

The QGARCH(1,1) model

(updated 30th Oct 2025). The QGARCH(1,1) model is a well known discrete-time model defined as

$$\begin{aligned} R_t &= \sqrt{V_t} Z_t \\ V_t &= \omega + \alpha R_{t-1}^2 + \beta V_{t-1} + \gamma R_{t-1} \end{aligned} \quad (1)$$

for $t = 1, 2, \dots$ (e.g. days) where $R_t = (S_t - S_{t-1})/S_{t-1}$ is the t 'th **stock price return** (note $R_t \geq -1$ since $S_t \geq 0$) and $\omega, \alpha, \beta > 0$, and Z_t is a sequence of i.i.d random variables with zero mean and variance σ^2 , e.g. $N(0, 1)$ or a student t -distribution with ν degrees of freedom if we want fatter tails for which $\sigma^2 = \frac{\nu}{\nu-2}$, so we need $\nu > 2$. Since we can re-write the model as

$$V_t = V_{t-1} + (1 - \beta)(\bar{\omega} - V_{t-1}) + \alpha R_{t-1}^2 + \gamma R_{t-1} \quad (2)$$

where $\bar{\omega} = \frac{\omega}{1-\beta}$, we see that $1 - \beta$ controls the **mean reversion** speed for V , and $\bar{\omega}$ is level around which V mean reverts. α controls the extent of **volatility clustering**, i.e. past large volatility giving rise to large future volatility and vice versa, and γ is a **skew term** which captures that squared volatility V_t tends to increase if $R_{t-1} < 0$ since usually $\gamma < 0$ as well so $\gamma R_{t-1} > 0$ (the so-called **leverage** effect). $\gamma < 0$ also allows the model to produce negatively skewed non-symmetric implied volatility smiles for European options which are seen in practice, particularly for Index and Equity options. The original Engle&Bollerslev **GARCH** model from 1986 has $\gamma = 0$, so the model above is sometimes known as the **asymmetric GARCH** model.

If we now instead say that V_{t+1} is V_t , then we can re-write the model in the **Euler-scheme** type form

$$\begin{aligned} S_t &= S_{t-1} + S_{t-1} \sqrt{V_{t-1}} Z_t \\ V_t &= V_{t-1} + (1 - \beta)(\bar{\omega} - V_{t-1}) + \alpha R_{t-1}^2 + \gamma R_{t-1} \\ &= V_{t-1} + (1 - \beta)(\bar{\omega} - V_{t-1}) + \alpha V_{t-1} Z_{t-1}^2 + \gamma \sqrt{V_{t-1}} Z_t \end{aligned} \quad (3)$$

then we see that (S_t, V_t) is **discrete-time Markov process**, since the distribution of S_t, V_t at time $t - 1$ depends only on (S_{t-1}, V_{t-1}) and does not require any further history of these two processes (note our original V_t is now V_{t-1} here).

Taking expectations in (1), we see that

$$\mathbb{E}(V_t) = \omega + \alpha \mathbb{E}(R_{t-1}^2) + \beta \mathbb{E}(V_{t-1}) + \gamma \mathbb{E}(R_{t-1}).$$

Using the **tower property** of conditional expectations, we can further re-write this as

$$\begin{aligned} \mathbb{E}(V_t) &= \omega + \alpha \mathbb{E}(\mathbb{E}(R_{t-1}^2 | V_{t-1})) + \beta \mathbb{E}(V_{t-1}) + \gamma \mathbb{E}(\mathbb{E}(R_{t-1} | V_{t-1})) \\ &= \omega + \alpha \mathbb{E}(\sigma^2 V_{t-1}) + \beta \mathbb{E}(V_{t-1}) + 0 \end{aligned} \quad (4)$$

where we have also used that $\mathbb{E}(R_{t-1}^2 | V_{t-1}) = \mathbb{E}(V_{t-1} Z_{t-1}^2 | V_{t-1}) = V_{t-1} \mathbb{E}(Z_{t-1}^2 | V_{t-1}) = V_{t-1} \mathbb{E}(Z_{t-1}^2) = V_{t-1} \sigma^2$. For V_t to have a **stationary distribution**, i.e. for V_t to have the same distribution for all t , this clearly requires that $\mathbb{E}(V_t) = \mathbb{E}(V_{t-1})$, so we can further re-write (4) as

$$\mathbb{E}(V_t) = \omega + \alpha \sigma^2 \mathbb{E}(V_t) + \beta \mathbb{E}(V_t).$$

