

## **Submission Number:EB-17-00495**

Appendices: Comparison of the GBM and VG process densities, and ADF test and autocorrelation function.

## A The geometric Brownian motion process

In this section, we sketch the main characteristics of the GBM process. Let  $\{P_t\}_{t \geq 0}$  be an asset price at time  $t$ . The GBM is defined as:

$$dP_t = \mu P_t dt + \sigma P_t W_t, \quad (5)$$

where  $P_0 > 0$ . In equation (5),  $\mu \in \mathbb{R}$  is the drift parameter, and  $\sigma > 0$  measures volatility. Additionally,  $W_t$  is the standard increment of a Wiener process.

Now, define  $y_t = \ln(P_t)$ . Applying Ito's lemma and using equation (5), we get:

$$dy_t = \left( \mu - \frac{1}{2}\sigma^2 \right) dt + \sigma W_t. \quad (6)$$

Equation (6) implies that  $y_t$  follows an arithmetic Brownian process with drift equal to  $(\mu - \frac{1}{2}\sigma^2)$  and volatility  $\sigma$ . By choosing a discrete time interval  $\Delta t = t - q$  with  $q < t$ , and letting  $X_t = y_t - y_q$  be the log price increments (continuously compounded returns) over a time period of  $\Delta t$ , we can derive a discrete-time version of equation (6). This is:

$$X_t = \left( \mu - \frac{1}{2}\sigma^2 \right) \Delta t + (W_t - W_q)\sigma. \quad (7)$$

The properties of the standard Brownian motion let us rewrite equation (7) as<sup>7</sup>

$$X_t = \left( \mu - \frac{1}{2}\sigma^2 \right) \Delta t + \sigma \varepsilon \sqrt{\Delta t}, \quad \varepsilon \sim \mathcal{N}(0, 1).$$

Then, it is easy to conclude that

$$X_t \sim \mathcal{N} \left( \left[ \mu - \frac{1}{2}\sigma^2 \right] \Delta t, \Delta t \sigma \right), \quad (8)$$

which implies that both the mean and volatility of  $X_t$  increase proportionally to the length of time over which the asset is held.

The parameters of a GBM process can easily be found by maximum likelihood estimation. By fixing  $\Delta t = 1$ , and taking into account that the log returns follow a normal distribution, we can compute the sample mean and variance as

$$\bar{x} = \frac{1}{n} \sum_{t=1}^T x_t, \quad s^2 = \frac{1}{n-1} \sum_{t=1}^T (x_t - \bar{x})^2.$$

Hence, from equation (8),

$$\hat{\sigma}^2 = s^2, \quad \hat{\mu} = \bar{x} + \frac{s^2}{2}. \quad (9)$$

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<sup>7</sup>See Venegas-Martínez (2006), for instance.

## B Comparison of the GBM and VG process densities

We show in Figure 3 how GBM and VG process densities compare to empirical density function. As we can see, none of the distributions adjust well the peak of the empirical distribution, but the variance-gamma density function is closer to the empirical mean value. It is also true that the variance-gamma distribution adjusts better in both tails compared to normal distribution. This is also evident from the log-density function in Figure 3.

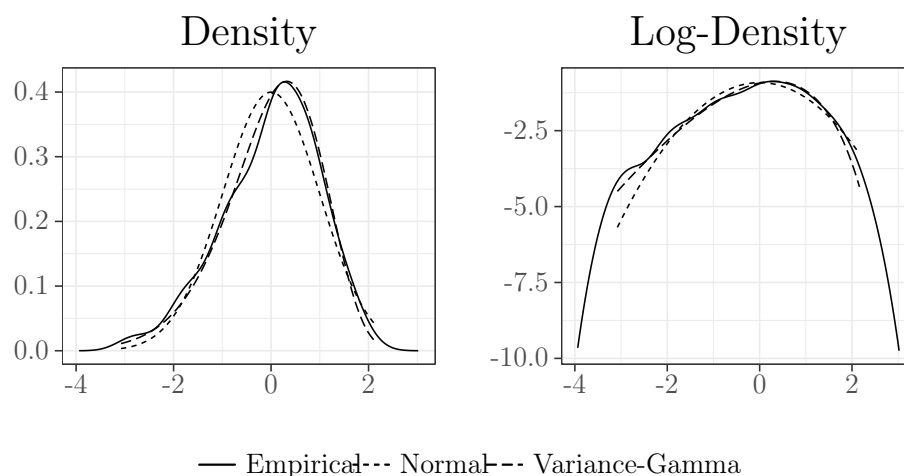


Figure 3: Empirical density function of fuel energy index log returns compared to estimated densities.

