Univariate Volatility Modeling

Kevin Sheppard

http://www.kevinsheppard.com

Oxford MFE

This version: January 30, 2020

January 2020

- Common Volatility Terminology
  - Volatility, Variance, Conditional Variance, Annualized Volatility
- ARCH(P) models
  - Basic ARCH(1) model

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2$$

$E[(x-\mu)^4]$

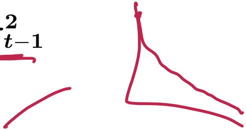
$[E(x-\mu)^2]^2$

3

  - Not empirically realistic
- Visualizing Volatility: Returns, Squares and Absolute Values
- Time-varying volatility produces heavy tails and excess kurtosis
- GARCH(1,1) models

$+ \quad \geq 0 \quad \geq 0$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \boldsymbol{\beta \sigma_{t-1}^2}$$



  - ARCH(∞) in disguise

$$\sigma_t^2 = \omega + \alpha \sum_{i=0}^{\infty} \beta^i \epsilon_{t-i-1}^2$$

Volatility Overview

- What is volatility?
- Why does it change?
- What are ARCH, GARCH, TARCH, EGARCH, SWARCH, ZARCH, APARCH, STARCH, *etc.* models?
- What does time-varying volatility *look like*?
- What are the basic properties of ARCH and GARCH models?
- What is the news impact curve?
- How are the parameters of ARCH models estimated? What about inference?
- Twists on the standard model
- Forecasting conditional variance
- *Realized Variance*
- Implied Volatility

The Complete GARCH model

Definition (GARCH(P,Q) process)

A Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process of orders P and Q is defined as

$P \leq 3$

$Q \leq 2$

$$
\begin{aligned}
r_t &= \mu_t + \epsilon_t \quad \to AR(0) \\
AR(S) \to \quad \mu_t &= \phi_0 + \phi_1 r_{t-1} + \ldots + \phi_s r_{t-S} \\
\sigma_t^2 &= \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \\
\epsilon_t &= \sigma_t e_t \\
e_t &\overset{\text{i.i.d.}}{\sim} N(0,1)
\end{aligned}
$$

$r_t - 0$

$r_t - \hat{\mu}$

$r_t - \hat{\mu}_t = \hat{\epsilon}_t$

$E_{t-1}[\hat{\epsilon}_t] = 0$

- Mean model can be altered to fit data – $AR(S)$ here
- Adds lagged variance to ARCH

Exponentially Weighted Moving Average Variance

A special case of a GARCH(1,1)

- Restricted model where $\mu_t = 0$ for all t, $\omega = 0$ and $\alpha = 1 - \beta$

$$\sigma_t^2 = (1-\lambda)\, r_{t-1}^2 + \lambda \sigma_{t-1}^2$$

$$\sigma_t^2 = (1-\lambda) \sum_{i=0}^{\infty} \lambda^i r_{t-i-1}^2$$

$\alpha + \beta = 1$

- Note that $\sum_{i=0}^{\infty} \lambda^i = {}^1\!/_{1-\lambda}$ so that $(1-\lambda)\sum_{i=0}^{\infty} \lambda^i = 1$
  - Leads to random-walk-like features

$\underline{0.94}$

$\underline{\alpha + \beta}$

Extensions

- Extends GARCH(1,1) to include an asymmetric term

Definition (Glosten-Jagannathan-Runkle (GJR)-GARCH process)

A GJR-GARCH(P,O,Q) process is defined as

$$
\begin{aligned}
r_t &= \mu_t + \epsilon_t \\
\mu_t &= \phi_0 + \phi_1 r_{t-1} + \ldots + \phi_s r_{t-S} \\
\sigma_t^2 &= \omega + \sum_{p=1}^{P} \alpha_p \epsilon_{t-p}^2 + \sum_{o=1}^{O} \gamma_o \epsilon_{t-o}^2 I_{[\epsilon_{t-o}<0]} + \sum_{q=1}^{Q} \beta_q \sigma_{t-q}^2 \\
\epsilon_t &= \sigma_t e_t \\
e_t &\overset{\text{i.i.d.}}{\sim} N(0,1)
\end{aligned}
$$

I [ ]

where $I_{[\epsilon_{t-o}<0]}$ is an indicator function that takes the value 1 if $\epsilon_{t-o} < 0$ and 0 otherwise.

GJR-GARCH(1,1,1) example

- GJR(1,1,1) model

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \gamma_1 \epsilon_{t-1}^2 I_{[\epsilon_{t-1}<0]} + \beta_1 \sigma_{t-1}^2$$

$$\alpha_1 + \gamma_1 \geq 0$$
$$\alpha_1 \geq 0$$
$$\beta_1 \geq 0$$
$$\omega > 0$$

- $\gamma_1 \epsilon_{t-1}^2 I_{[\epsilon_{t-1}<0]}$: Variances are larger after negative shocks than after positive shocks
- "Leverage Effect"

$$\left\{ \begin{array}{ll} + & \alpha \\ - & \alpha + \gamma \end{array} \right\}$$

Threshold ARCH

- Threshold ARCH is similar to GJR-GARCH
- Also known as ZARCH (Zakoain (1994)) or AVGARCH when symmetric

Definition (Threshold ARCH (TARCH) process)

A TARCH(P,O,Q) process is defined

$$
\begin{aligned}
r_t &= \mu_t + \epsilon_t \\
\mu_t &= \phi_0 + \phi_1 r_{t-1} + \ldots + \phi_s r_{t-S} \\
\overset{2}{\sigma_t} &= \omega + \sum_{p=1}^{P} \alpha_p \overset{1}{|\epsilon_{t-p}|} + \sum_{o=1}^{O} \gamma_o \overset{1}{|\epsilon_{t-o}|} I_{[\epsilon_{t-o}<0]} + \sum_{q=1}^{Q} \beta_q \overset{\cdot\ 1}{\sigma_{t-q}} \\
\epsilon_t &= \sigma_t e_t \\
e_t &\overset{\text{i.i.d.}}{\sim} N(0,1)
\end{aligned}
$$

where $I_{[\epsilon_{t-o}<0]}$ is an indicator function that is 1 if $\epsilon_{t-o} < 0$ and 0 otherwise.

TARCH(1,1,1) example

- TARCH(1,1,1) model

$$\sigma_t^{1} = \omega + \alpha_1|\epsilon_{t-1}|^{1} + \gamma_1|\epsilon_{t-1}|^{1} I_{[\epsilon_{t-1}<0]} + \beta_1\sigma_{t-1}^{1}$$

$$\alpha_1 + \gamma_1 \geq 0$$

$$\omega > 0, \alpha_1 \geq 0, \beta_1 \geq 0$$

- Note the different power: σ_t and $|\epsilon_{t-1}|$
  - Model for conditional standard deviation
- *Nonlinear* variance models complicate some things
  - Forecasting
  - Memory of volatility
  - *News impact curves*
- GARCH(P,Q) becomes TARCH(P,O,Q) or GJR-GARCH(P,O,Q)
- TARCH and GJR-GARCH are sometimes (*wrongly*) used interchangeably.

Definition (EGARCH(P,O,Q) process)

An Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) process of order P, O and Q is defined

$$
\begin{aligned}
r_t &= \mu_t + \epsilon_t \\
\mu_t &= \phi_0 + \phi_1 r_{t-1} + \ldots + \phi_s r_{t-S} \\
\ln(\sigma_t^2) &= \omega + \sum_{p=1}^{P} \alpha_p \left(\left| \frac{\epsilon_{t-p}}{\sigma_{t-p}} \right| - \sqrt{\frac{2}{\pi}} \right) + \sum_{o=1}^{O} \gamma_o \frac{\epsilon_{t-o}}{\sigma_{t-o}} + \sum_{q=1}^{Q} \beta_q \ln(\sigma_{t-q}^2) \\
\epsilon_t &= \sigma_t e_t \\
e_t &\overset{\text{i.i.d.}}{\sim} N(0,1)
\end{aligned}
$$

In the original parameterization of Nelson (1991), P and O were required to be identical.

