

# QML Estimation

$$y_t = \mu + \epsilon_t$$

$$\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2 \exp(h_t))$$

$$h_{t+1} = \mu + \phi(h_t - \mu) + \xi_t$$

$$\text{where } \xi_t \sim \mathcal{N}(0, \sigma_\xi^2)$$

In [365...

```
import numpy as np
import pandas as pd
import random as rd
import math
import scipy as sp
import matplotlib.pyplot as plt
```

## i) Simulate the Model

In [366...

```
from SV_Functions import sv_simul, sv_simul_v2
from scipy.optimize import minimize
```

# QML Estimation (Francq, Zakoian)

## canonical SV Model

$$\epsilon_t = \sqrt{h_t} \eta_t$$

$$\log(h_t) = \omega + \beta \log(h_{t-1}) + \sigma v_t$$

$$\eta_t \sim \mathcal{N}(0, 1)$$

$$v_t \sim \mathcal{N}(0, 1)$$

## State-space model

$$\log(\epsilon_t^2) = \log(h_t) + \mu_Z + u_t$$

$$\log(h_t) = \beta \log(h_{t-1}) + \omega + \sigma v_t$$

In [367...

```
def sv_simul_can(theta, log_h0):
    omega = theta[0]
    alpha = theta[1]
    sigma = theta[2]
    eta = np.random.normal(0, 1, T)
    v = np.random.normal(0, 1, T)
    epsilon_t = np.empty(0)
    log_h = np.empty(0)

    log_h = np.append(log_h, omega + beta * log_h0 + sigma * v[0])
    epsilon_t = np.append(epsilon_t, np.sqrt(np.exp(log_h[0])) * eta[0])

    for t in range(1, T):
        log_h = np.append(log_h, omega + beta * log_h[t-1] + sigma * v[t])
```

```
ε_t = np.append(ε_t, np.sqrt(np.exp(log_h[t])) * η[t])
```

```
return ε_t, log_h
```

In [368...

```
# Inputs
ω = 1e-3
β = 0.9
σ = 0.8
θ = ω, β, σ
log_h0 = ω
T = 500
```

In [369...

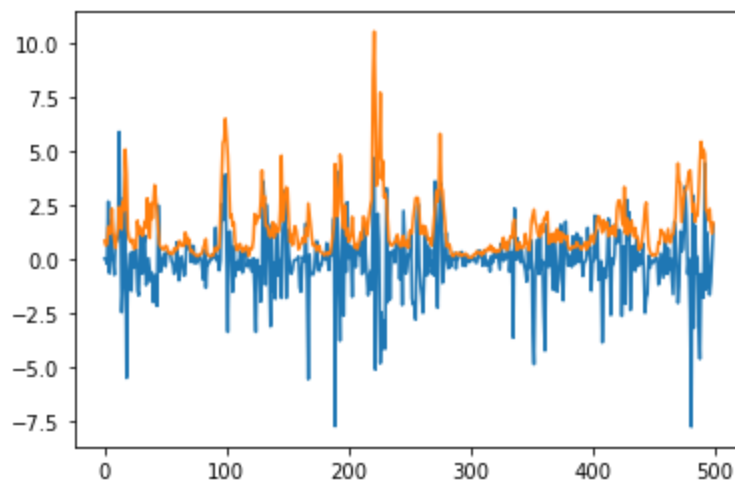
```
data = sv_simul_can(θ, log_h0)
ε_t = data[0]
log_h = data[1]
```

In [370...

```
plt.plot(range(T), ε_t)
plt.plot(range(T), np.sqrt(np.exp(log_h)))
```

Out[370...

[<matplotlib.lines.Line2D at 0x19d68c80a00>]



