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Improve the Estimation For Stochastic Volatility Model: Quasi-Likelihood Approach

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ABSTRACT

Background: The Stochastic Volatility Model (SVM) is a frequently used model for returns of financial assets. The existing techniques for parameter estimation in SVM models are mostly based on maximum likelihood. This means that the probability structure of stochastic process has to be known. Usually it is assumed that SVM has conditional Gaussian distribution. This is a valid concern in finance as empirical data reveal fat tails and skewness which contradicts conditional normality**. Objective:** In this paper, how to improve the estimation for Stochastic Volatility Model (SVM) using Quasi-Likelihood method is proposed. In the proposed method, both the state variables and unknown parameters are estimated using Quasi-Likelihood approach. **Results:** The Quasi-Likelihood approach is quite simple and standard and can be carried out without full knowledge on the probability structure of relevant Stochastic Volatility Model. Application of the QL method to weekdays closing pound-to-dollar exchange rates modeled by SVM model is considered. **Conclusion:** When the probability structure of underlying systems is complex or unknown and when the maximum likelihood or mixture of maximum likelihood cannot be easily implemented, the approach proposed in this paper can be considered for estimating parameters in SVMs**.**

INTRODCTION

The Stochastic Volatility Model (SVM) is a model frequently used in returns of financial assets. The stochastic volatility process is defined by the following equations,

$$y_t = \sigma_t \xi_t = e^{\alpha_t/2}\xi_t, t = 1,2,\cdots,T, \tag{1}$$

and

$$\alpha_t = \gamma + \phi\alpha_{t-1} + \eta_t, t = 1,2,\cdots,T, \tag{2}$$

where both ξ_t and η_t are i.i.d respectively; η_t has a mean 0 and variance σ_η^2 whereas ξ_t has a mean 0 and variance σ_ξ^2. The applications and the estimation for SVM can be found in various studies such as Jacquire, et al (1994); Breidtand Carriquiry (1996); Harvey and Streible (1998); Sandmann and Koopman (1998); Pitt and Shepard (1999); Davis and Rodriguez-Yam (2005) ; Alzghool and Lin (2008); Alzghool (2008); Osarumwense and Waziri (2013); Islam (2013); Chan and Grant (2015) and Pinho and Silva (2016).

Sandmann and Koopman (1998) introduced the Monte-Carlo maximum likelihood method of estimating Stochastic Volatility Models (SVM). Davis and Rodriguez-Yam (2005) proposed an alternative estimation procedure based on approximation to the likelihood function. The existing techniques for parameter estimation in SVM models are mainly based on maximum likelihood. This denotes that the probability structure of

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stochastic process has to be known. Usually it is assumed that the SVM has conditional Gaussian distribution. This is a valid concern in finance as empirical data reveals 'fat tails' and 'skewness' which contradicts conditional normality**.**

In this paper, Quasi-Likelihood (QL), a different approach is followed to estimate the parameters and predictors of Stochastic Volatility Model (SVM). In the literature, the QL approach has been applied to SVM by Papanastastiou and Ioannides (2004). They used and extended the set of Kalman filter equations in their estimation procedure but have restricted themselves to a linear-state space model. The 'Kalman filter' and the 'smoother' are the methods used to estimate the predictors of state-variables and one-step-ahead predictors of observations. Usually, the Kalman filter is derived through maximum likelihood method. This denotes the need to know the probability structure of the underlying model. However, in practice, it is not realistic to know the system probability structureand the likelihood function is often difficult to calculate. For these reasons, the maximum likelihood method is often challenging to be implemented whereas the Kalman filter involves many complex matrices calculation that sometimes make the estimation procedure a complex one. Unlike QL approach proposed by Papanastastiou and Ioannides (2004), We propose to apply the QL method only to the whole estimation procedure of SVM to avoid complex expression of Kalman filter matrix. The current paper demonstrates and shows how simple the proposed estimating procedure is and how easily implemented in estimating the state and parameters in SVM.

This paper is structured as follows. The QL approaches are introduced and the SVM model estimation using the QL methods are written in Section 2. Reports of simulation outcomes, and numerical cases are presented under Section 3. The QL techniques are applied to weekdays closing pound-to-dollar exchange rates modeled by SVM in Section 4. The fifth section summarizes and concludes the paper.