EGARCH(1,1,1)

- EGARCH(1,1,1)

$E[|e|] = \sqrt{2/\pi}$ $\quad e \sim N(0,1)$ $\qquad \ln y = Bx + u$

$$r_t = \mu + \epsilon_t$$

$$\ln(\sigma_t^2) = \omega + \alpha_1 \left(\left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma_1 \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \ln(\sigma_{t-1}^2)$$

$$\epsilon_t = \sigma_t e_t, \quad e_t \overset{\text{i.i.d.}}{\sim} N(0,1)$$

$|e_{t-1}|$ $\qquad e_{t-1}$ $\qquad \sim 0$ $\qquad \ln(\epsilon_t) = \ln(\sigma_t) + \ln(e_t)$

- Modeling using $\ln$ removes any parameter restrictions ($|\beta_1| < 1$)
- AR(1) with *two* shocks

shock 1 $\qquad$ shock 2

$$\ln(\sigma_t^2) = \omega + \alpha_1 \left(|e_{t-1}| - \sqrt{\frac{2}{\pi}} \right) + \gamma_1 e_{t-1} + \beta_1 \ln(\sigma_{t-1}^2)$$

  - Symmetric shock $\left(|e_{t-1}| - \sqrt{\frac{2}{\pi}} \right)$ and asymmetric shock e_{t-1}
    - Note, shocks are standardized residuals (unit variance)
- Often provides a better fit that GARCH(P,Q)

Asymmetric Power ARCH

- Nests ARCH, GARCH, TARCH, GJR-GARCH, EGARCH (almost) and other specifications
- Only present the APARCH(1,1,1):

(0.7, 1.2)

$$\sigma_t^{\delta} = \omega + \alpha_1 \left(|\epsilon_{t-1}| + \gamma_1 \epsilon_{t-1}\right)^{\delta} + \beta_1 \sigma_{t-1}^{\delta}$$

$$\alpha_1 > 0, \quad -1 \leq \gamma_1 \leq 1, \quad \delta > 0, \quad \beta_1 \geq 0, \quad \omega > 0$$

- Parameterizes the "power" parameter
- Different values for δ affect the persistence.
  - Lower values $\Rightarrow$ higher persistence of shocks
    - ARCH: $\gamma = 0, \beta = 0, \delta = 2$
    - GARCH: $\gamma = 0, \delta = 2$
    - GJR-GARCH: $\delta = 2$
    - AVGARCH: $\gamma = 0, \delta = 1$
    - TARCH: $\delta = 1$
    - EGARCH: (almost) $\lim \delta \to 0$

S&P Results

ARCH(5)

ω	α_1	α_2	α_3	α_4	α_5	Log Lik.
0.294	0.095	0.204	0.189	0.193	0.143	−7008
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Pval

0.85

GARCH(1,1)

ω	α_1	β_1	Log Lik.
0.018	0.102	0.885	−6888
(0.000)	(0.000)	(0.000)	

.987

te = +1

EGARCH(1,1,1)

−1

ω	α_1	γ_1	β_1	Log Lik.
0.000	0.136	−0.153	0.975	−6767
(0.909)	(0.000)	(0.000)	(0.000)	

$\alpha(|+1|) + \gamma(+1) = -.02$

$.271 \qquad .136 - .153(-1) \qquad \alpha(|-1|) + \gamma(-1)$

Comparing different models

- Comparing models which are not nested can be difficult
- The *News Impact Curve* provides one method
- Defined:

$$n(e_t) = \sigma^2_{t+1}(e_t | \sigma^2_t = \bar{\sigma}^2)$$

$$NIC(e_t) = n(e_t) - n(0)$$

- Measures the effect of a shock *starting* at the unconditional variance
- Allows for asymmetric shapes

GARCH(1,1)

$$NIC(e_t) = \alpha_1 \bar{\sigma}^2 e_t^2$$? ε_t^2

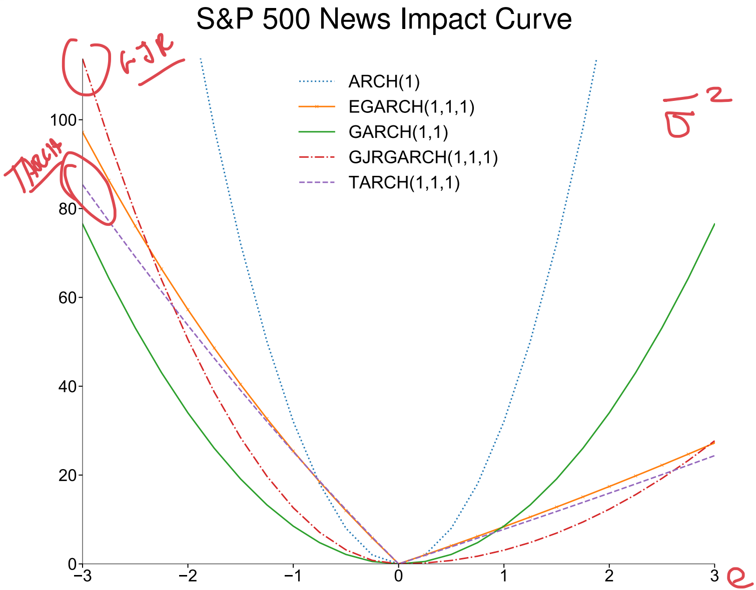
GJR-GARCH(1,1,1)

$$NIC(e_t) = (\alpha_1 + \gamma_1 I_{[e_t<0]})\bar{\sigma}^2 e_t^2$$

TARCH(1,1,1)

$$NIC(e_t) = (\alpha_1 + \gamma_1 I_{[\epsilon_t<0]})^2 \bar{\sigma}^2 e_t^2 + (2\omega + 2\beta_1\bar{\sigma})(\alpha_1 + \gamma_1 I_{[\epsilon_t<0]})|\epsilon_t|$$

S&P 500 News Impact Curves



Estimation and Inference

Estimation

$$\mu_t = \mu$$

$$r_t = \mu_t + \epsilon_t$$
$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$
$$\epsilon_t = \sigma_t e_t$$
$$e_t \overset{\text{i.i.d.}}{\sim} N(0,1)$$

$$\hat{e}_t = \frac{r - \hat{\mu}}{\hat{\sigma}_t}$$

- So:

$$r_t | \mathcal{F}_{t-1} \sim N(\mu_t, \sigma_t^2)$$

- Need initial values for σ_0^2 and ϵ_0^2 to start recursion
  - Normal Maximum Likelihood is a natural choice

$$\theta = [\mu, \omega, \alpha, \beta]$$

$$f(\mathbf{r};\boldsymbol{\theta}) = \prod_{t=1}^{T} (2\pi\sigma_t^2)^{-\frac{1}{2}} \exp\left(-\frac{(r_t - \mu_t)^2}{2\sigma_t^2}\right)$$

$$l(\boldsymbol{\theta};\mathbf{r}) = \sum_{t=1}^{T} -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{(r_t-\mu_t)^2}{2\sigma_t^2}.$$

- MLE are asymptotically normal

$$\sqrt{T}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) \xrightarrow{d} N(0, \mathcal{I}^{-1}), \quad \mathcal{I} = -\mathrm{E}\left[\frac{\partial^2 l(\boldsymbol{\theta}_0; r_t)}{\partial \boldsymbol{\theta} \partial \boldsymbol{\theta}'}\right]$$

- If data are not conditionally normal, Quasi MLE (QMLE)

$$\sqrt{T}(\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}_0) \xrightarrow{d} N(0, \underbrace{\mathcal{I}^{-1}\mathcal{J}\mathcal{I}^{-1}}_{\text{White s.e.}}), \quad \mathcal{J} = \mathrm{E}\left[\frac{\partial l(\boldsymbol{\theta}_0; r_t)}{\partial \boldsymbol{\theta}} \frac{\partial l(\boldsymbol{\theta}_0; r_t)}{\partial \boldsymbol{\theta}'}\right]$$

$\Sigma_{xx}^{-1} S \Sigma_{xx}^{-1}$

- Known as Bollerslev-Wooldridge Covariance estimator in GARCH models
  - Also known as a "*sandwich*" covariance estimator
  - Default `vcvrobust` in MFE GARCH code
  - White and Newey-West Covariance estimators are also sandwich estimators

$\hat{\theta} \sim N(\theta_0, \mathcal{I}^{-1}/T)$

Independence of the mean and variance

The mean and the variance can be estimated consistently using 2-stages. Standard errors are also correct as long as a robust VCV estimator is used.

- Use LS to estimate mean parameters, then use estimated residuals in GARCH
- Efficient estimates one of two ways
- Joint estimation of mean and variance parameters using MLE
- GLS estimation
  - Estimate mean and variance in 2-steps as above
  - Re-estimate mean using GLS
  - Re-estimate variance using new set of residuals

(1) y $T^{-1}\sum r_t = \hat{\mu}$, $\underline{\hat{\varepsilon}_t} = r_t - \hat{\mu}$

GARCH(1,1)

The mean and the variance can be estimated consistently using 2-stages. Standard errors from a robust VCV (White) are also correct.

