 t}\left\{\beta_3+\beta_0\int_0^t e^{-\beta_1 s}\,ds\right\} + O(n^{-1}) = \log\sigma_t^2 + O(n^{-1}).\end{aligned} \tag{46}$$

As deterministic σ_t^2 given by (45) is smooth in t and $\bar{\sigma}_{n,t}^2 = s_n^{-1}\int_{t-s_n}^t \sigma_u^2\,du$ is the average of σ_t^2 over an interval of length s_n, simple calculations show $\bar{\sigma}_{n,t}^2 = \sigma_t^2 + O(n^{-1})$. This result together with (46) implies that uniformly over all $\beta_0, \beta_1, \beta_3$ and $t \in [0, 1]$,

$$\bar{\sigma}_{n,t}^2 = \sigma_{n,t}^2 + O(n^{-1}). \tag{47}$$

Plugging (47) into (44) we conclude that uniformly over all $\theta = (\beta_0, \beta_1, 0, \beta_3, \gamma_0, \gamma_1) \in \Theta'$, $H^2(P_{n,\theta}, Q_{n,\theta})$ is of order n^{-1}. Finally we complete the proof by applying (23). $\square$

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REFERENCES

AÏT-SAHALIA, Y. (1996). Nonparametric pricing of interest rate derivative securities. *Econometrica* **64** 527–560.

BASAWA, I. and PRAKASA RAO, B. L. S. (1980). *Statistical Inference for Stochastic Processes.* Academic Press, New York.

BLACK, F. and SCHOLES, M. (1973). The pricing of options and corporate liabilities. *J. Political Economy* **81** 637–659.

BOLLERSLEV, T. (1986). Generalized autoregressive conditional heteroskedasticity. *J. Econometrics* **31** 307–327.

BOLLERSLEV, T., CHOU, R. Y. and KRONER, K. F. (1992). ARCH modeling in finance. A review of the theory and empirical evidence. *J. Econometrics* **52** 5–59.

BROWN, L. and LOW, M. (1996). Asymptotic equivalence of nonparametric regression and white noise. *Ann. Statist.* **24** 2384–2398.

BROWN, L., WANG, Y. and ZHAO, L. H. (2001). Statistical equivalence at suitable frequencies of GARCH and stochastic volatility models with the corresponding diffusion model. Unpublished manuscript.

DANIELSSON, J. (1994). Stochastic volatility in asset prices: Estimation with simulated maximum likelihood. *J. Econometrics* **64** 375–400.

DOTHAN, M. U. (1990). *Prices in Financial Markets.* Oxford Univ. Press.

DROST, F. C. and KLAASSEN, C. A. J. (1997). Efficient estimation in semiparametric GARCH models. *J. Econometrics* **81** 193–221.

DUAN, J. C. (1995). The GARCH option pricing model. *Math. Finance* **5** 13–32.

DUAN, J. C. (1997). Augmented GARCH(p, q) process and its diffusion limit. *J. Econometrics* **79** 97–127.

DUFFIE, D. (1992). *Dynamic Asset Pricing Theory*. Princeton Univ. Press.

ENGLE, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica* **50** 987–1007.

ENGLE, R. F. and BOLLERSLEV, T. (1986). Modeling the persistence of conditional variances (with discussion). *Econometric Rev.* **5** 1–87.

FLORENS-ZMIROU, D. (1989). Approximate discrete time schemes for statistics of diffusion processes. *Statistics* **20** 547–557.

GALLANT, A. R., HSIEH, D., and TAUCHEN, G. (1997). Estimation of stochastic volatility models with diagnostics. *J. Econometrics* **81** 159–192.

GALLANT, A. R. and LONG, J. R. (1997). Estimating stochastic differential equations efficiently by minimum chi-squared. *Biometrika* **84** 125–141.

GALLANT, A. R. and TAUCHEN, G. (1998). Reprojecting partially observed systems with application to interest rate diffusions. *J. Amer. Statist. Assoc.* **93** 10–24.

GENON-CATALOT, V. (1990). Maximum contrast estimation for diffusion processes from discrete observations. *Statistics* **21** 99–116.