2 Parameter estimation of SVM using QL method:

In this section, the parameter estimation for SVM model, which include non-linear and non-Gaussian models is given. We propose QL approach for estimation of SVM. The estimations of unknown parameters are considered without any distribution assumptions, concerning the processes involved.

2.1 The Quasi-Likelihood approach:

The QL method was first introduced by Wedderburn (1974) whose work was mainly based on generalized linear model. At the same time, a similar technique was independently developed by Godambe and Heyde also. Later, this technique was called "Quasi-Likelihood" (see, Godambe and Heyde, (1987)). The technique focused more on the applications to the inference of stochastic processes. These two independently developed Quasi-Likelihood methods were defined in different ways because the original approaches were different. The definition given by Godambe and Heyde (1987) is more general than that given by Wedderburn (1974) Refer Lin and Heyde (1993). In this paper, the definition of the quasi-likelihood given by Godambe and Heyde (1987) is adopted. For detail knowledge on the Quasi-Likelihood method, see Heyde (1997).

Consider a stochastic process $y_t \in R^r$,

$$y_t = \mu_t(\theta) + m_t, 0 \leq t \leq T \tag{3}$$

where $\theta \in \Theta \in R^p$ is the parameter needed to be estimated; μ_t is a function vector of $\{y_s\}_{s<t}$; (in other words, μ_t is F_{t-1}-measurable); m_t is an error process with $E(m_t|F_{t-1}) = E_{t-1}(m_t) = 0$. When the following estimating function space,

$$G_T = \{\sum_{t=1}^{T} A_t(y_t - \mu_t)|\, A_t \quad is\ a \quad F_{t-1} - measurable\ \ p \times r\ \ matrix\,\}$$

is considered, the standard quasi-score estimating function in the space forms

$$G_T^*(\theta) = \sum_{i=1}^{T} E_{t-1}(\dot{m}_t)(E_{t-1}(m_t m_t^{'}))^{-1} m_t, \tag{4}$$

where $\dot{m}_t = \frac{\partial m_t}{\partial \theta}$ and "'" denotes transpose. The solution of $G_T^*(\theta) = 0$ is the quasi-likelihood estimator of θ. For a special scenario, considering sub estimating function spaces of G_T, for example,

$$G_T^{(t)} = \{A_t(y_t - \mu_t)|\, A_t\ \ is\ a \quad F_{t-1} - measurable\ \ p \times r\ \ matrix\,\} \subset G_T, t < T,$$

then, the standard quasi-score estimating function in this space is

$$G_{(t)}^*(\theta) = E_{t-1}(\dot{m}_t)(E_{t-1}(m_t m_t^{'}))^{-1} m_t \tag{5}$$

and $G_{(t)}^*(\theta) = 0$ will give the quasi-likelihood estimator based on the information provided by $G_T^{(t)}$.

2.2 Parameter estimation of SVM using the QL method:

This subsection discuss about how to use the QL approach to estimate parameters in SVM without borrowing the transition matrix introduced in the standard Kalman filter method. Consider the following stochastic volatility model,

$y_t = f(\alpha_t, \theta) + \varepsilon_t, t = 1,2 \cdots, T,$ (6)
$\alpha_t = h(\alpha_{t-1}, \theta) + \eta_t, t = 1,2 \cdots, T,$ (7)
where $\{y_t\}$ represents the time series of observations, $\{\alpha_t\}$ represents the state variables and θ represents the unknown parameter taking value in an open subset Θ of p-dimensional Euclidean space. Both f and h are the functions that satisfy certain regularity conditions, and the error terms ε_t and η_t are independent. Denote $\delta_t = (\varepsilon_t, \eta_t)'$. Then δ_t is a martingale difference with

$$E_{t-1}(\delta_t) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

and

$$Var_{t-1}(\delta_t) = \begin{pmatrix} \sigma_\varepsilon^2 & 0 \\ 0 & \sigma_\eta^2 \end{pmatrix}$$