- First Order Condition:

$$l(r_t|\boldsymbol{\theta}) = -\frac{1}{2}\log(2\pi) - \frac{1}{2}\log(\sigma_t^2) - \frac{(r_t-\mu_t)^2}{2\sigma_t^2}$$

$E_{t-1}[\varepsilon_t]$

The second order condition is

$$\frac{\partial^2 l(\mathbf{r}|\boldsymbol{\theta})}{\partial\mu_t\partial\sigma_t}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi} = \sum_{t=1}^{T}\frac{(r_t-\mu_t)}{\sigma_t^4}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}$$

$E_{t-1}[r_t - \hat{\mu}_t] = \underline{0}$

$$\mathrm{E}\left[\frac{\partial^2 l(\mathbf{r}|\boldsymbol{\theta})}{\partial\mu_t\partial\sigma_t}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}\right] = \mathrm{E}\left[\sum_{t=1}^{T}\frac{\mathrm{E}_t\left[r_t-\mu_t\right]}{\sigma_t^4}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}\right]$$

$$\mathrm{E}\left[\frac{\partial^2 l(\mathbf{r}|\boldsymbol{\theta})}{\partial\mu_t\partial\sigma_t}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}\right] = \mathrm{E}\left[\sum_{t=1}^{T}\frac{0}{\sigma_t^4}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}\right]$$

$$\mathrm{E}\left[\frac{\partial^2 l(\mathbf{r}|\boldsymbol{\theta})}{\partial\mu_t\partial\sigma_t}\frac{\partial\mu_t}{\partial\phi}\frac{\partial\sigma_t^2}{\partial\psi}\right] = 0$$

- Use LS to for mean parameters, then use estimated residuals in GARCH

GARCH-in-mean models

- Your finance professor would like to believe there is a risk-return tradeoff
- In a GARCH model this can be expressed

$\mu + \delta\sigma_t^2$

$$
\begin{aligned}
r_t &= \mu + \boxed{\delta\sigma_t^2} + \epsilon_t \\
\sigma_t^2 &= \omega + \alpha_1\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \\
\epsilon_t &= \sigma_t e_t \\
e_t &\overset{\text{i.i.d.}}{\sim} N(0,1)
\end{aligned}
$$

- δ measures the reward per unit variance risk σ_t^2.
- For GIM, ignore my previous rant about estimation
  - Must be estimated together
- Alternative forms

$$r_t = \mu + \delta\sigma_t + \epsilon_t$$

or

$$r_t = \mu + \delta\ln(\sigma_t^2) + \epsilon_t$$

GARCH-in-mean on the S&P 500

TYPO

- Standard GIM model with GARCH(1,1) variance

GJR

$$r_t = \mu + \delta g(\sigma_t^2) + \epsilon_t$$

$$\epsilon_t \sim N(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$+ \gamma I_{[\epsilon_{t-1}<0]} \epsilon_{t-1}^2$

- Parameter estimates

S&P 500 Garch-in-Mean Estimates

$g(\sigma^2)$	μ	δ	ω	α	γ	β	Log Lik.
σ^2	0.004 (0.753)	0.022 (0.074)	0.022 (0.000)	0.000 (0.999)	0.183 (0.000)	0.888 (0.000)	−6773.7
σ	−0.034 (0.304)	0.070 (0.087)	0.022 (0.000)	0.000 (0.999)	0.182 (0.000)	0.887 (0.000)	−6773.4
$\ln \sigma^2$	0.038 (0.027)	0.030 (0.126)	0.022 (0.000)	0.000 (0.999)	0.183 (0.000)	0.888 (0.000)	−6773.8

P value

Alternative Distributional Assumptions

- Equity returns are *not* conditionally normal
- Can replace the normal likelihood with a more realistic one
- Common choices:
- Standardized Student's T
  - Nests the normal as $\nu \to \infty$
- Generalized error distribution
  - Nests the normal when $\nu = 2$
- Hansen's Skew-T
  - Captures both skewness and heavy tails
  - Use *hyperparameters* to control shape (ν and λ)
- All can have heavy tails
- Only Skew-T is skewed
- Dozens more in academic research
- But for what gain?

$Y \sim$ std t ν

$V(Y) = \frac{\nu}{\nu-2}$

$e_t \overset{iid}{\sim} N(0,1)$

$\hat{e}_t = \frac{r_t - \hat{\mu}_t}{\hat{\sigma}_t}$

$(-)$

$X = \frac{Y}{\sqrt{\frac{\nu}{\nu-2}}}$

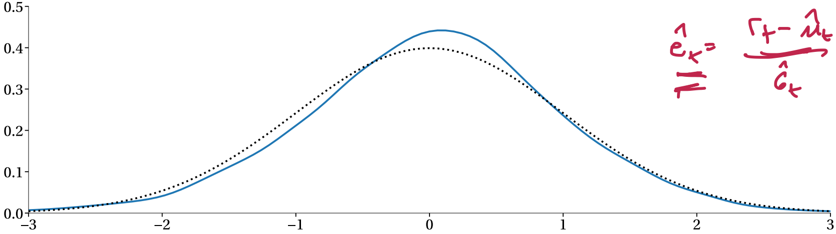
$\nu > 2$

$V(X) = 1$

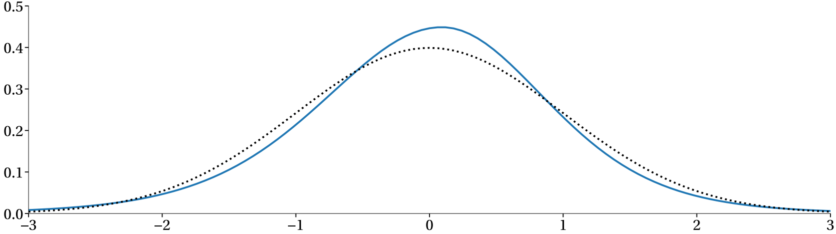
S&P 500 Density

$$\hat{e}_t = \frac{r_t - \hat{\mu}_t}{\hat{\sigma}_t}$$

Empirical



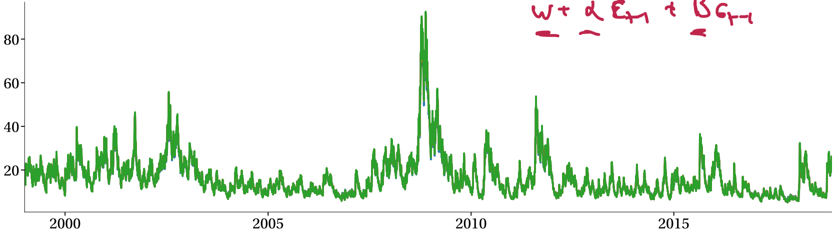
Skew t



Effect of dist. choice on estimated volatility

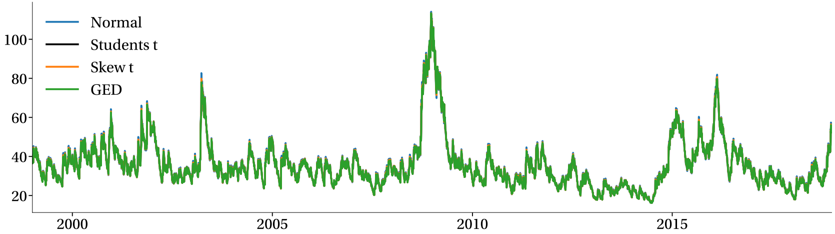
S&P 500

$\omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$



WTI

$e_t \overset{iid}{\sim} N(0,1)$



What are fat tails?

- "Fat-tailed" and "Thin-tailed"

Definition (Leptokurtosis)

A random variable x_t is said to be leptokurtotic if its kurtosis,

$$\kappa = \frac{\mathrm{E}[(x_t - \mathrm{E}[x_t])^4]}{\mathrm{E}[(x_t - \mathrm{E}[x_t])^2]^2}$$

is greater than that of a normal ($\kappa > 3$). Leptokurtotic variables are also known as "heavy tailed" or "fat tailed".

Definition (Platykurtosis)

A random variable x_t is said to be platykurtotic if its kurtosis,

$$\kappa = \frac{\mathrm{E}[(x_t - \mathrm{E}[x_t])^4]}{\mathrm{E}[(x_t - \mathrm{E}[x_t])^2]^2}$$

is less than that of a normal ($\kappa < 3$). Platykurtotic variables are also known as "thin tailed".