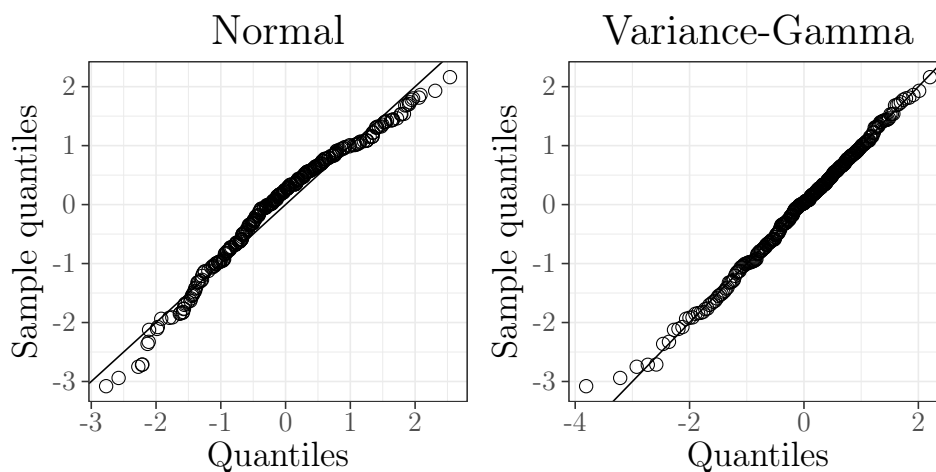


Figure 4: QQ-Plots, normal and variance-gamma distributions.

We can also see the performance of both processes by looking at the qq-plots in Figure 4. Again, it is clear that the variance-gamma distribution shows a better fit to data. This is particularly true for higher quantiles.

### C Augmented Dickey-Fuller Test and Autocorrelation Functions

We show in Table IV that the IMF's fuel energy index is stationary as the hypothesis of unit root is always rejected.

Table IV: p-values for augmented Dickey-Fuller test for several lags.

Lag	p-values	
	<i>Actual Returns</i>	<i>Filtered Returns</i>
1	<0.01	<0.01
2	<0.01	<0.01
3	<0.01	<0.01
4	<0.01	<0.01
5	<0.01	<0.01
6	<0.01	<0.01

In Figure 5 we show the autocorrelation function for both  $X_t^2$  and  $\hat{Y}_t^2$ . We can see that the former is autocorrelated and the later is not.

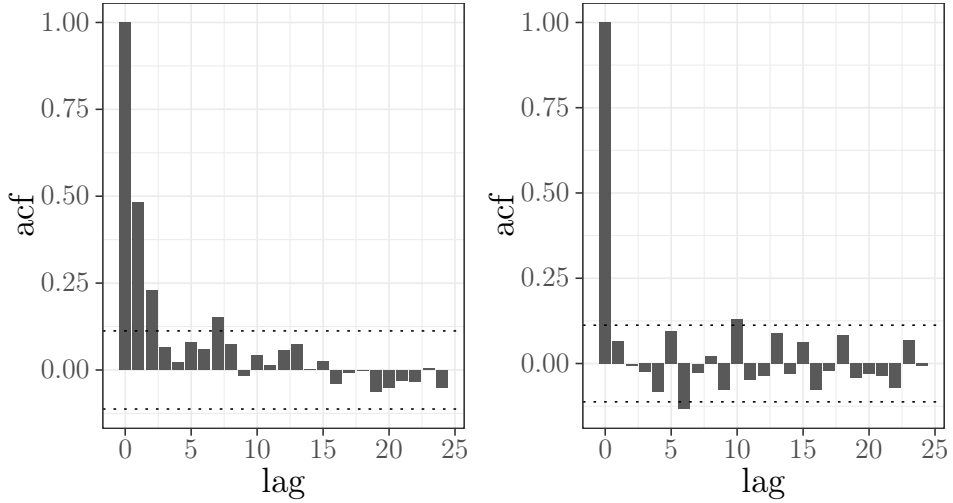


Figure 5: Autocorrelation function for the squared log-returns of actual data (left) and the squared returns of filtered data (right).