Traditionally, normality or conditional normality condition is assumed and the estimation of parameters are obtained by the ML approach. However, in many applications, the normality assumption is not realistic. Further, the probability structure of the model may not be known. Thus, the maximum likelihood method is not applicable or otherwise it is too complex to estimate the parameters through ML method as the calculation involved is complex sometimes. The QL approach for estimating the parameters in SVM is introduced in the following section. This approach can be carried out without a full knowledge of the system probability structure. It involves decision making about the initial values of θ and iterative procedure. Each iterative procedure consists of two steps. The first step is to use the QL method to obtain the optimal estimation for each α_t, say $\hat{\alpha}_t$. The second step is to combine the information of $\{y_t\}$ and $\{\hat{\alpha}_t\}$ to adjust the estimate of θ through the QL method.

In Step 1, assign an initial value to θ and consider the following martingale difference

$$\delta_t = \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} = \begin{pmatrix} y_t - E(y_t|F_{t-1}) \\ \alpha_t - E(\alpha_t|F_{t-1}) \end{pmatrix}$$

and estimating function space

$$G_T^{(t)} = \{A_t\delta_t | \, A_t \;\; is \quad F_{t-1} \;\; measurable\, \},$$

where α_t is considered as an unknown parameter. As mentioned in the equation (5), a standardized optimal estimating function in this estimating function space is given below.

$$G_{(t)}^*(\alpha_t) = E_{t-1}(\frac{\partial \delta_t}{\partial \alpha_t})[Var_{t-1}(\delta_t)]^{-1}\delta_t.$$

To obtain the QL estimate $\hat{\alpha}_t$ of α_t, lets assume $G_{(t)}^*(\alpha_t) = 0$ and the equation for α_t is solved. This estimation is the same as given by Kalman filter approach when the underlying system has a normal probability structure. (Refer Lin, (2007) for further reading).

In Step 2, θ is considered as an unknown parameter and the estimating function space is considered as follows

$$G_T = \{\sum_{t=1}^{T} A_t\delta_t | \, A_t \;\; is \quad F_{t-1} \;\; measurable\, \}$$

Then the standardized optimal estimating function in this estimating function space is as follows

$$G_T^*(\theta) = \sum_{t=1}^{T} E_{t-1}(\frac{\partial \delta_t}{\partial \theta})[Var_{t-1}(\delta_t)]^{-1}\delta_t$$

To obtain the QL estimate $\hat{\theta}$ for θ, lets assume $G_T^*(\theta) = 0$ and the equation is solved while replacing α_t by $\hat{\alpha}_t$ obtained from Step 1. The $\hat{\theta}$ obtained from Step 2 will be used as a new initial value for the θ in Step 1 in the next iterative procedure. The above mentioned two steps are alternatively repeated till certain criterion is met.

When σ_ε^2 and σ_η^2 are unknown, a procedure for estimating σ_ε^2 and σ_η^2 is conducted. In Step 1, initial value for σ_ε^2 and σ_η^2 need to be provided. By the end of Step 2, the estimations of σ_ε^2 and σ_η^2 will be completed which will be the new initial value for σ_ε^2 and σ_η^2 respectively in the next step. For details, see the simulation studies in the upcoming section. Simulation studies on this approach is presented below based on the basic Stochastic Volatility Model (SVM).

3. Simulation study:

For the simulation example, we considered the stochastic volatility process defined by the following equations

$y_t = \sigma_t \xi_t = e^{\alpha_t/2} \xi_t, t = 1,2,\cdots,T,$ (8)
and
$\alpha_t = \gamma + \phi\alpha_{t-1} + \eta_t, t = 1,2,\cdots,T,$ (9)
where both ξ_t and η_t i.i.d respectively; η_t has mean 0 and variance σ_η^2. A key feature of the SVM (8) is that it can be transformed into a linear model by taking the logarithm of the square of observations