Model Building

- ARCH and GARCH models are essentially ARMA models
  - Box-Jenkins Methodology
    - Parsimony principle

$\boxed{\hat{e}_t^2 - 1}$

Steps:

1. Inspect the ACF and PACF of ϵ_t^2

$$\underline{\epsilon_t^2} = \omega + (\alpha + \beta)\epsilon_{t-1}^2 - \beta\nu_{t-1} + \nu_t$$

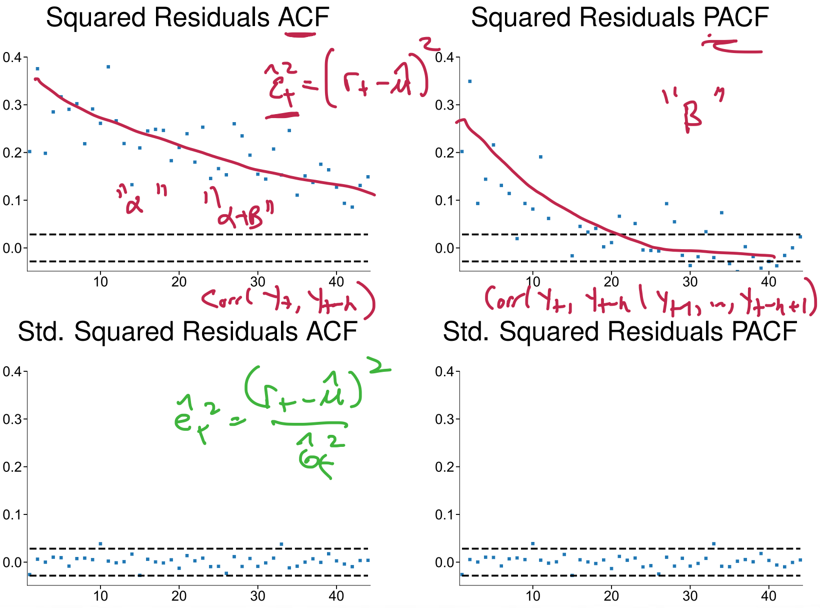
   - ACF indicates α (or ARCH of any kind)
   - PACF indicates β

$\cancel{\varepsilon_t}$ $\cancel{e_t}$

2. Build initial model based on these observation
3. Iterate between model and ACF/PACF of $\hat{e}_t^2 = \frac{\epsilon_t^2}{\hat{\sigma}_t^2}$

$$\underline{\hat{e}_t^2} = \frac{(r_t - \hat{\mu}_t)^2}{\sigma_t^2} = \frac{\hat{\varepsilon}_t^2}{\hat{\sigma}_t^2}$$

S&P 500 ϵ_t^2 ACF/PACF



$\hat{\epsilon}_t^2 = (r_t - \hat{\mu})^2$

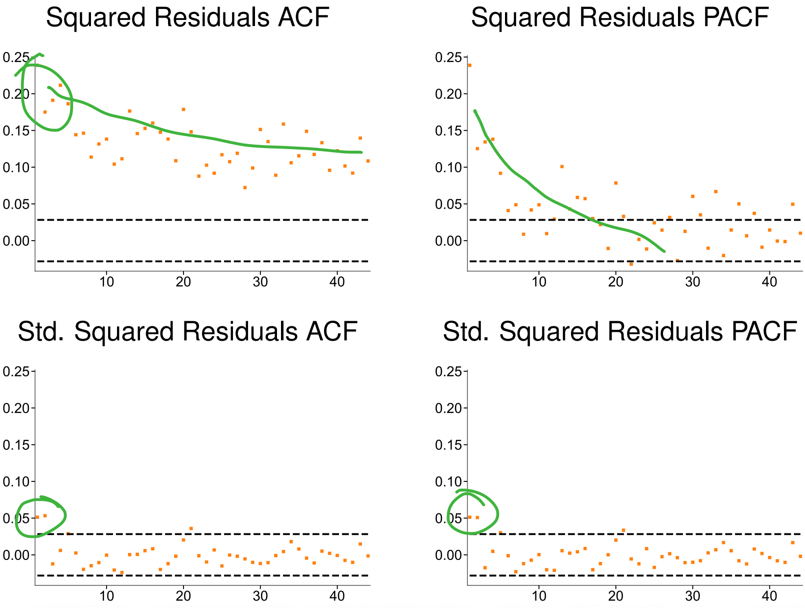
"α" "$\alpha+\beta$" "β"

$\mathrm{Corr}(Y_t, Y_{t-h})$

$\mathrm{Corr}(Y_t, Y_{t-h} \mid Y_{t-1}, \dots, Y_{t-h+1})$

$\hat{e}_t^2 = \dfrac{(r_t - \hat{\mu})^2}{\hat{\sigma}_t^2}$

WTI ϵ_t^2 ACF/PACF



How I built a model for the S&P 500

	α_1	α_2	γ_1	γ_2	β_1	β_2	Log Lik.
GARCH(1,1)	0.102 (0.000)				0.885 (0.000)		−6887.6
GARCH(1,2)	0.102 (0.000)				0.885 (0.000)	0.000 (0.999)	−6887.6
GARCH(2,1)	0.067 (0.003)	0.053 (0.066)			0.864 (0.000)		−6883.5
GJR-GARCH(1,1,1)	0.000 (0.999)		0.185 (0.000)		0.891 (0.000)		−6775.1
GJR-GARCH(1,2,1)	0.000 (0.999)		0.158 (0.000)	0.033 (0.460)	0.887 (0.000)		−6774.5
TARCH(1,1,1)*	~~0.000 (0.999)~~	TARCH(0,1,1)	0.172 (0.000)	frei	0.909 (0.000)		−6751.9
TARCH(1,2,1)	0.000 (0.999)		0.165 (0.000)	~~0.009 (0.786)~~	0.908 (0.000)		−6751.8
TARCH(2,1,1)	0.000 (0.999)	~~0.003 (0.936)~~	0.171 (0.000)		0.907 (0.000)		−6751.9
EGARCH(1,0,1)	0.211 (0.000)				0.979 (0.000)		−6908.4
EGARCH(1,1,1)	0.136 (0.000)		−0.153 (0.000)		0.975 (0.000)		−6766.7
EGARCH(1,2,1)	0.129 (0.000)		−0.213 (0.000)	0.067 (0.045)	0.977 (0.000)		−6761.7
EGARCH(2,1,1)	0.020 (0.651)	0.131 (0.006)	−0.162 (0.000)		0.970 (0.000)		~~−6757.6~~

Testing for (G)ARCH

- ARCH is autocorrelation in ϵ_t^2
- All ARCH processes have this, whether GARCH or EGARCH or other
  - ARCH-LM test
  - Directly test for autocorrelation:

$\hat{\epsilon}_t^2 = (r_t - \hat{\mu})^2$

$$\epsilon_t^2 = \phi_0 + \phi_1 \epsilon_{t-1}^2 + \ldots + \phi_P \epsilon_{t-P}^2 + \eta_t$$

  - $H_0 : \phi_1 = \phi_2 = \ldots = \phi_P = 0$
  - $T \times R^2 \xrightarrow{d} \chi_P^2$
  - Standard LM test from a regression.
  - More powerful test: Fit an ARCH(P) model
  - The forbidden hypothesis

$\epsilon_t^2 = \phi_0 + \eta_t$

$$\sigma_t^2 = \omega + \overset{0}{\alpha_1} \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

$$H_0 : \alpha_1 = 0, \ H_1 \alpha > 0$$

Forecasting

Forecasting: ARCH(1)

- Simple ARCH model

$E_t[\varepsilon^2_{t+1}] = E_t[\sigma^2_{t+1}]$

σ^2_{t+1}

$$\epsilon_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2$$

$E_t[\varepsilon^2_{t+h}] = E[\sigma^2_{t+h}]$

$E_t[e^2_{t+h}\,\sigma^2_{t+h}] =$

$E_t[E_{t+h-1}[e^2_{t+h}\,\sigma^2_{t+h}]]$

  - **1-step ahead forecast is known today**
  - All ARCH-family models have this property

$$\epsilon_t \sim N(0, \sigma_t^2)$$
$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2$$
$$\mathrm{E}_t[\sigma_{t+1}^2] = \mathrm{E}_t[\omega + \alpha_1 \epsilon_t^2]$$
$$\boxed{= \omega + \alpha_1 \epsilon_t^2}$$

$E_t[\sigma^2_{t+h}\, E_{t+h-1}[e^2_{t+h}]]$

1

  - Note: $\mathrm{E}_t[\epsilon_{t+1}^2] = \mathrm{E}_t[e_{t+1}^2 \sigma_{t+1}^2] = \sigma_{t+1}^2 \mathrm{E}_t[e_{t+1}^2] = \sigma_{t+1}^2$

    1
  - Further:

    $\mathrm{E}_t[\epsilon_{t+h}^2] = \mathrm{E}_t[\mathrm{E}_{t+h-1}[e_{t+h}^2 \sigma_{t+h}^2]] = \mathrm{E}_t[\mathrm{E}_{t+h-1}[e_{t+h}^2]\sigma_{t+h}^2] = \mathrm{E}_t[\sigma_{t+h}^2]$