In [371...

```
def obj_sv(θ, ε_t):
    α_t = np.empty(0)
    P_t = np.empty(0)
    F_t = np.empty(0)
    K_t = np.empty(0)
    ω = θ[0]
    β = θ[1]
    σ = θ[2]
    μ_Z = -1.270
    σ_Z = np.pi**2 / 2
    a0 = 0
    β0 = 0.8
```

```

P0 =  $\sigma^2$ 
F0 = P0 +  $\sigma_Z^2$ 
T = len( $\epsilon_t$ )
y_t = np.log(np.square( $\epsilon_t$ ))

 $\alpha_t$  = np.append( $\alpha_t$ ,  $\beta_0 * a_0 + \omega$ )
P_t = np.append(P_t,  $\sigma^2$ )
K_t = np.append(K_t,  $\beta * P_0 * 1/F_0$ )

for t in range(1,T):
    F_t = np.append(F_t, P_t[t-1] +  $\sigma_Z^2$ )
    K_t = np.append(K_t,  $\beta * P_t[t-1] * 1/F_t[t-1]$ )
     $\alpha_t$  = np.append( $\alpha_t$ ,  $\beta * \alpha_t[t-1] + K_t[t] * (y_t[t-1] - \alpha_t[t-1] - \mu_Z) + \omega$ )
    P_t = np.append(P_t,  $\beta^2 * P_t[t-1] - K_t[t]^2 * F_t[t-1] + \sigma^2$ )
    F_t = np.append(F_t, P_t[T-1] +  $\sigma_Z^2$ )

    qml = -T/2 * np.log(2*np.pi) - 1/2 * np.sum(np.log(F_t) +
np.square((np.log(np.square( $\epsilon_t$ )) -  $\alpha_t$  -  $\mu_Z$ )) / F_t)
    return -qml

```

In [372...

```

def estim_sv( $\theta_0$ ,  $\epsilon_t$ ):
    valinit =  $\theta_0$ 
    res = minimize(obj_sv, valinit, args=( $\epsilon_t$ ), bounds=((1e-5, math.inf), (0,
0.99), (0, math.inf)))
     $\theta_{\text{hat}}$  = res.x
    likeli = res.fun
    return  $\theta_{\text{hat}}$ , likeli

```

In [373...

```

 $\omega_0$  = 1e-3
 $\beta_0$  = 0.85
 $\sigma_0$  = 0.9
 $\theta_0$  =  $\omega_0$ ,  $\beta_0$ ,  $\sigma_0$ 

```

In [374...

```

estimation = estim_sv( $\theta_0$ ,  $\epsilon_t$ )
 $\theta_{\text{hat}}$  = estimation[0]
 $\theta_{\text{hat}}$ 

```

Out[374...

```
array([1.e-05, 0.e+00, 0.e+00])
```

## SV Model Estimation - Monte Carlo

In [375...

```
M = 2000
```

```

In [376... ω_spread = np.empty(0)
β_spread = np.empty(0)
σ_spread = np.empty(0)
for j in range(M):
    results = garch_simul(θ, T)
    ε_t = results[0]
    estimation = estim_garch(θ0, ε_t)
    θ_hat = estimation[0]
    ω_hat = θ_hat[0]
    β_hat = θ_hat[1]
    σ_hat = θ_hat[2]
    ω_spread = np.append(ω_spread, ω_hat - ω)
    β_spread = np.append(β_spread, β_hat - β)
    σ_spread = np.append(σ_spread, σ_hat - σ)

```

```

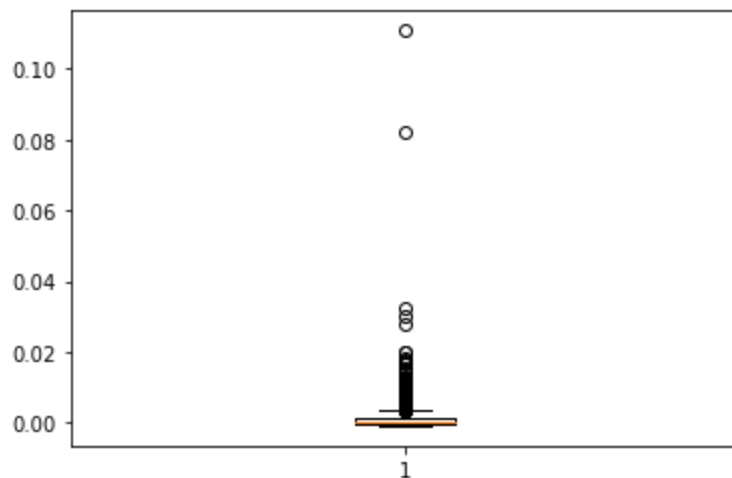
In [377... plt.boxplot(ω_spread)
np.seterr(divide = 'ignore')