and

$$\mathbb{E}(R_t^2) = \mathbb{E}(\mathbb{E}(R_t^2 | V_t)) = \mathbb{E}(V_t).$$

Re-arranging, we see that

$$\bar{V} := \mathbb{E}(V_t) = \frac{\omega}{1 - \alpha \sigma^2 - \beta}.$$

Since V_t cannot be negative, we must have that $\alpha \sigma^2 + \beta < 1$, which we call the **stationarity condition**. If V starts at time zero, then

$$\begin{aligned} \mathbb{E}(V_t) &= \frac{1}{1 - \alpha \sigma^2} (\omega + \beta \mathbb{E}(V_{t-1})) \\ \Rightarrow \mathbb{E}(V_t) - \bar{V} &= \frac{1}{1 - \alpha \sigma^2} (\omega + \beta \mathbb{E}(V_{t-1})) - \bar{V} = \frac{\beta}{1 - \alpha \sigma^2} (\mathbb{E}(V_{t-1}) - \bar{V}) \end{aligned}$$

i.e. a **linear recurrence** relation of the form $r_t = \alpha r_{t-1}$, with solution $r_t = \mathbb{E}(V_t) - \bar{V} = (\frac{\beta}{1 - \alpha \sigma^2})^t (V_0 - \bar{V})$.

Moreover

$$V_t = \omega + \alpha R_{t-1}^2 + \beta V_{t-1} + \gamma R_{t-1} \geq \omega + \alpha R_{t-1}^2 + \gamma R_{t-1}$$

and (using basic calculus) the right-hand side is ≥ 0 for all R_{t-1} if $\omega \geq \frac{\gamma^2}{4\alpha}$. This is known as the **positivity condition**.

Let

$$\mathbb{E}(R_t^4) = \mathbb{E}(\mathbb{E}(R_t^4 | \mathcal{F}_{t-1})) = \mathbb{E}(V_t^2 \mathbb{E}(Z_t^4 | \mathcal{F}_{t-1})) = \mathbb{E}(Z_t^4) \mathbb{E}(V_t^2). \quad (5)$$

For $\gamma = 0$ and $\sigma = 1$, we have

$$\begin{aligned} \mathbb{E}(V_t^2) &= (3 + K_\varepsilon) \mathbb{E}(V_t^2) \alpha^2 + 2 \mathbb{E}(R_{t-1}^2 V_{t-1}) \alpha \beta + \mathbb{E}(V_t^2) \beta^2 + 2 \mathbb{E}(V_t) \alpha \omega + 2 \mathbb{E}(V_t) \beta \omega + \omega^2 \\ &= (\dots) + 2 \alpha \beta \mathbb{E}(V_{t-1} \mathbb{E}_{t-2}(R_{t-1}^2)) \\ &= (\dots) + 2 \alpha \beta \mathbb{E}(V_{t-1}^2) \\ &= (\dots) + 2 \alpha \beta \mathbb{E}(V_t^2) \end{aligned}$$

Re-arranging the final expression, we see that

$$\mathbb{E}(V_t^2) = \frac{\omega(2\mathbb{E}(V_t)(\beta + \alpha) + \omega)}{1 - ((3 + K_\varepsilon)\alpha^2 + \beta^2 + 2\alpha\beta)}$$

if the denominator is positive.

Quasi Maximum Likelihood Estimates for the GARCH parameters, and asymptotic normality

If V_1 is fixed and known and we start the model at time zero rather than $t = -\infty$, the joint density of R_1, \dots, R_n can be easily expressed as a product of conditional densities of the returns:

$$L = p(R_1) p(R_2 | R_1) p(R_3 | R_1, R_2) \dots = p(R_1) p(R_2 | V_2) \dots p(R_n | V_n) = \prod_{j=1}^n f\left(\frac{R_j}{\sqrt{V_j}}\right) \frac{1}{\sqrt{V_j}} \quad (6)$$

where f is the density of each Z_t in (1). This is true because

$$\mathbb{P}(R_j \leq x | V_j) = \mathbb{P}(Z_j \leq \frac{x}{\sqrt{V_j}} | V_j) = F\left(\frac{x}{\sqrt{V_j}}\right)$$

where F is the distribution function of Z_t . Using *observed* values for R_1, \dots, R_n , and given parameter values for the model, the values of $Z_j = \frac{R_j}{\sqrt{V_j}}$ are known as the **residuals** and L is the likelihood function of R_1, \dots, R_n . We can then maximize L over all admissible parameter combinations to compute MLEs for the model parameters $\omega, \alpha, \beta, \gamma$, and the parameter(s) for the distribution of each Z_t (this is conceptually similar to Part 2).