$$\ln(y_t^2) = \alpha_t + \ln{\xi_t}^2, t = 1,2,\cdots,T. \tag{10}$$

If ξ_t were standard normal, then the values are $E(\ln\xi_t^2) = -1.2704$ and $Var(\ln\xi_t^2) = \pi^2/2$ respectively (see Abramowitz and Stegun (1970), p943). Lets take $\varepsilon_t = \ln\xi^2 + 1.2704$. The disturbance ε_t is defined so as to have zero mean. But, if ξ_t was not standard normal, then $E(\ln\xi_t^2) = \mu$ and $Var(\ln\xi_t^2) = \sigma_\varepsilon^2$. So lets take $\varepsilon_t = \ln\xi^2 - \mu$. Based on this situation, the following martingale difference is cosidered

$$\begin{pmatrix}\varepsilon_t \\ \eta_t\end{pmatrix} = \begin{pmatrix}\ln(y_t^2) - \alpha_t - \mu \\ \alpha_t - \gamma - \phi\alpha_{t-1}\end{pmatrix}.$$

In Step 1, let α_t act as an unknown parameter. The standard quasi-score estimating function determined by the estimating function space

$$G = \{A_t \begin{pmatrix}\varepsilon_t \\ \eta_t\end{pmatrix} | \ A_t \ is \ \ F_{t-1} \ measurable \ \}$$

is

$$G_{(t)}(\alpha_t) = (-1,1)\begin{pmatrix}\sigma_\varepsilon^2 & 0 \\ 0 & \sigma_\eta^2\end{pmatrix}^{-1}\begin{pmatrix}\ln(y_t^2) - \alpha_t - \mu \\ \alpha_t - \gamma - \phi\alpha_{t-1}\end{pmatrix}$$
$$= \sigma_\varepsilon^{-2}(\ln(y_t^2) - \alpha_t - \mu) + \sigma_\eta^{-2}(\alpha_t - \gamma - \phi\alpha_{t-1}). \tag{11}$$

Let $\hat{\alpha}_0 = 0$ and initial values are $\psi_0 = (\gamma_0, \phi_0, \sigma_{\eta_0}^2, \mu_0, \sigma_{\varepsilon_0}^2)$. Given that $\hat{\alpha}_{t-1}$ is the optimal estimation of α_{t-1}, the quasi-likelihood estimation of α_t, i.e. the optimal estimation of α_t will be given when solving $G_{(t)}(\alpha_t) = 0$, i.e.

$$\hat{\alpha}_t = \frac{\sigma_{\eta_0}^2(\ln(y_t^2)-\mu)+\sigma_{\varepsilon_0}^2(\phi\hat{\alpha}_{t-1}+\gamma)}{\sigma_{\eta_0}^2+\sigma_{\varepsilon_0}^2}, t = 1,2,\cdots,T. \tag{12}$$

In Step 2, based on $\{\hat{\alpha}_t\}$ and $\{y_t\}$, let γ, μ and ϕ act as unknown parameters, and QL approach is used to estimate them. The standard quasi-score estimating function related to the estimating function space

$$G = \{\sum_{t=1}^{T} A_t \begin{pmatrix}\varepsilon_t \\ \eta_t\end{pmatrix} | \ A_t \ is \ \ F_{t-1} \ measurable \}$$

is

$$G_T(\mu,\gamma,\phi) = \sum_{t=1}^{T}\begin{pmatrix}-1 & 0 \\ 0 & -1 \\ 0 & -\alpha_{t-1}\end{pmatrix}\begin{pmatrix}\sigma_{\varepsilon_0}^2 & 0 \\ 0 & \sigma_{\eta_0}^2\end{pmatrix}^{-1}\begin{pmatrix}\ln(y_t^2) - \alpha_t - \mu \\ \alpha_t - \gamma - \phi\alpha_{t-1}\end{pmatrix}.$$