```

```

Out[377... {'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}

```



```

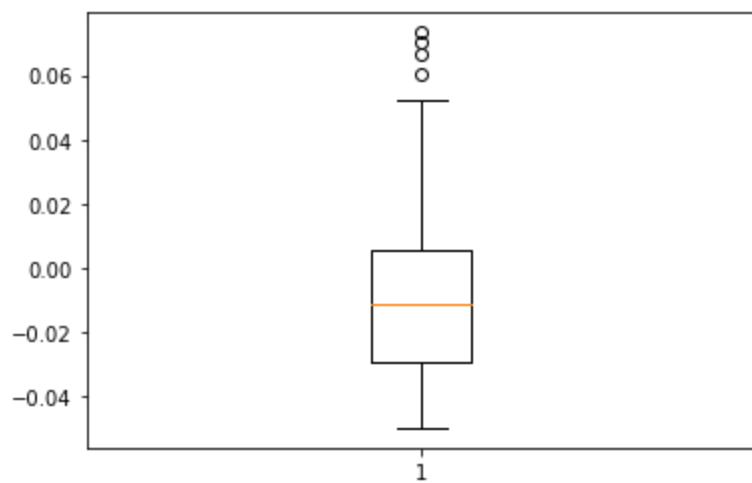
In [378... plt.boxplot(α_spread)
np.seterr(divide = 'ignore')

```

```

Out[378... {'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}

```

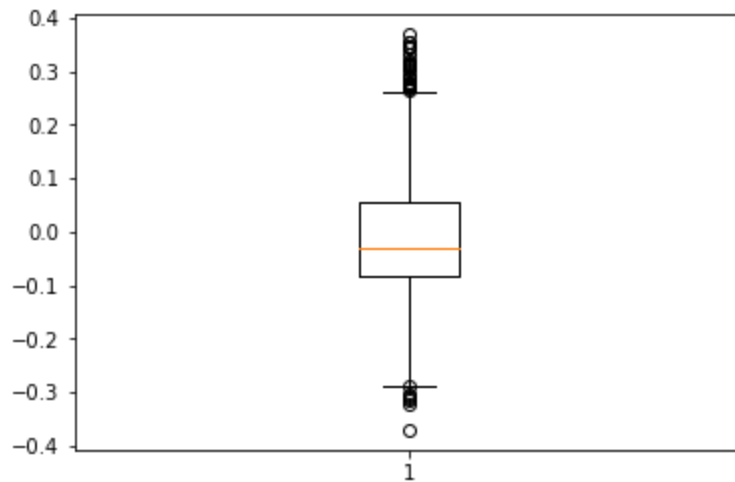


In [379]...

```
plt.boxplot( $\beta\_spread$ )
np.seterr(divide = 'ignore')
```

Out[379]...

```
{'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}
```



## Estimate GARCH Models

In [74]:

```
def garch_simul( $\theta$ , T):
     $\eta$  = np.random.normal(0, 1, T)
     $\epsilon\_t$  = np.empty(0)
     $\sigma^2$  = np.empty(0)
     $\omega$  =  $\theta[0]$ 
     $\alpha$  =  $\theta[1]$ 
     $\beta$  =  $\theta[2]$ 

     $\epsilon\_t$  = np.append( $\epsilon\_t$ , np.sqrt( $\omega$ ) *  $\eta[0]$ )
     $\sigma^2$  = np.append( $\sigma^2$ ,  $\omega$ )

    for t in range(1, T):
         $\sigma^2$  = np.append( $\sigma^2$ ,  $\omega$  +  $\alpha$  *  $\epsilon\_t[t-1]**2$  +  $\beta$  *  $\sigma^2[t-1]$ )
         $\epsilon\_t$  = np.append( $\epsilon\_t$ , np.sqrt( $\sigma^2[t]$ ) *  $\eta[t]$ )
```

```
return  $\epsilon_t$ ,  $\sigma^2$ 
```

In [75]:

```
def obj_garch( $\theta$ ,  $\epsilon_t$ ):  
     $\omega$  =  $\theta[0]$   
     $\alpha$  =  $\theta[1]$   
     $\beta$  =  $\theta[2]$   
    T = len( $\epsilon_t$ )  
     $\sigma^2$  = np.empty(0)  
  
     $\sigma^2$  = np.append( $\sigma^2$ ,  $\omega$ )  
    for t in range(1,T):  
         $\sigma^2$  = np.append( $\sigma^2$ ,  $\omega$  +  $\alpha * \epsilon_t[t-1]**2$  +  $\beta * \sigma^2[t-1]$ )  
    qml = np.mean(np.log( $\sigma^2[1:T]$ ) + np.square( $\epsilon_t[1:T]$ ) /  $\sigma^2[1:T]$ )  
    return qml
```