Forecasting: ARCH(1)

- 2-step ahead

$$\mathrm{E}_t[\sigma^2_{t+2}] = \mathrm{E}_t\left[\omega + \alpha\,\varepsilon^2_{t+1}\right]$$

$$= \omega + \alpha\,\mathrm{E}_t\left[\varepsilon^2_{t+1}\right]$$

$$= \omega + \alpha\,\sigma^2_{t+1}$$

$$= \omega + \alpha\left(\omega + \alpha\,\varepsilon^2_t\right)$$

$$= \omega + \alpha\omega + \alpha^2\varepsilon^2_t$$

- h-step ahead forecast

$$\omega + \alpha\omega + \alpha^2\omega + \alpha^3\omega + \alpha^4\omega + \cdots$$

$$\omega(\alpha^0 + \alpha^1 + \alpha^2 + \alpha^3 + \cdots)$$

$$\boxed{\frac{\omega}{1-\alpha}}$$

$$\mathrm{E}_t[\sigma^2_{t+h}] = \underbrace{\sum_{i=0}^{h-1}\alpha_1^i\omega}\; + \underbrace{\alpha_1^h\epsilon_t^2}_{\approx 0}$$

$$= \underbrace{\omega + \alpha\omega + \alpha^2\omega} + \underbrace{\alpha^3\varepsilon_t^2}$$

  - Just the AR(1) forecasting formula
    - Why?

Forecasting: GARCH(1,1)

- 1-step ahead

$$\mathrm{E}_t[\sigma_{t+1}^2] = \mathrm{E}_t[\omega + \alpha_1 \epsilon_t^2 + \beta_1 \sigma_t^2]$$
$$= \omega + \alpha_1 \epsilon_t^2 + \beta_1 \sigma_t^2$$

$E_t[\varepsilon_{t+h}^2] = E_t[\sigma_{t+h}^2]$

- 2-step ahead

$$\mathrm{E}_t[\sigma_{t+2}^2] = E_t[\omega + \alpha\, \varepsilon_{t+1}^2 + \beta \sigma_{t+1}^2]$$
$$= \omega + \alpha E_t[\varepsilon_{t+1}^2] + \beta E_t[\sigma_{t+1}^2]$$

$E_t[\varepsilon_{t+1}^2] = E[\sigma_{t+1}^2]$

$$\omega + (\alpha+\beta) E_t[\sigma_{t+1}^2]$$

$$\omega + (\alpha+\beta)\omega + (\alpha+\beta)(\alpha\varepsilon_t^2 + \beta\sigma_t^2) = \omega + (\alpha+\beta)(\omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2)$$

- h-step ahead

$h \to \infty$

$$E_t[\sigma^2_{t+h}] = \sum_{i=0}^{h-1}(\alpha_1+\beta_1)^i\omega + \underbrace{\overbrace{(\alpha_1+\beta_1)}^{<1}{}^{h-1}}_{\approx 0}\cancel{(\alpha_1\epsilon_t^2+\beta_1\sigma_t^2)}$$

- Also essentially an AR(1), technically ARMA(1,1)

$$w + (\alpha+\beta)w + (\alpha+\beta)^2 w + (\alpha+\beta)^3 w + \ldots\ldots$$

$$w\sum_{i=0}^{\infty}(\alpha+\beta)^i \Rightarrow w/(1-\alpha-\beta) = \bar{\sigma}^2$$

$$w/(1-(\alpha+\beta))$$

GARCH (1,1)

Forecasting: TARCH(1,0,0)

- This one is a mess
  - *Nonlinearities* cause problems
    - All ARCH-family models are nonlinear, but some are linearity in ϵ_t^2
    - Others are not

$$\sigma_t = \underline{\omega + \alpha_1 |\epsilon_{t-1}|}$$

  - **Forecast for $t+1$ is known at time t**
    - **Always, always, always,** ...

$$\begin{aligned}
\mathrm{E}_t[\sigma_{t+1}^2] &= \mathrm{E}_t[(\omega + \alpha_1 |\epsilon_t|)^2] \\
&= \mathrm{E}_t[\omega^2 + 2\omega\alpha_1 |\epsilon_t| + \alpha_1^2 \epsilon_t^2] \\
&= \omega^2 + 2\omega\alpha_1 \mathrm{E}_t[|\epsilon_t|] + \alpha_1^2 \mathrm{E}_t[\epsilon_t^2] \\
&= \omega^2 + 2\omega\alpha_1 |\epsilon_t| + \alpha_1^2 \epsilon_t^2
\end{aligned}$$

TARCH(1,0,0) continued...

- Multi-step is less straightforward

$\sqrt{\frac{2}{\pi}}$

$E_t[|e_{t+1}|]$

$E_t[e_{t+1}^2] = 1$

$$\begin{aligned}
\mathrm{E}_t[\sigma_{t+2}^2] &= \mathrm{E}_t[(\omega + \alpha_1|\epsilon_{t+1}|)^2] \\
&= \mathrm{E}_t[\omega^2 + 2\omega\alpha_1|\epsilon_{t+1}| + \alpha_1^2\epsilon_{t+1}^2] \\
&= \omega^2 + 2\omega\alpha_1\mathrm{E}_t[|\epsilon_{t+1}|] + \alpha_1^2\mathrm{E}_t[\epsilon_{t+1}^2] \\
&= \omega^2 + 2\omega\alpha_1\mathrm{E}_t[|e_{t+1}|\sigma_{t+1}] + \alpha_1^2\mathrm{E}_t[e_t^2\sigma_{t+1}^2] \\
&= \omega^2 + 2\omega\alpha_1\mathrm{E}_t[|e_{t+1}|]\mathrm{E}_t[\sigma_{t+1}] + \alpha_1^2\mathrm{E}_t[e_t^2]\mathrm{E}_t[\sigma_{t+1}^2] \\
&= \omega^2 + 2\omega\alpha_1\mathrm{E}_t[|e_{t+1}|](\omega + \alpha_1|\epsilon_t|) + \alpha_1^2 \cdot 1 \cdot (\omega^2 + 2\omega\alpha_1|\epsilon_t| + \alpha_1^2\epsilon_t^2)
\end{aligned}$$

If $e_{t+1} \sim N(0,1)$, $E[|e_{t+1}|] = \sqrt{\frac{2}{\pi}}$

$\hat{e}_1, \hat{e}_2, \ldots, \hat{e}_T$

$$\mathrm{E}_t[\sigma_{t+2}^2] = \omega^2 + 2\omega\alpha_1\sqrt{\frac{2}{\pi}}(\omega + \alpha_1|\epsilon_t|) + \alpha_1^2(\omega^2 + 2\omega\alpha_1|\epsilon_t| + \alpha_1^2\epsilon_t^2)$$

Assessing forecasts: Augmented MZ

STOP

- Start from $\mathrm{E}_t[r^2_{t+h}] \approx \sigma^2_{t+h|t}$
  - Standard Augmented MZ regression:

$$\epsilon^2_{t+h} - \hat{\sigma}^2_{t+h|t} = \gamma_0 + \gamma_1 \hat{\sigma}^2_{t+h|t} + \gamma_2 z_{1t} + \ldots + \gamma_{K+1} z_{Kt} + \eta_t$$

  - η_t is heteroskedastic in proportion to σ^2_t: Use GLS.
  - An improved GMZ regression (GMZ-GLS)

$$\frac{\epsilon^2_{t+h} - \hat{\sigma}^2_{t+h|t}}{\hat{\sigma}^2_{t+h|t}} = \gamma_0 \frac{1}{\hat{\sigma}^2_{t+h|t}} + \gamma_1 1 + \gamma_2 \frac{z_{1t}}{\hat{\sigma}^2_{t+h|t}} + \ldots + \gamma_{K+1} \frac{z_{Kt}}{\hat{\sigma}^2_{t+h|t}} + \nu_t$$

  - Better to use *Realized Variance* to evaluate forecasts

$$RV_{t+h} - \hat{\sigma}^2_{t+h|t} = \gamma_0 + \gamma_1 \hat{\sigma}^2_{t+h|t} + \gamma_2 z_{1t} + \ldots + \gamma_{K+1} z_{Kt} + \eta_t$$

  - Also can use GLS version
  - Both RV_{t+h} and ϵ^2_{t+h} are proxies for the variance at $t+h$
    - RV is just better, often 10×+ more precise