Then the log likelihood is

$$\ell_n(\theta) = \sum_{t=1}^n \log f\left(\frac{R_t}{\sqrt{V_t}}\right) - \frac{1}{2} \log V_t$$

and recall that V_j actually depends on R_1, \dots, R_{j-1} and the model parameters which we collectively denote by θ . Then the Fisher information matrix when the residuals are i.i.d. $N(0, 1)$ for the true stationary GARCH model is

$$\begin{aligned} I(\theta) &= -\mathbb{E}\left(\frac{\partial^2}{\partial \theta^2} \ell_n(\theta)\right) = \sum_{t=1}^n \mathbb{E}\left(-\frac{2R_t^2 + V_t(\theta)}{2V_t(\theta)^3} \frac{\partial V_t(\theta)}{\partial \theta_i} \frac{\partial V_t(\theta)}{\partial \theta_j} + (R_t^2 - V_t(\theta)) V_t(\theta) \frac{\partial^2 V_t(\theta)}{\partial \theta_i \partial \theta_j}\right) \\ &= \sum_{t=1}^n \mathbb{E}\left(\frac{1}{2V_t(\theta)^2} \frac{\partial V_t(\theta)}{\partial \theta_i} \frac{\partial V_t(\theta)}{\partial \theta_j}\right) \\ &= n \mathbb{E}\left(\frac{1}{2V_1(\theta)^2} \frac{\partial V_1(\theta)}{\partial \theta_i} \frac{\partial V_1(\theta)}{\partial \theta_j}\right) \end{aligned} \quad (7)$$

as $n \rightarrow \infty$, using the stationarity of V , where we have also used the tower property in the final line. For this to be useful we need to be able to sample from the stationary density for V_t , which we can approximate by considering n large for the model which starts at zero instead of $-\infty$. Then it can be shown that $\hat{\theta}_n$ is consistent and $\sqrt{n}(\hat{\theta}_n - \theta)$ tends to a multivariate $N(0, I(\theta)^{-1})$ random variable as $n \rightarrow \infty$, so intuitively we want parameters in the model such that $\frac{\partial V_1(\theta)}{\partial \theta_i}$ are larger.

Computing the stationary distribution for V

We note that

$$V_t \sim \omega + \alpha V_{t-1} Z_{t-1} + \beta V_{t-1} = \omega + (\alpha Z_{t-1} + \beta) V_{t-1} = \omega + A V_{t-1}$$

where $A = \alpha Z_{t-1}^2 + \beta$. To enforce that $V_{t-1} \sim V_t$, (conditioning on $A = a$) this implies that the stationary density $f_V(v)$ for V satisfies:

$$f_V(v) = \int_{\beta}^{\infty} f_V\left(\frac{v-\omega}{a}\right) \frac{1}{a} p_A(a) da \quad (8)$$

where $p_A(a)$ is density of A , and note A is just a linear transformation of a χ^2 -random variable when $Z \sim N(0,1)$. (8) is a **linear Fredholm integral equation** for $f_V(v)$, which in principle can be solved by discretizing it and solving a linear system of equations.

Goodness-of-fit tests for the residuals

If e.g. we assume $Z_t \sim N(0,1)$, we can then perform standard normality tests like **Kolmogorov Smirnov**, **Shapiro-Wilk**, **Jarque-Bera** or **Andersen-Darling** to test whether the Z_t values are indeed i.i.d. Normals. Otherwise, if we use a different distribution for Z_t (e.g. a **t -distribution** with ν degrees of freedom which will give the returns fatter tails), we have to transform these back Z values to Normal RVs before applying these normality tests, using inverse cdfs.