GEWEKE, J. (1986). Comment on "Modeling the persistence of conditional variances," by R. F. Engle and T. Bollerslev. *Econometric Rev.* **5** 57–61.

GOURIÉROUX, C. (1997). *ARCH Models and Financial Applications.* Springer, New York.

HARRISON, J. M. and KREPS, D. (1979). Martingales and arbitrage in multiperiod securities markets. *J. Econom. Theory* **20** 381–408.

HARRISON, J. M. and PLISKA, S. (1981). Martingales and stochastic integrals in the theory of continuous trading. *Stochastic Process. Appl.* **11** 215–260.

HSIEH, D. (1991). Chaos and nonlinear dynamics: Application to financial markets. *J. Finance* **46** 1839–1877.

HULL, J. (1997). *Options, Futures, and Other Derivatives,* 3rd ed. Prentice-Hall, Englewood Cliffs, NJ.

HULL, J. and WHITE, A. (1987). The pricing of options on assets with stochastic volatilities. *J. Finance* **42** 281–300.

IKEDA, N. and WATANABE, S. (1989). *Stochastic Differential Equations and Diffusion Processes,* 2nd ed. North-Holland, Amsterdam.

INGERSOLL, J. E. (1987). *Theory of Financial Decision Making.* Rowman and Littlefield, Lanham, MD.

JACOD, J. and SHIRYAEV, A. N. (1987). *Limit Theorems for Stochastic Processes.* Springer, New York.

JACQUIER, E., POLSON, N. G. and ROSSI, P. E. (1994). Bayesian analysis of stochastic volatility models (with discussion). *J. Bus. Econom. Statist.* **12** 371–417.

KARATZAS, I. and SHREVE, S. E. (1991). *Brownian Motion and Stochastic Calculus*, 2nd ed. Springer, New York.

KESSLER, M. (1997). Estimation of an ergodic diffusion from discrete observations. *Scand. J. Statist.* **24** 211–229.

KOMLÓS, J., MAJOR, P. and TUSNÁDY, G. (1975). An approximation of partial sums of independent RVs and the sample DF. I. *Z. Wahrsch. Verw. Gebiete* **32** 111–131.

LE CAM, L. (1986). *Asymptotic Methods in Statistical Decision Theory.* Springer, Berlin.

LE CAM, L. and YANG, G. (1990). *Asymptotics in Statistics. Some Basic Concepts.* Springer, New York.

MERTON, R. (1973). The theory of rational option pricing. *Bell J. Econom. Management Sci.* **4** 141–183.

MERTON, R. (1990). *Continuous-Time Finance.* Blackwell, Cambridge.

MYKLAND, P. A. (1996). Options pricing in incomplete markets: an asymptotic approach. Technical Report 430, Dept. Statist., Univ. Chicago.

NELSON, D. B. (1990). ARCH models as diffusion approximations. *J. Econometrics* **45** 7–38.

NELSON, D. B. (1992). Filtering and forecasting with misspecified ARCH models I. Getting the right variance with the wrong model. *J. Econometrics* **52** 61–90.

NUSSBAUM, M. (1996). Asymptotic equivalence of density estimation and Gaussian white noise. *Ann. Statist.* **24** 2399–2430.

PANTULA, S. G. (1986). Comment on "Modeling the persistence of conditional variances," by R. F. Engle and T. Bollerslev. *Econometric Rev.* **5** 71–74.

PRAKASA RAO, B. L. S. (1988). Statistical inference from sampled data for stochastic processes. In *Statistical Inference from Stochastic Processes* (N. U. Prabha, ed.) 249–284. Amer. Math. Soc., Providence, RI.

ROSSI, P. E. (1996). *Modeling Stock Market Volatility.* Academic Press, New York.

STRASSER, H. (1985). *Mathematical Theory of Statistics.* de Gruyter, Berlin.

STROOCK, D. W. and VARADHAN, S. R. S. (1979). *Multidimensional Diffusion Processes.* Springer, New York.

TUSNÁDY, G. (1977). A remark on the approximation of the sample distribution function in the multidimensional case. *Period. Math. Hungar.* **8** 53–55.

YOSHIDA, N. (1992). Estimation for diffusion processes from discrete observations. *J. Multivariate Anal.* **41** 220–242.

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