When α_t is replaced by $\hat{\alpha}_t$, $t = 1,2,\cdots,T$, the QL estimate of μ, γ and ϕ is provided by solving $G_T(\mu,\gamma,\phi) = 0$. Therefore

$$\hat{\mu} = \frac{\sum_{t=1}^{T}\ln(y_t^2) - \sum_{t=1}^{T}\hat{\alpha}_t}{T}, t = 1,2,\cdots,T. \tag{13}$$

$$\hat{\phi} = \frac{\sum_{t=1}^{T}\hat{\alpha}_t\sum_{t=1}^{T}\hat{\alpha}_{t-1} - T\sum_{t=1}^{T}\hat{\alpha}_{t-1}\hat{\alpha}_t}{(\sum_{t=1}^{T}\hat{\alpha}_{t-1})^2 - T\sum_{t=1}^{T}\hat{\alpha}_{t-1}^2}, t = 1,2,\cdots,T, \tag{14}$$

$$\hat{\gamma} = \frac{\sum_{t=1}^{T}\hat{\alpha}_t - \hat{\phi}\sum_{t=1}^{T}\hat{\alpha}_{t-1}}{T}, t = 1,2,\cdots,T. \tag{15}$$

and let

$$\hat{\sigma}_{\eta}^{2} = \frac{\sum_{t=1}^{T}(\hat{\eta}_t - \bar{\hat{\eta}})^2}{T-1} \quad (16)$$

$$\hat{\sigma}_{\varepsilon}^{2} = \frac{\sum_{t=1}^{T}(\hat{\varepsilon}_t - \bar{\hat{\varepsilon}})^2}{T-1} \quad (17)$$

where $\hat{\varepsilon}_t = \ln(y_t^2) - \hat{\alpha}_t - \hat{\mu}$, and $\hat{\eta}_t = \hat{\alpha}_t - \hat{\gamma} - \hat{\phi}\hat{\alpha}_{t-1}, t = 1,2,\cdots,T$. The above two steps are iteratively repeated till certain criterion is met. As mentioned earlier, $\hat{\psi} = (\hat{\mu}, \hat{\gamma}, \hat{\phi}, \hat{\sigma}_{\eta}^2, \hat{\sigma}_{\varepsilon}^2)$ will be used as an initial value for next step in the iterative procedure.

The final estimation results for SVM might be jointly affected by the initial values α_0 and ψ_0, which was initially assigned to the underlying model during inference procedure. Refer Alzghool and Lin (2011) for extensive discussion on a standard approach for assigning initial values in the Quasi-Likelihood (QL) estimation procedures.

The format for this simulation study is the same as the layout considered by Rodriguez-Yam(2003). From empirical studies (e.g Harvey and Shepard, 1993; Jacquire et, al., (1994)), the value of ϕ which is between 0.9 and 0.98 are of primary interest. For this simulation study, we considered a sample size of T=1000 and computed RMSE for $\hat{\phi}$,$\hat{\gamma}$,$\hat{\sigma}_{\eta}^2$, $\hat{\mu}$ and $\hat{\sigma}_{\varepsilon}^2$ based on (N=1000) independent samples. The results are shown in Table 1. QL denotes the Quasi-Likelihood estimate.

Table 1: QL estimates based on 1000 replication. Root Mean Square Error of estimates are reported below for each estimate

	γ	ϕ	σ_η	μ	σ_ε	γ	ϕ	σ_η	μ	σ_ε
true	-0.821	0.90	0.675	-1.271	2.22	-0.411	0.95	0.484	-1.271	2.22
QL	-0.809	0.901	0.344	-1.366	2.15	-0.450	0.947	0.334	-1.048	2.094
	0.108	0.013	0.331	0.157	0.123	0.089	0.010	0.151	0.239	0.164
true	-0.736	0.90	0.363	-1.271	2.22	-0.368	0.95	0.260	-1.271	2.22
QL	-0.889	0.881	0.321	-1.199	2.02	-0.511	0.931	0.318	-1.185	2.01
	0.176	0.022	0.046	0.099	0.23	0.159	0.021	0.061	0.098	0.23
true	-0.706	0.90	0.135	-1.271	2.22	-0.353	0.95	0.096	-1.271	2.22
QL	-0.695	0.905	0.040	-1.043	2.21	-0.364	0.946	0.070	-1.660	2.17
	0.017	0.006	0.095	0.247	0.12	0.019	0.006	0.026	0.404	0.13
true	-0.147	0.98	0.166	-1.271	2.22	-0.141	0.98	0.061	-1.271	2.22
QL	-0.169	0.977	0.072	-1.327	2.23	-0.140	0.979	0.018	-1.705	2.22
	0.027	0.004	0.094	0.155	0.12	0.003	0.001	0.043	0.450	0.12