Estimating V_0 from the stock price history

If we assume $\gamma = 0$ for simplicity, then iterating the definition of V_t we see that

$$\begin{aligned} V_t &= \omega + \beta V_{t-1} + \alpha R_{t-1}^2 \\ &= \omega + \beta(\omega + \beta V_{t-2} + \alpha R_{t-2}^2) + \alpha R_{t-1}^2 \\ &= \omega + \beta(\omega + \beta(\omega + \beta V_{t-3} + \alpha R_{t-3}^2) + \alpha R_{t-2}^2) + \alpha R_{t-1}^2 \\ &= \omega(1 + \beta + \beta^2 + \dots) + \frac{\alpha}{\beta} \sum_{\tau=1}^{\infty} \beta^{\tau} R_{t-\tau}^2 = \bar{\omega} + \frac{\alpha}{\beta} \sum_{\tau=1}^{\infty} e^{-b\tau} R_{t-\tau}^2 \end{aligned} \quad (9)$$

where b is defined by $\beta = e^{-b}$ and $\bar{\omega}$ is defined above, and note the first term on the right-hand side is the mean reversion level from above. So we see that the effect of past returns on volatility decays exponentially, and re-doing this computation with $\gamma \neq 0$, we find that the last line just changes to

$$V_t = \frac{\omega}{1-\beta} + \frac{\alpha}{\beta} \sum_{\tau=1}^{\infty} e^{-b\tau} R_{t-\tau}^2 + \frac{\gamma}{\beta} \sum_{\tau=1}^{\infty} e^{-b\tau} R_{t-\tau}.$$

In particular, we also see that

$$V_0 = \bar{\omega} + \frac{\alpha}{\beta} \sum_{\tau=1}^{\infty} e^{-b\tau} R_{-\tau}^2 + \frac{\gamma}{\beta} \sum_{\tau=1}^{\infty} e^{-b\tau} R_{-\tau}$$

so we can estimate V_0 by truncating this sum in practice rather than fitting V_0 as an additional free parameter for the MLE maximization computation described above, since V_0 is already fixed by the history of the returns.

Stochastic volatility as the diffusive limit of QGARCH

Consider the following variant of the model above:

$$\begin{aligned} S_t &= S_{t-\Delta t} + S_{t-\Delta t} \sqrt{V_{t-\Delta t}} Z_t \\ V_t &= V_{t-\Delta t} + \kappa \theta \Delta t + \frac{\eta}{\sqrt{\Delta t}} (R_t^2 - V_{t-\Delta t} \Delta t) - \kappa V_{t-\Delta t} \Delta t + \gamma R_t \\ &= V_{t-\Delta t} + \kappa(\theta - V_{t-\Delta t}) \Delta t + \frac{\eta}{\sqrt{\Delta t}} V_{t-\Delta t} (Z_t^2 - \Delta t) + \gamma \sqrt{V_{t-\Delta t}} Z_t \\ &= V_{t-\Delta t} + \bar{\kappa}(\bar{\theta} - V_{t-\Delta t}) \Delta t + \frac{\eta}{\sqrt{\Delta t}} R_t^2 + \gamma R_t \end{aligned}$$

for some $\bar{\kappa}$, $\bar{\theta}$, with Z_1, Z_2, \dots i.i.d. as above and V_{t-1} here is our old V_t , and now assume $\text{Var}(Z_t) = \Delta t$ and $\eta = O(1)$, and impose that $\nu > 4$ so $\mathbb{E}(Z_i^4) < \infty$, and from the final line we see that V_t is still of the QGARCH(1,1) form in (3). Then as $\Delta t \rightarrow 0$, the model tends to the mean-reverting **Markov stochastic volatility** model:

$$\begin{aligned} dS_t &= S_t \sqrt{V_t} dW_t \\ dV_t &= \kappa(\theta - V_t)dt + 2\eta V_t dB_t + \gamma \sqrt{V_t} dW_t \end{aligned} \quad (10)$$

where W and B are standard independent Brownian motions, so we see that the specific form of the distribution of the Z_t 's does not show up in the $\Delta t \rightarrow 0$ limit and the independent Brownian motion B appears almost by magic. When η is larger, the implied volatility smile will be more U -shaped as a function of strike K , and will be symmetric as a function of $x = \log \frac{K}{S_0}$ if $\gamma = 0$. If ν is smaller, the smile may just be monotonically decreasing as a function of K over relevant strike ranges.

The limiting model in (10) is hybrid of the well known **Hull-White** and **Heston** models (the well known Heston model has a $\sqrt{V_t}$ term in it). To see why this is true, we first note that

$$\frac{1}{\sqrt{\Delta t}} \sum_{i=1}^{[nt]} (Z_i^2 - \Delta t) = \sqrt{n} \sum_{i=1}^{[nt]} (\Delta t \tilde{Z}_i^2 - \Delta t) = \frac{1}{\sqrt{n}} \sum_{i=1}^{[nt]} (\tilde{Z}_i^2 - 1) \quad (11)$$

where $\tilde{Z}_i = Z_t / \sqrt{\Delta t} \sim N(0, 1)$, and that $\text{Var}(\tilde{Z}_i^2 - 1) = \mathbb{E}((\tilde{Z}_i^2 - 1)^2) = 3 - 2 + 1 = 2$.

We now recall **Donsker's theorem**. Let X_i be a sequence of i.i.d. random variables with $\mathbb{E}(X_i) = 0$ and $\text{Var}(X_i) = 1$, and let $S_n = \sum_{i=1}^n X_i$. Now consider the **random function**:

$$W_t^n = \frac{S_{[nt]}}{\sqrt{n}} \quad (t \in [0, 1])$$

where $[nt]$ denotes the largest integer less than or equal to nt . Then by the **Central Limit Theorem**, $W_1^n = \frac{S_n}{\sqrt{n}}$ tends to an $N(0, 1)$ random variable as $n \rightarrow \infty$. More precisely, $\lim_{n \rightarrow \infty} \mathbb{E}(F(W_1^n)) = \mathbb{E}(F(Z))$ for any bounded continuous function F (this is known as **weak convergence**). Donsker's theorem, states that the random function W_t^n tends weakly to a random function which is a Brownian motion as $n \rightarrow \infty$. This shows that we can numerically approximate Brownian motion using X_i 's with any distribution with finite variance. Thus (11) falls exactly under the framework of Donsker's theorem, aside from $\tilde{Z}_i^2 - 1$ having a variance of 2 not 1, which is why there is a **factor of 2** in (10).

Changing from \mathbb{P} to \mathbb{Q} measure

If the Z_t 's have a non-zero density under \mathbb{P} , then the Z_t 's can have any non-zero density under \mathbb{Q} (does not have to be equal to the original density), so long as $\mathbb{E}^{\mathbb{Q}}(Z_t) = 0$, then S will still be a martingale under \mathbb{Q} , which is equivalent to \mathbb{P} since both densities are non-zero by assumption.

Intraday dynamics consistent with the QGARCH model

The t -distribution is infinitely divisible which means a random variable Z with this distribution can be written as a sum of n i.i.d random variables Z_i^n , for any n . The characteristic function $\mathbb{E}(e^{iuZ_i^n})$ of Z_i^n is then $\phi(u)^{1/n}$ where $\phi(u) = \mathbb{E}(e^{iuZ})$. This gives us a way to extend the model from modelling daily returns to intraday returns with n i.i.d residuals per day, keeping V constant within any given day.

Bayesian analysis

If we set $X = (R_1, \dots, R_n)$ and $\theta = (\alpha, \beta, \gamma, \nu)$, then from Bayes formula, we know that

$$p(\theta|X) = \frac{p(X|\theta)p(\theta)}{p(X)}$$

where the p 's refer to densities or conditional densities here. $p(X)$ does not depend on θ , and if assume a uniform prior $p(\theta) = \text{const.}$ for θ on some finite hypercube in \mathbb{R}^4 (and zero elsewhere), then

$$p(\theta|X) = \text{const.} \times p(X|\theta)$$

so the conditional density of θ given X is proportional to the likelihood function $p(X|\theta)$, and by integrating in the other 3 parameters we can compute e.g. the marginal density of α , β , γ or ν given X . This is easier if e.g. we fix $\gamma = 0$ and fix $1 - \beta$ to its lower bound, so we only have two free parameters.

Power-kernel model

We can modify the model as follows:

$$\begin{aligned} R_t &= \sqrt{V_t} Z_t \\ V_t &= \omega + c \sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau}^2 + \gamma \sum_{\tau=1}^{\infty} \tau^{-\alpha_2} R_{t-\tau} \end{aligned}$$

for $\alpha, \alpha_2 > 2$ (add mean reversion?) which corresponds to **power decay**, and again we have to take care to ensure positivity and stationarity. In this case, using the same tower law argument as above

$$\mathbb{E}(V_t) = \omega + c \sum_{\tau=1}^{\infty} \tau^{-\alpha} \mathbb{E}(R_{t-\tau}^2) = \omega + c \sum_{\tau=1}^{\infty} \tau^{-\alpha} \mathbb{E}(\mathbb{E}(R_{t-\tau}^2 | V_{t-\tau})) = \omega + c\sigma^2 \sum_{\tau=1}^{\infty} \tau^{-\alpha} \mathbb{E}(V_{t-\tau}).$$

If V is stationary, then

$$\mathbb{E}(V_t) = \omega + c\sigma^2 \sum_{\tau=1}^{\infty} \tau^{-\alpha} \mathbb{E}(V_t) = \omega + c\sigma^2 \mathbb{E}(V_t) \zeta(\alpha)$$

which we can re-arrange as $\mathbb{E}(V_t) = \frac{\omega}{1 - c\sigma^2 \zeta(\alpha)}$, where $\zeta(\alpha) = \sum_{n=1}^{\infty} n^{-\alpha}$ denotes the **zeta function**, so clearly a necessary condition for stationarity is that $c\sigma^2 \zeta(\alpha) < 1$.

If $\alpha = \alpha_2$, then can re-write as

$$V_t = \sum_{\tau=1}^{\infty} \tau^{-\alpha} (\bar{\omega} + cR_{t-\tau}^2 + \gamma R_{t-\tau})$$

where $\bar{\omega} = \frac{\omega}{\zeta(\alpha)}$, so we have essentially the same **positivity condition** as before $\bar{\omega} \geq \frac{\gamma^2}{4c}$. This is a discrete-time version of the **rough Heston model**.

Quadratic Rough Heston-type model

We can also generalize to a quadratic rough Heston-type model:

$$V_t = \omega + c \sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau}^2 + b \left(\sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau} - a \right)^2 + \gamma \sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau}.$$

Then again assuming stationarity, we now see that

$$\begin{aligned} \mathbb{E}(V_t) &= \omega + c\sigma^2 \zeta(\alpha) \mathbb{E}(V_t) + b \mathbb{E} \left(\sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau} - a \right)^2 \\ &= \omega + c\sigma^2 \zeta(\alpha) \mathbb{E}(V_t) + b \mathbb{E} \left(\sum_{\tau=1}^{\infty} \tau^{-\alpha} R_{t-\tau} \right)^2 + a^2 \\ &= \omega + c\sigma^2 \zeta(\alpha) \mathbb{E}(V_t) + b(\zeta(2\alpha) \mathbb{E}(V_t) + a^2) \end{aligned}$$

using that $\mathbb{E}(R_i R_j) = \mathbb{E}(R_i \mathbb{E}(R_j | R_i, V_j)) = 0$ for $i < j$, so the stationarity condition now reads as $c\sigma^2 \zeta(\alpha) + b(\zeta(2\alpha) < 1$.

Numerical results

Below we compute MLEs and apply the Kolmogorov Smirnov, Shapiro-Wilk and Jarque-Bera normality tests on the (transformed) residuals implied by the MLEs for the model in (1) using daily prices, with a 1yr/3yr/1yr test window (the initial 1yr window is used to compute the V_0 for the middle window from the initial 1yr history of returns; the middle 3yr period is used for in-sample (i/s) testing, and final year used for out-of-sample testing, all three periods are consecutive with no gaps/overlap), ending 11/08/2023. Although the fits are very good, the sample variance of the MLEs using synthetic paths with the fitted parameters are much higher than we would ideally like.

MLEs/ p -vals	α	β	γ	ν	KS i/s	SW i/s	JB i/s	KS o/s	SW o/s	JB o/s
EUR/USD	0.0293	0.962	-5.405e-05	8.684	0.835	0.870	0.706	0.912	0.714	0.643
GBP/USD	0.0303	0.932	-0.000252	6.192	0.966	0.836	0.712	0.119	0.224	0.279
USD/JPY	0.0830	0.875	-0.000299	5.9611	0.292	0.476	0.352	0.0603	0.0907	0.229
AMZN	0.03482	0.9420	-0.000505	5.008	0.401	0.811	0.951	0.560	0.607	0.570
BRK-B	0.103	0.868	-0.00103	8.929	0.168	0.921	0.950	0.611	0.676	0.984
INTC	0.0280	0.943	-5.940e-05	3.914	0.375	0.0634	0.0404	0.229	0.262	0.236
AZN	0.0496	0.904	-0.000897	4.153	0.247	0.587	0.428	0.103	0.206	0.195
N225	0.0982	0.856	-0.00129	6.271	0.281	0.443	0.349	0.0713	0.236	0.354
HSI	0.06222	0.898	-0.000834	5.108	0.491	0.226	0.358	0.530	0.121	0.161

To fix SPX historical prices well, we need a skewed t -distribution for the residuals