In [76]:

```
def estim_garch( $\theta$ ,  $\epsilon_t$ ):  
    valinit =  $\theta$   
    res = minimize(obj_garch, valinit, args=( $\epsilon_t$ ), bounds=((1e-4, math.inf),  
    (0, math.inf), (0, 0.999)))  
     $\theta_{\text{hat}}$  = res.x  
    likeli = res.fun  
    return  $\theta_{\text{hat}}$ , likeli
```

In [77]:

```
 $\omega$  = 1e-3  
 $\alpha$  = 0.05  
 $\beta$  = 0.9  
 $\theta$  =  $\omega$ ,  $\alpha$ ,  $\beta$ 
```

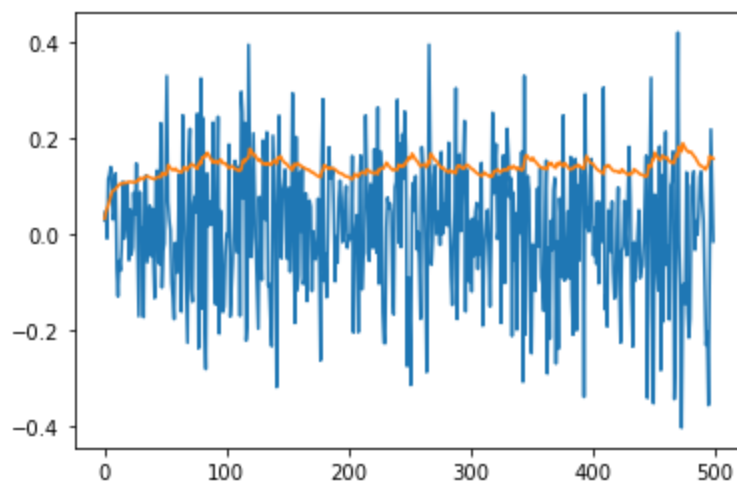
In [78]:

```
results = garch_simul( $\theta$ , T)  
 $\epsilon_t$  = results[0]  
 $\sigma^2$  = results[1]
```

In [79]:

```
plt.plot(range(T),  $\epsilon_t$ )  
plt.plot(range(T), np.sqrt( $\sigma^2$ ))
```

Out[79]: [`matplotlib.lines.Line2D` at 0x19d62fb5280>]



```
In [80]:
 $\omega_0$  = 1e-3
 $\alpha_0$  = 0.1
 $\beta_0$  = 0.8
 $\theta_0$  =  $\omega_0$ ,  $\alpha_0$ ,  $\beta_0$ 
```

```
In [81]:
estimation = estim_garch( $\theta_0$ ,  $\epsilon_t$ )
 $\theta_{\text{hat}}$  = estimation[0]
 $\theta_{\text{hat}}$  -  $\theta$ 
```

```
Out[81]: array([ 0.00146761,  0.03494167, -0.10814077])
```

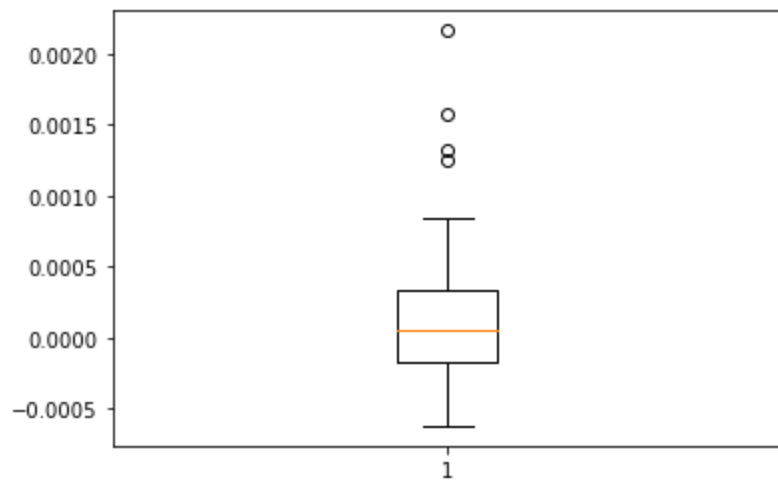
## GARCH Monte Carlo Experiment

```
In [82]:
M = 100
```

```
In [83]:
 $\omega_{\text{spread}}$  = np.empty(0)
 $\alpha_{\text{spread}}$  = np.empty(0)
 $\beta_{\text{spread}}$  = np.empty(0)
for j in range(M):
    results = garch_simul( $\theta$ , T)
     $\epsilon_t$  = results[0]
    estimation = estim_garch( $\theta_0$ ,  $\epsilon_t$ )
     $\theta_{\text{hat}}$  = estimation[0]
     $\omega_{\text{hat}}$  =  $\theta_{\text{hat}}$ [0]
     $\alpha_{\text{hat}}$  =  $\theta_{\text{hat}}$ [1]
     $\beta_{\text{hat}}$  =  $\theta_{\text{hat}}$ [2]
     $\omega_{\text{spread}}$  = np.append( $\omega_{\text{spread}}$ ,  $\omega_{\text{hat}}$  -  $\omega$ )
     $\alpha_{\text{spread}}$  = np.append( $\alpha_{\text{spread}}$ ,  $\alpha_{\text{hat}}$  -  $\alpha$ )
     $\beta_{\text{spread}}$  = np.append( $\beta_{\text{spread}}$ ,  $\beta_{\text{hat}}$  -  $\beta$ )
```