Table 2: QL estimates based on 1000 replication. Root Mean Square Error of estimates are reported below for each estimate

		γ	ϕ	σ_η	μ	σ_ε
	true	-0.141	0.98	0.061	-1.271	2.22
T=20	QL	-0.1405	0.978	0.017	-2.428	2.16
		0.0041	0.005	0.044	1.258	0.567
T=50	QL	-0.1405	0.978	0.017	-2.179	2.19
		0.0036	0.002	0.044	0.961	0.367
T=100	QL	-0.141	0.979	0.018	-1.98	2.22
		0.0035	0.0015	0.043	0.750	0.251
T=200	QL	-0.1402	0.979	0.018	-1.809	2.22
		0.0034	0.0012	0.043	0.567	0.182
T=500	QL	-0.140	0.979	0.018	-1.705	2.22
		0.003	0.001	0.043	0.450	0.12

The effect of the sample size on the estimation of parameters is considered. Samples of sizes n = 20, 50, 100, 200, and 500 were generated. In Table 2, the simulation results also indicated that larger the sample size is, smaller the Root Mean Squared Error will be.

4. Application to SVM:

The estimation procedure described in previous section is applied to a real case where the observations are assumed to satisfy SVM ((8) and (9)) (Davis and Rodriguez-Yam (2005); Rodriguez-Yam (2003); Durbin and

Koopman (2001)). The data to be studied is pound/dollar of the daily observations of weekdays closing pound-to-dollar exchange rates $x_t, t = 1, \cdots, 945$ from 1/10/81 to 28/6/85 (Davis and Rodriguez-Yam, 2005; Rodriguez-Yam, 2003; Durbin and Koopman, 2001). x_t appear not be stationary as indicated in Fig. 4.1.)

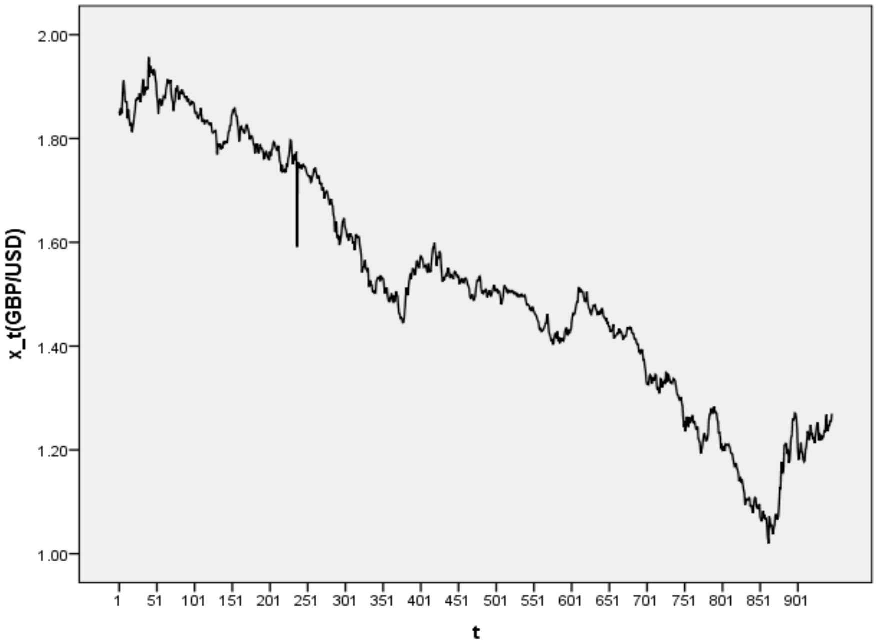

Fig. 4.1: The plot of the daily exchange rates of $x_t = GBP/USD$ (UK Pound / US Dollar).

In the literature, SVM (8) and (9) are used to model $y_t = log(x_t) - log(x_{t-1})$. The series of y_t is presented in Fig. 4.2. Then, the set of parameter is $\psi = (\mu, \gamma, \phi, \sigma_\eta^2, \sigma_\varepsilon^2)$.

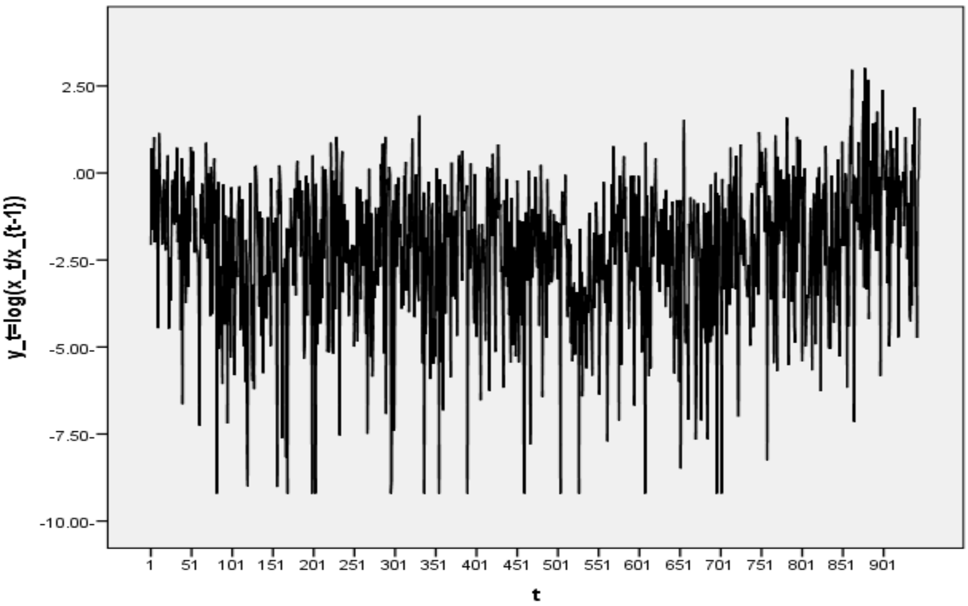

Fig. 4.2: The plot of $y_t = log(x_t/x_{t-1})$

The Table 3 shows the estimates of ψ obtains by various methods in which 'QL' denotes the estimate obtained by Quasi-Likelihood approach. 'AL' is the estimate obtained by maximizing the Approximate Likelihood proposed by Davis and Rodriguez-Yam (2003) and MCL is the estimate obtained by Maximizing the estimate of the Likelihood proposed by Durbin and Koopman (1997). It is to be noted that AL and MCL outputs are taken from Rodriguez-Yam (2003). The QL estimations are slightly different from the estimation of AL and

MCL.

Table 3: Estimation of γ, ϕ, σ_η, μ and σ_ε^2 for Pound/Dollar exchange rate data.

	γ	ϕ	σ_η	μ	σ_ε
QL	-0.0250	0.974	0.0210	-1.27	2.140
AL	-0.0227	0.957	0.0267		
MCL	-0.0227	0.975	0.0273		

The estimation of of γ, ϕ, σ_η, μ and σ_ε^2 by QL, AL and MCL are close to each other. These three methods are carried out under the same assumption i.e., both ξ_t and η_t are independent. This indicates that the performance of QL, AL, and MCL are similar. However, QL relaxes the distribution assumptions and only assume knowledge of the first two conditional moments.

Conclusion:

This paper shows an alternative approach to estimate the parameters in SVMs. Instead of using traditional 'kalman filter formulae' to estimate the state variables, this approach used the QL method to estimate the state variables. From the results, it is inferred that the whole estimation processes looks very straightforward and can be easily implemented. During the instance, when the probability structure of underlying systems is complex or unknown and when maximum likelihood or mixture of maximum likelihood could not be easily implemented, then the approach proposed in this paper can be considered for estimating parameters in SVMs. The results from the simulation study indicate that the QL method is an efficient estimation procedure. Application of the QL method to weekdays closing pound-to-dollar exchange rates modeled by SVM model is considered. The real data case shows that the QL method can be used to obtain a reasonable estimation for unknown parameters in the SVM.

Further research will focus on the consistency of parameter estimation and the limit distributions of parameter estimations.

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