Assessing forecasts: Diebold-Mariano

- Relative forecast performance
  - MSE loss

$$\delta_t = \left(\epsilon^2_{t+h} - \hat{\sigma}^2_{A,t+h|t}\right)^2 - \left(\epsilon^2_{t+h} - \hat{\sigma}^2_{B,t+h|t}\right)^2$$

  - $H_0 : \mathrm{E}[\delta_t] = 0$, $H_1^A : \mathrm{E}[\delta_t] < 0$, $H_1^B : \mathrm{E}[\delta_t] > 0$

$$\hat{\bar{\delta}} = R^{-1} \sum_{r=1}^{R} \delta_r$$

  - Standard t-test, 2-sided alternative
  - Newey-West covariance always needed
  - Better DM using “Q-Like” loss (Normal log-likelihood “Kernel”)

$$\delta_t = \left(\ln(\hat{\sigma}^2_{A,t+h|t}) + \frac{\epsilon^2_{t+h}}{\hat{\sigma}^2_{A,t+h|t}}\right) - \left(\ln(\hat{\sigma}^2_{B,t+h|t}) + \frac{\epsilon^2_{t+h}}{\hat{\sigma}^2_{B,t+h|t}}\right)$$

  - Patton & Sheppard (2009)

Realized Variance

Realized Variance

- Variance measure computed using ultra-high-frequency data (UHF)
  - Uses all available information to estimate the variance over some period
    - Usually 1 day
  - Variance estimates from RV can be treated as "observable"
    - Standard ARMA modeling
    - Variance estimates are consistent
    - Asymptotically unbiased
    - Variance converges to 0 as the number of samples increases
  - Problems arise when applied to market data
    - Noise (bid-ask bounce)
    - Market closure
    - Prices discrete
    - Prices not continuously observable
    - Data quality

Realized Variance

- Assumptions
  - Log-prices are generated by an arbitrage-free semi-martingale
    - Prices are observable
    - Prices can be sampled often
  - Defined

$$RV_t^{(m)} = \sum_{i=1}^{m} \left(p_{i,t} - p_{i-1,t}\right)^2 = \sum_{i=1}^{m} r_{i,t}^2.$$

    - m-sample Realized Variance
    - $p_{i,t}$ is the ith log-price on day t
    - $r_{i,t}$ is the ith return on day t
  - Only uses information on day t to estimate the variance on day t
  - Consistent estimator of the integrated variance

$$\int_t^{t+1} \sigma_s^2 ds$$

  - "Total variance" on day t

Why Realized Variance Works

- Consider a simple Brownian motion

$$dp_t = \mu\,\mathrm{d}t + \sigma\,\mathrm{d}W_t$$

  - m-sample Realized Variance

$$RV_t^{(m)} = \sum_{i=1}^{m} r_{i,t}^2$$

  - Returns are IID normal

$$r_{i,t} \overset{\text{i.i.d.}}{\sim} N\left(\frac{\mu}{m}, \frac{\sigma^2}{m}\right)$$

  - Nearly unbiased

$$\mathrm{E}\left[RV_t^{(m)}\right] = \frac{\mu^2}{m} + \sigma^2$$

  - Variance close to 0

$$\mathrm{V}\left[RV_t^{(m)}\right] = 4\frac{\mu^2\sigma^2}{m^2} + 2\frac{\sigma^4}{m}$$

Why Realized Variance Works

- Works for models with time-varying drift and stochastic volatility

$$dp_t = \mu_t \, dt + \sigma_t \, dW_t$$

  - No arbitrage imposes some restrictions on μ_t
  - Works with price processes with jumps
  - In the general case:

$$RV_t^{(m)} \xrightarrow{p} \int_0^1 \sigma_s^2 ds + \sum_{n=1}^{N} J_n^2$$

  - J_n are jumps

Why Realized Variance Doesn't Work

- Multiple prices at the same time
  - Define the price as the average share price (volume weighted price)
  - Use simple average or median
  - Not a problem
- Prices only observed on a discrete grid
  - $.01 or £.0025
  - Nothing can be done
  - Small problem
- Data quality
  - UHF price data is generally messy
  - Typos
  - Wrong time-stamps
  - Pre-filter to remove obvious errors
  - Often remove "round trips"
- No price available at some point in time
  - Use the last observed price: *last price interpolation*
  - Averaging prices before and after leads to bias

Solutions to bid-ask bounce type noise

- Bid-ask bounce is a big problem
  - Simple model with "pure" noise

$$p_{i,t} = p^*_{i,t} + \nu_{i,t}$$

    - $p_{i,t}$ is the observed price with noise
    - $p^*_{i,t}$ is the unobserved efficient price
    - $\nu_{i,t}$ is the noise
  - Easy to show

$$r_{i,t} = r^*_{i,t} + \eta_{i,t}$$

    - $r^*_{i,t}$ is the unobserved efficient return
    - $\eta_{i,t} = \nu_{i,t} - \nu_{i-1,t}$ is a MA(1) error
  - RV is badly biased

$$RV_t^{(m)} \approx \widehat{RV}_t + m\tau^2$$

    - Bias is increasing in m
    - Variance is also increasing in m

Simple solution

- Do not sample frequently
  - 5-30 minutes
    - Better than daily but still inefficient
  - Remove MA(1) by filtering
    - $\eta_{i,t}$ is an MA(1)
    - Fit an MA(1) to observed returns

$$r_{i,t} = \theta\epsilon_{i-1,t} + \epsilon_{i,t}$$

    - Use fit residuals $\hat{\epsilon}_{i,t}$ to compute RV
    - Generally biased downward
  - Use mid-quotes
    - A little noise
    - My usual solution

A modified Realized Variance estimator: RV^{AC1}

- Best solution is to use a modified RV estimator
  - RV^{AC1}

$$RV_t^{AC1(m)} = \sum_{i=1}^{m} r_{i,t}^2 + 2\sum_{i=2}^{m} r_{i,t} r_{i-1,t}$$

  - Adds a term to RV to capture the MA(1) noise
  - Looks like a simple Newey-West estimator
  - Unbiased in pure noise model
  - Not consistent
  - Realized Kernel Estimator
    - Adds more weighted cross-products
    - Consistent in the presence of many realistic noise processes
    - Fairly easy to implement

One final problem

- Market closure
  - Markets do not operate 24 hours a day (in general)
  - Add in close-to-open return squared

$$RV_t^{(m)} = r_{\text{CtO},t}^2 + \sum_{i=1}^{m} r_{i,t}^2$$

    - $r_{\text{CtO},t} = p_{\text{Open},t} - p_{\text{Close},t-1}$
  - Compute a modified RV by weighting the overnight and open hour estimates differently

$$\widetilde{RV}_t^{(m)} = \lambda_1 r_{\text{CtO},t}^2 + \lambda_2 RV_t^{(m)}$$

The volatility signature plot

- Hard to know how often to sample
  - Visual inspection may be useful

Definition (Volatility Signature Plot)

The volatility signature plot displays the time-series average of Realized Variance

$$\overline{RV}_t^{(m)} = T^{-1} \sum_{t=1}^{T} RV_t^{(m)}$$

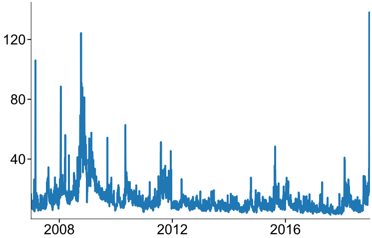
as a function of the number of samples, m. An equivalent representation displays the amount of time, whether in calendar time or tick time (number of trades between observations) along the X-axis.

Some empirical results

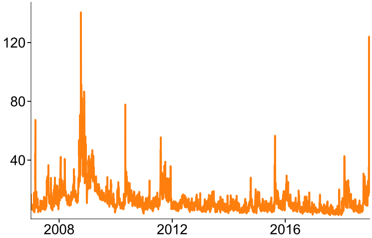
- S&P 500 Depository Receipts
  - SPiDeRs
  - AMEX: SPY
  - Exchange Traded Fund
  - Ultra-liquid
    - 100M shares per day
    - Over 100,000 trades per day
    - 23,400 seconds in a typical trading day
  - January 1, 2007 – December 31, 2018
  - Filtered by daily High-Low data
  - Some cleaning of outliers

SPDR Realized Variance (RV)

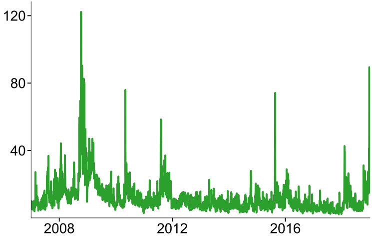
RV, 15 seconds



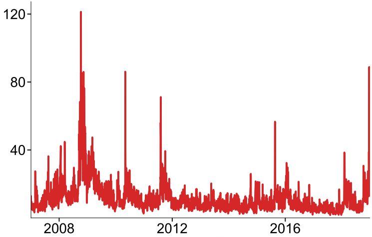
RV, 1 minute



RV, 5 minutes

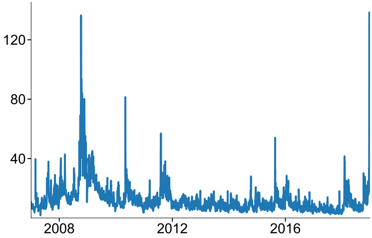


RV, 15 minutes

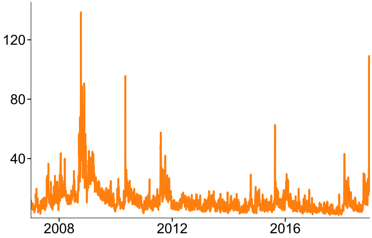


SPDR Realized Variance (RV^{AC1})

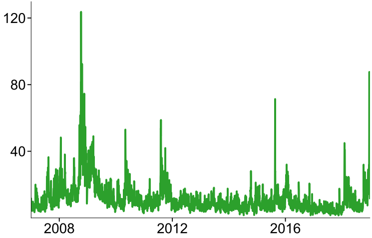
RV^{AC1}, 15 seconds



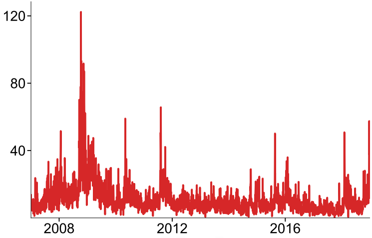
RV^{AC1}, 1 minute



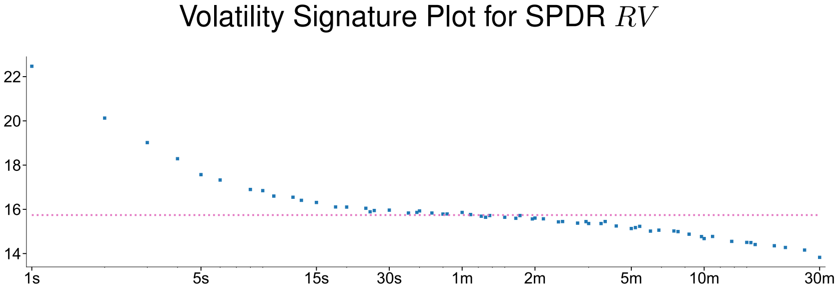
RV^{AC1}, 5 minutes

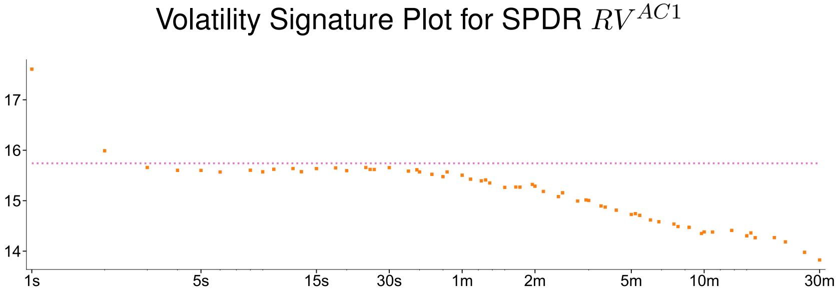


RV^{AC1}, 15 minutes



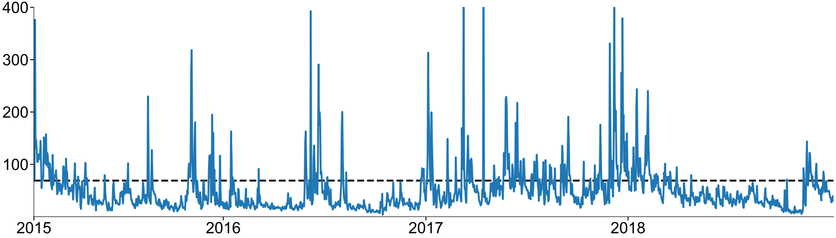
Volatility Signature Plots



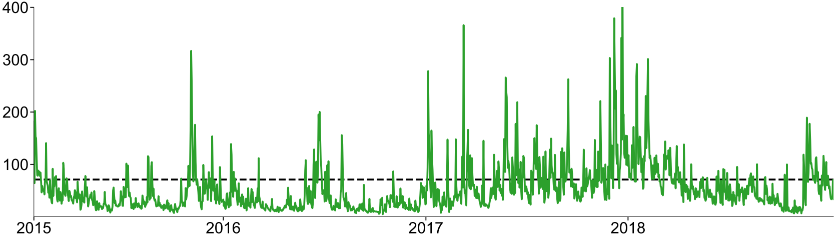


Bitcoin Realized Variance

5-second RV



5-minute RV



Modeling Realized Variance

- Two choices
- Treat volatility as observable and model as ARMA
  - Really simply to do
  - Forecasts are equally simple
  - Theoretical motivation why RV may be well modeled by an ARMA(P,1)
- Continue to treat volatility as latent and use ARCH-type model
  - Realized Variance is still measured with error
  - A more precise measure of conditional variance that daily returns squared, r_t^2, but otherwise similar

Treating σ_t^2 as observable

- *If* RV is σ_t^2,then variance is observable
- Main model used is a Heterogeneous Autoregression
- Restricted AR(22) in levels

$$RV_t = \phi_0 + \phi_1 RV_{t-1} + \phi_5 \overline{RV}_{5,t-1} + \phi_{22} \overline{RV}_{22,t-1} + \epsilon_t$$

- Or in logs

$$\ln RV_t = \phi_0 + \phi_1 \ln RV_{t-1} + \phi_5 \ln \overline{RV}_{5,t-1} + \phi_{22} \ln \overline{RV}_{22,t-1} + \epsilon_t$$

  where $\overline{RV}_{j,t-1} = j^{-1} \sum_{i=1}^{j} RV_{t-i}$ is a j lag moving average
- Model picks up volatility changes at the daily, weekly, and monthly scale
- Fits and forecasts RV fairly well
  - MA term may still be needed

Leaving σ_t^2 latent

- Alternative if to treat RV as a proxy of the latent vairance and use a *non-negative multiplicative error model* (MEM)
- MEMs specify the mean of a process as $\mu_t \times \psi_t$ where ψ_t is a mean *1* shock.
- A χ_1^2 is a natural choice here
- ARCH models are special cases of a non-negative MEM model
- Easy to model RV using existing ARCH mdoes
  1. Construct $\tilde{r}_t = \operatorname{sign}(r_t)\sqrt{RV_t}$
  2. Use standard ARCH model building to construct a model for $\tilde{r}_t$

$$\sigma_t^2 = \omega + \alpha_1 \tilde{r}_{t-1}^2 + \gamma_1 \tilde{r}_{t-1}^2 I_{[\tilde{r}_{t-1}<0]} + \beta_1 \sigma_{t-1}^2$$

becomes

$$\sigma_t^2 = \omega + \alpha_1 RV_{t-1} + \gamma_1 RV_{t-1} I_{[r_{t-1}<0]} + \beta_1 \sigma_{t-1}^2$$

Implied Variance

Implied Volatility and VIX

- Implied volatility is very different from ARCH and Realized measures
- Market based: Level of volatility is calculated from options prices
- Forward looking: Options depend on future price path
- “Classic” implied relies on the Black-Scholes pricing formula
- “Model free” implied volatility exploits a relationship between the second derivative of the call price with respect to the strike and the risk neutral measure
- VIX is a Chicago Board Options Exchange (CBOE) index based on a model free measure
- Allows volatility to be directly traded

Black-Scholes Implied Volatility

- Black-Scholes Options Pricing
- Prices follow a geometric Brownian Motion

$$\mathrm{d}S_t = \mu S_t \mathrm{d}t + \sigma S_t \mathrm{d}W_t$$

- Constant drift and volatility
- Price of a call is

$$C(T,K) = S\Phi(d_1) + Ke^{-rT}\Phi(d_2)$$

where

$$d_1 = \frac{\ln(S/K) + \left(r + \sigma^2/2\right)T}{\sigma\sqrt{T}}$$

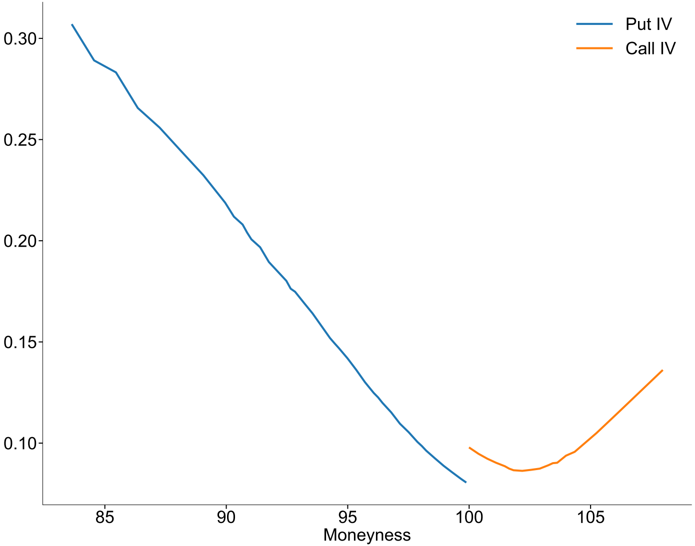
$$d_2 = \frac{\ln(S/K) + \left(r - \sigma^2/2\right)T}{\sigma\sqrt{T}}.$$

- Can invert to produce a formula for the volatility given the call price $C(T,K)$

$$\sigma_t^{\text{Implied}} = g\left(C_t(T,K), S_t, K, T, r\right)$$

BSIV against Moneyness for SPY

Jan 15, 2018 options expiring on Feb 2, 2018



Model Free Implied Volatility

- Model free uses the relationship between option prices and RN density
- The price of a call option with strike K and maturity t is

$$C(t,K) = \int_K^\infty (S_t - K)\,\phi_t(S_t)\,dS_t$$

- $\phi_t(S_t)$ is the *risk-neutral* density at maturity t
- Differentiating with respect to strike yields

$$\frac{\partial C(t,K)}{\partial K} = -\int_K^\infty \phi_t(S_t)\,dS_t$$

- Differentiating again with respect to strike yields

$$\frac{\partial^2 C(t,K)}{\partial K^2} = \phi_t(K)$$

- The change in an option price as a function of the strike K is the probability of the stock price having value K at time t
- Allows for risk-neutral density to be recovered from a continuum of options *without assuming a model for stock prices*

Model Free Implied Volatility

- The previous result allows a model free IV to be computed from

$$\mathrm{E}_{\mathbb{F}}\left[\int_0^t \left(\frac{\partial F_s}{F_s}\right)^2 ds\right] = 2\int_0^\infty \frac{C^F(t,K) - (F_0 - K)^+}{K^2}\mathsf{d}K$$

- Devil is in the details
  - Only finitely many calls
  - Thin trading
  - Truncation

$$\sum_{m=1}^{M} \left[g(T,K_m) + g(T,K_{m-1})\right](K_m - K_{m-1})$$

  where

$$g(T,K) = \frac{C(t, K/B(0,t)) - (S_0 - K)^+}{K^2}$$

- See Jiang & Tian (2005, *RFS*) for a very useful discussion

- VIX is continuously computed by the CBOE
- Uses a model-free style formula
- Uses both calls and puts
- Focuses on out-of-the-money options
  - OOM options are more liquid
- Formula:

$$\sigma^2 = \frac{2}{T} e^{rT} \sum_{i=1}^{N} \frac{\Delta K_i}{K_i^2} Q(K_i) - \frac{1}{T} \left(\frac{F_0}{K_0} - 1 \right)^2$$

  - $Q(K_i)$ is the mid-quote for a strike of K_i, K_0 is the first strike below the forward index level
  - Only uses out-of-the-money options
  - VIX appears to have information about future *realized* volatility that is not in other backward looking measures (GARCH/RV)

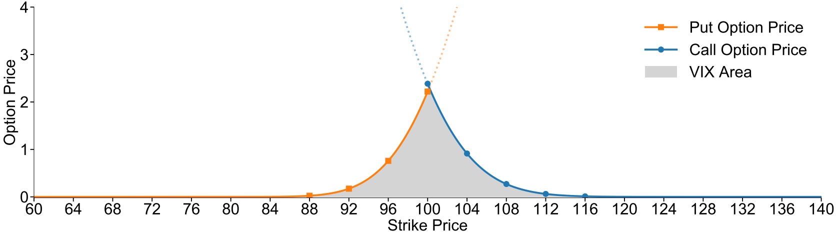
Model-Free Example

- MFIV works under weak conditions on the underlying price process
  - Geometric Brownian motion is included
- Put and call options prices computed from Black-Scholes
  - Annualized volatiltiy either 20% or 60%
  - Risk-free rate 2%, time-to-maturity 1 month $(T = {}^{1}/_{12})$
  - Current price 100 (normalized to moneyness), strikes every 4%
- Contribution is $\frac{2}{T} e^{rT} \frac{\Delta K_i}{K_i^2} Q(K_i)$

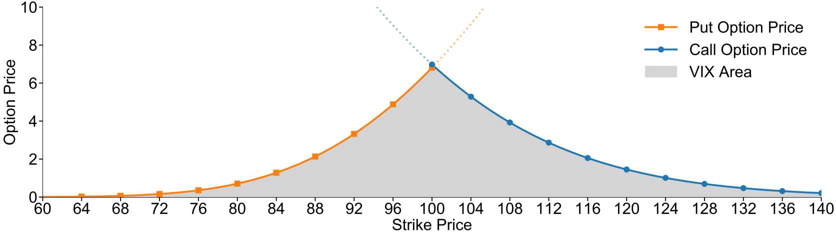
Strike	Call	Put	Abs. Diff.	VIX Contrib.
88	12.17	0.02	12.15	0.0002483
92	8.33	0.17	8.15	0.0019314
96	4.92	0.76	4.16	0.0079299
100	2.39	2.22	0.17	0.0221168
104	0.91	4.74	3.83	0.0080904
108	0.27	8.09	7.82	0.0022259
112	0.06	11.88	11.81	0.0004599
116	0.01	15.82	15.81	7.146e-05
Total				0.0430742

Model-Free Example

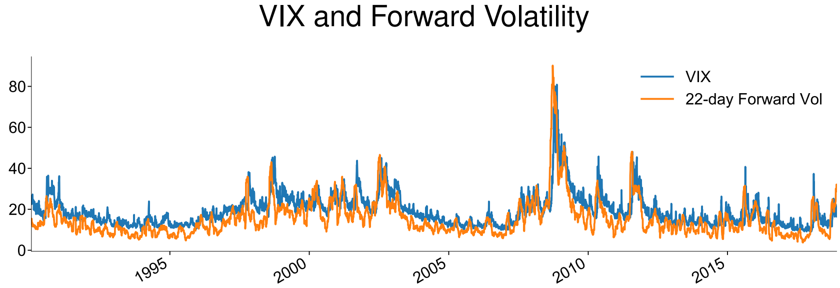
20% Annualized Volatility

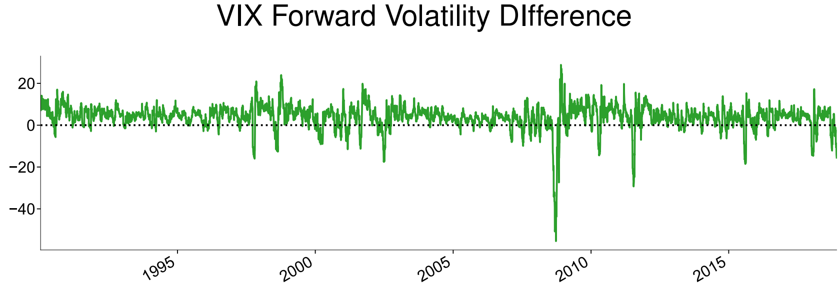


60% Annualized Volatility



VIX against TARCH(1,1,1) Forward-vol





Variance Risk Premium

- Difference between VIX and forward volatility is a measure of the return to selling volatility
- Variance Risk Premium is strictly forward looking

$$\mathrm{E}_t^{\mathbb{Q}}\left[\int_0^{t+h}\left(\frac{\partial F_s}{F_s}\right)^2 ds\right]-\mathrm{E}_t^{\mathbb{P}}\left[\int_t^{t+h}\left(\frac{\partial F_s}{F_s}\right)^2 ds\right]$$

- Defined as the difference between RN $(\mathrm{E}^{\mathbb{Q}})$ and physical $(\mathrm{E}^{\mathbb{P}})$ variance
  - RN variance measured using VIX or other MFIV
  - Physical forecast from HAR or other model based on Realized Variance
    - RV matters, using daily is sufficiently noisy that prediction is not useful

Lag 2

ACF

$$y_t = \phi + \hat{\rho}_2 \, y_{t-2} + u_t$$

3

4

5

:

PACF

$$y_t = \phi_0 + \phi_1 y_{t-1} + \rho_2 y_{t-2} + u_t$$