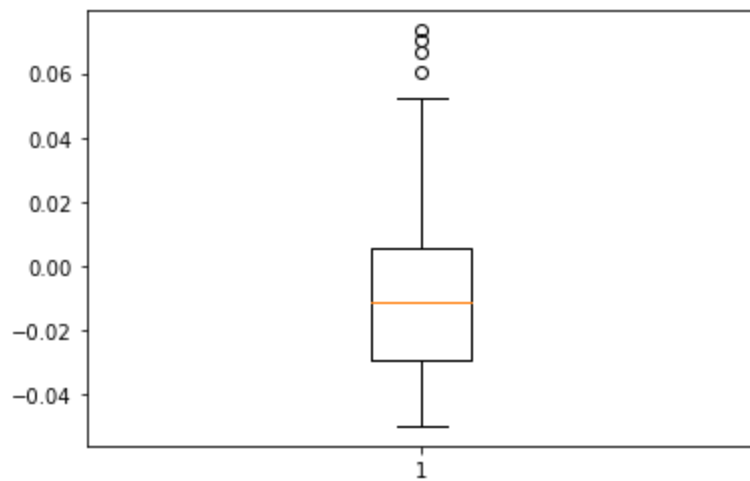
```
In [84]:
plt.boxplot( $\omega_{\text{spread}}$ )
np.seterr(divide = 'ignore')
```

Out[84]: {'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}



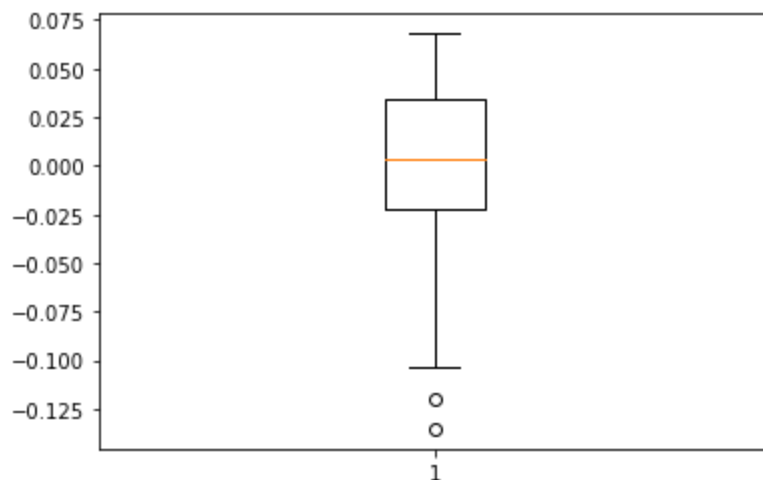
```
In [85]: plt.boxplot( $\alpha_{\text{spread}}$ )  
np.seterr(divide = 'ignore')
```

Out[85]: {'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}



```
In [86]: plt.boxplot( $\beta_{\text{spread}}$ )  
np.seterr(divide = 'ignore')
```

Out[86]: {'divide': 'ignore', 'over': 'warn', 'under': 'ignore', 'invalid': 'warn'}



In [ ]:



