Computational Finance

AMSTERDAM BUSINESS SCHOOL

Business

Plotting Basics

- Plotting in (scientific) Python is mostly done via the `matplotlib` library ([Documentation (https://matplotlib.org/users/index.html)](https://matplotlib.org/users/index.html)), which is inspired by the plotting facilities of Matlab®.
- Its main plotting facilities reside in its `pyplot` module. Usually imported as

In [2]:
```
import matplotlib.pyplot as plt
%matplotlib inline
```

- The second line is an [ipython magic (http://ipython.readthedocs.io/en/stable/interactive/magics.html)](http://ipython.readthedocs.io/en/stable/interactive/magics.html). It makes plots appear inline in the notebook.
- The `seaborn` library ([Documentation (https://seaborn.pydata.org/tutorial.html)](https://seaborn.pydata.org/tutorial.html)) provides higher-level statistical visualizations:

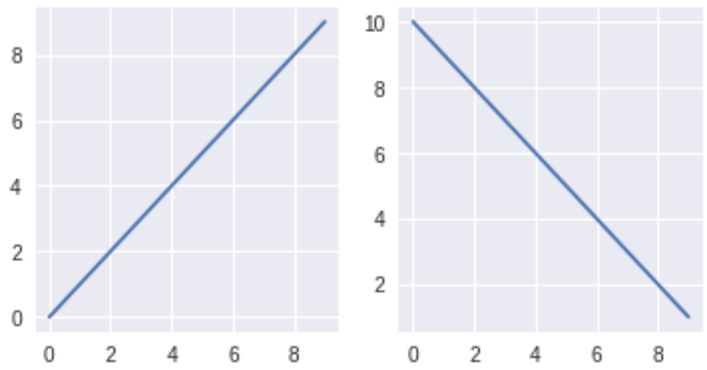
In [3]:
```
import seaborn as sns
```

- Finally, `statsmodels` is useful for QQ plots (see below):

In [4]:
```
import statsmodels.api as sm
```

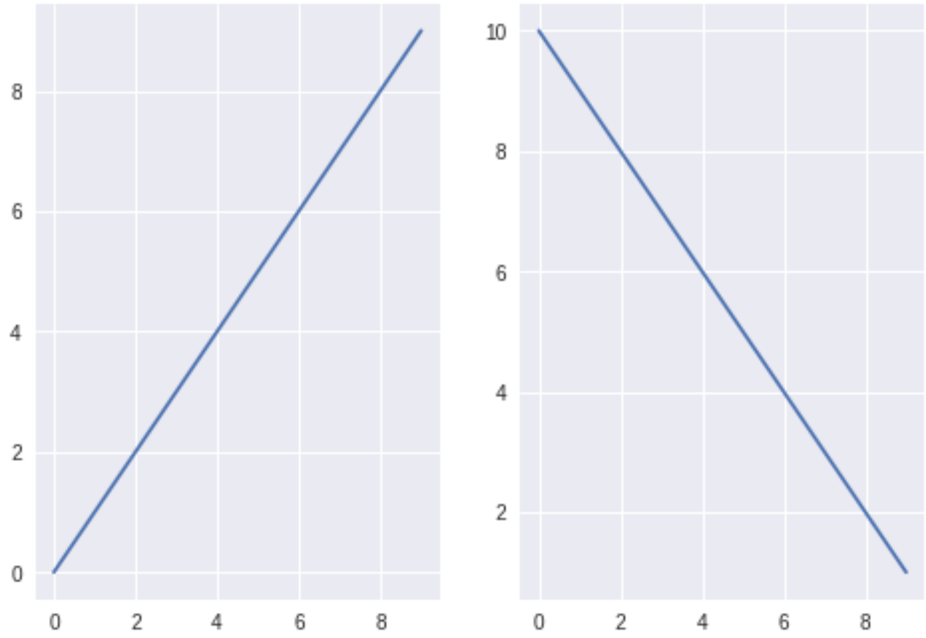
- I will only give a brief introduction to matplotlib here. However, the code for all graphs shown below is included in the notebook (though sometimes hidden in slide mode), and should be studied.
- The fundamental object in matplotlib is a `figure`, inside of which reside `subplots` (or `axes`).
- To create a new figure, add an axis, and plot to it:

In [5]:
```
#with the inline backend, these need to be in the same cell.
fig=plt.figure(figsize=(6,3)) #create a new empty figure object. Size is optional.
ax1=fig.add_subplot(121) #(1x2) axes and make the first one current (what plt.* com
mands operate on)
ax2=fig.add_subplot(122) #(1x2) axes and make the second one current
ax1.plot(range(10))
ax2.plot(range(10,0,-1));
```



- By default matplotlib plots into the current axis, creating one (and a figure) if needed. Using the convenience method `subplot`, this allows us to achieve the same without explicit reference to figures and axes:

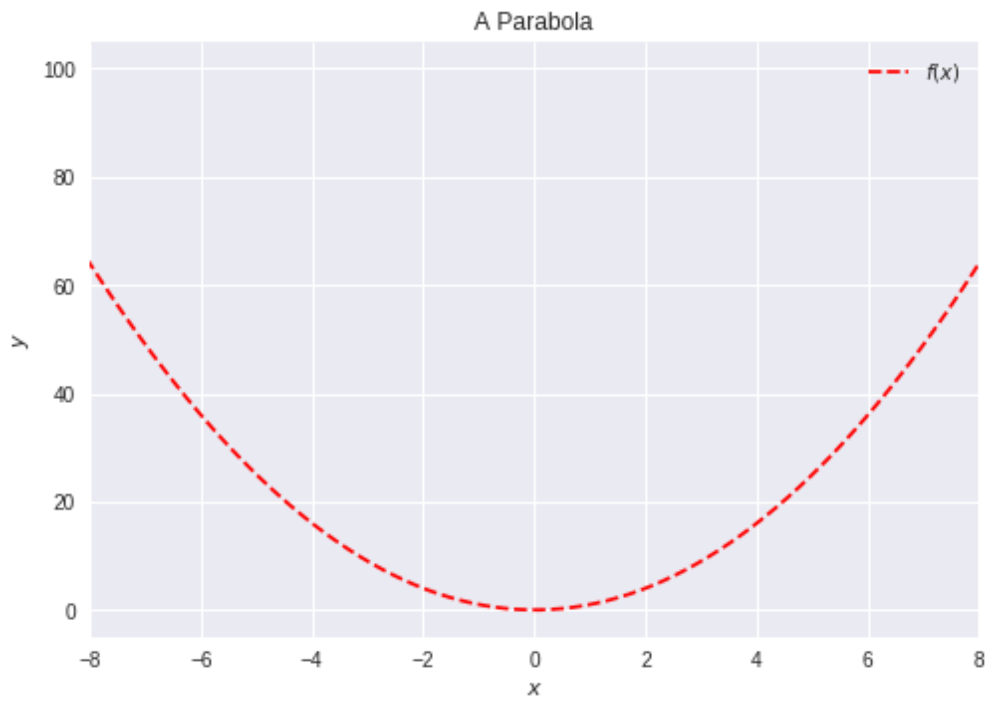
In [6]:
```
plt.subplot(121)
plt.plot(range(10))
plt.subplot(122)
plt.plot(range(10, 0, -1));
```



- To plot two vectors x and y against each other:

In [7]:

```
import numpy as np
x=np.linspace(-10,10,100)
y=x**2
plt.plot(x,y,'r--') #dashed red line; see table on p. 114
plt.xlabel('$x$') #LaTeX equations can be included by enclosing in $$
plt.ylabel('$y$')
plt.title('A Parabola')
plt.legend(['$f(x)$']); #Expects a list of strings
plt.xlim(xmin=-8, xmax=8); #axis limits
#plt.savefig('filename.svg') #to save a plot to disk
```



Risk Measures

Introduction

- The Basel Accords mandate that financial institutions report the risk associated with their positions, so that regulators may check the adequacy of the economic capital as a buffer against market risk.
- Reporting is in the form of a *risk measure*, which condenses the risk of a position into a single number.
- Currently, the mandated measure is *Value at Risk* (VaR), but there are debates of replacing it with an alternative (*Expected Shortfall*).
- Banks are allowed to use their own, internal models for the computation of VaR, but the adequacy of these models should be backtested.

Value at Risk

- Consider a portfolio with value V_t and daily (simple) returns R_t.
- Define the one-day loss on the portfolio as
$$\$Loss_{t+1} = -\left[V_{t+1} - V_t\right].$$
- I will distinguish between the dollar Value at Risk (an amount) and the return Value at Risk (a percentage). When unqualified, I mean the latter.
- The one-day $100p\%$ dollar Value at Risk $\$VaR_{t+1}^{p}$ is the loss on the portfolio that we are $100\left(1-p\right)\%$ confident will not be exceeded. The Basel committee prescribes $p = 0.01$.

- The *return Value at risk* VaR^p_{t+1} expresses $\$VaR^p_{t+1}$ as a percentage of the portfolio value:

$$VaR^p_{t+1} = \frac{\$VaR^p_{t+1}}{V_t}.$$

- Hence

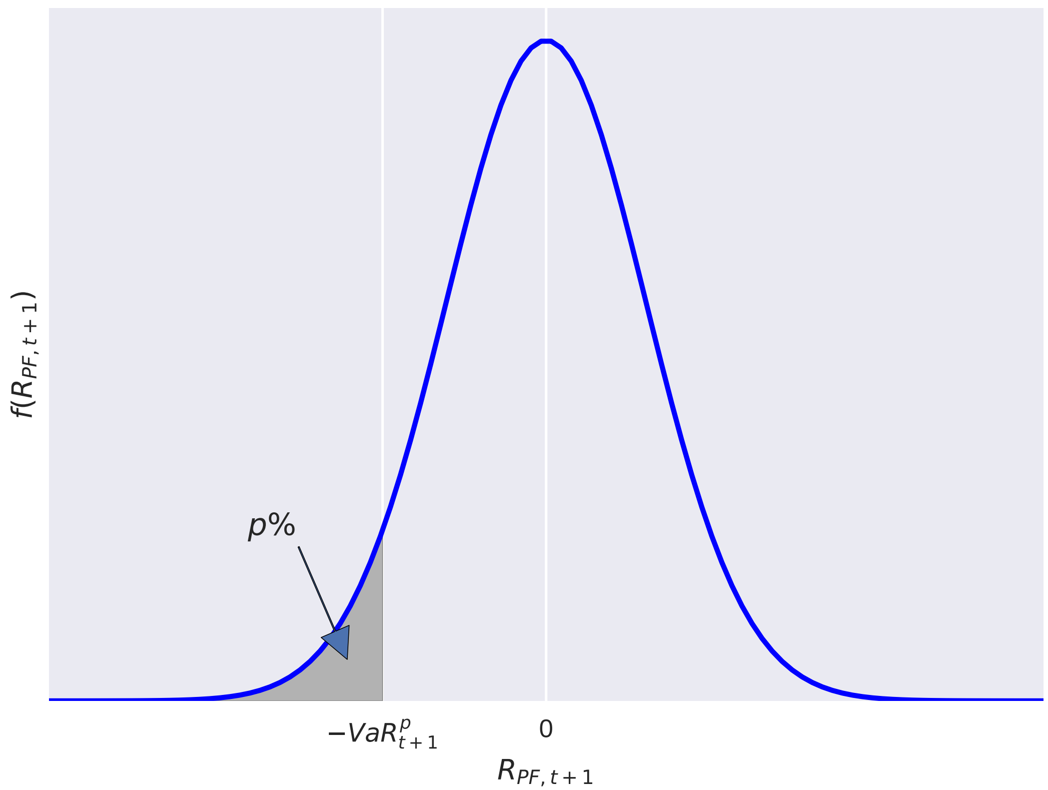
$$\Pr(R_{t+1} < -VaR^p_{t+1}) = p,$$

because

$$R_{t+1} = -\frac{\$Loss_{t+1}}{V_t}.$$

This holds approximately for log returns, too.

- Thus VaR^p_{t+1} is minus the $100p$th *percentile* (or minus the pth *quantile*) of the return distribution.

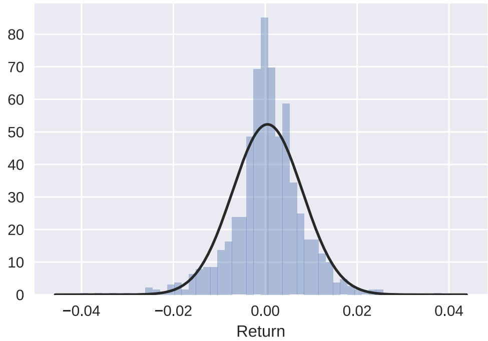

$p\%$
$-VaR^{p}_{t+1}$
0
$R_{PF,t+1}$
$f(R_{PF,t+1})$

Asset Returns: Stylized Facts

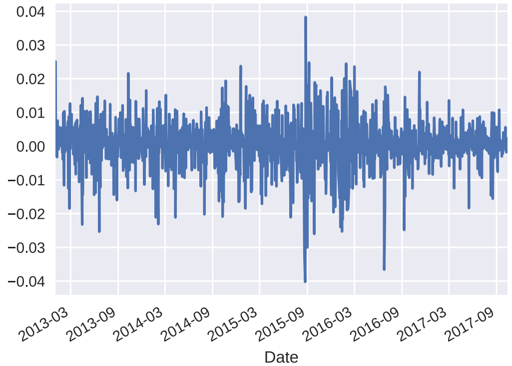
- Stylized facts about asset returns include
  - Lack of autocorrelation
  - Leverage effects
  - Heavy tails of return distribution
  - Volatility clustering
- These need to be taken into account when creating VaR forecasts.

In [9]:

```
import pandas as pd
import pandas_datareader.data as web
p=web.DataReader("^GSPC", 'yahoo', start='1/1/2013', end='10/12/2017')['Adj Close']
r=np.log(p)-np.log(p).shift(1)
r.name='Return'
r=r[1:] #remove first observation (NaN)
plt.figure(figsize=(12,4))
plt.subplot(121)
sns.distplot(r, kde=False, fit=stats.norm) #histogram overlaid with fitted normal d
ensity
plt.subplot(122)
r.plot() #note that this is a pandas method! looks prettier than plt.plot(r)
plt.savefig('img/stylizedfacts.svg') #save to file
plt.close()
```



80
70
60
50
40
30
20
10
0
−0.04
−0.02
0.00
0.02
0.04
Return



0.04
0.03
0.02
0.01
0.00
−0.01
−0.02
−0.03
−0.04
2013-03
2013-09
2014-03
2014-09
2015-03
2015-09
2016-03
2016-09
2017-03
2017-09
Date

VaR Methods: Unconditional

Non-parametric: Historical Simulation

- Historical simulation assumes that the distribution of tomorrow's portfolio returns is well approximated by the empirical distribution (histogram) of the past m observations $\{R_t, R_{t-1}, \ldots, R_{t+1-m}\}$.

- This is as if we draw, with replacement, from the last m returns and use this to simulate the next day's return distribution.

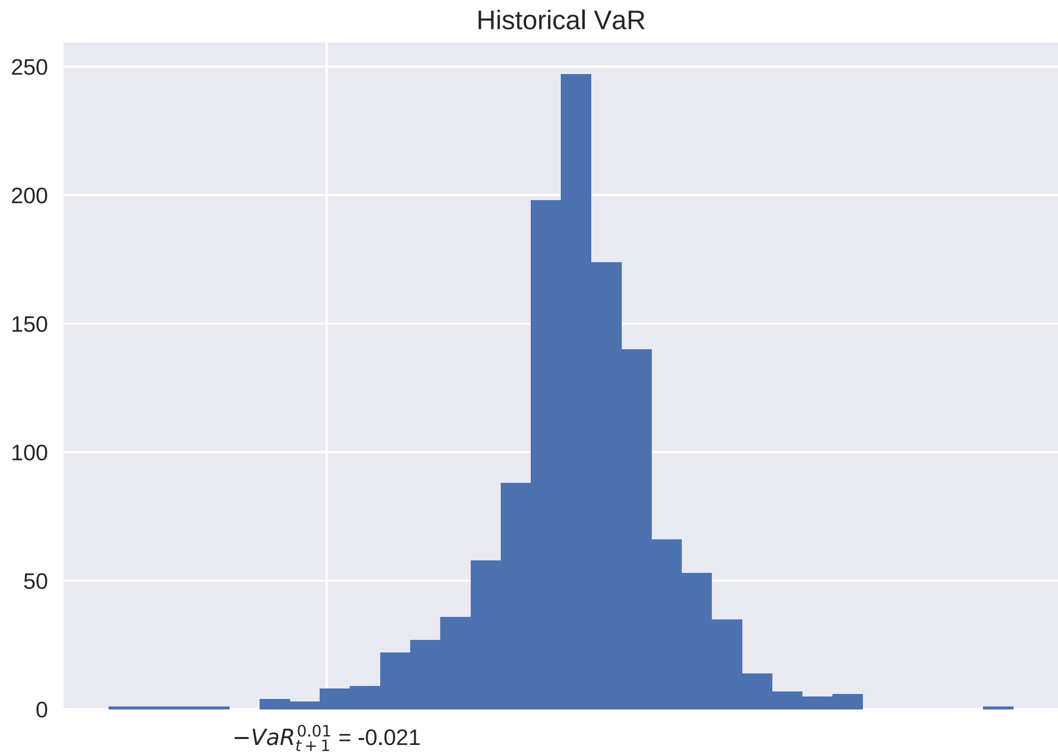
- The estimator of VaR is given by minus the pth *sample quantile* of the last m portfolio returns, i.e., $\widehat{VaR}_{t+1}^{p} = -R_p^m$, where R_p^m is the number such that $100p\%$ of the observations are smaller than it.

- In Python, we can use NumPy's `quantile` method, or the `percentile` function (or `nanpercentile` which ignores NaNs). Hilpisch uses `scoreatpercentile`, but that is is deprecated.

In [10]:
```
VaR_hist=-r.quantile(.01) #Alternatively, VaR=np.percentile(r,1)
VaR_hist
```

Out[10]:
```
0.02131716077914799
```

In [11]:
```
ax=r.hist(bins=30) #another pandas method: histogram with 30 bins
ax.set_xticks([-VaR_hist])
ax.set_xticklabels(['$-VaR_{t+1}^{0.01}$ = -%4.3f' %VaR_hist]) #4.3f means 4 digits
, of which 3 decimals
plt.title('Historical VaR')
plt.savefig('img/var_hist.svg')
plt.close()
```



Historical VaR
250
200
150
100
50
0
$-VaR^{0.01}_{t+1}$ = -0.021

- Problem: Last year(s) of data not necessarily representative for the next few days (e.g. because of volatility clustering).
- Exacerbated by the fact that a large m is required to compute 1% VaR with any degree of precision (only 1% of the data are really used).

Parametric: Normal and t Distributions

- Another simple approach is to assume $R_{t+1} \sim N(\mu, \sigma^2)$, and to estimate μ and σ^2 from historical data (for daily data, $\mu \approx 0$).
- The VaR is then determined from

$$\begin{aligned} \Pr\left(R_{t+1} < -VaR^p_{t+1}\right) &= \Pr\left(\frac{R_{t+1} - \mu}{\sigma} < \frac{-VaR^p_{t+1} - \mu}{\sigma}\right) \\ &= \Pr\left(z_{t+1} < \frac{-VaR^p_{t+1} - \mu}{\sigma}\right) \\ &= \Phi\left(\frac{-VaR^p_{t+1} - \mu}{\sigma}\right) = p, \end{aligned}$$

where $\Phi(z)$ is the cumulative standard normal distribution.

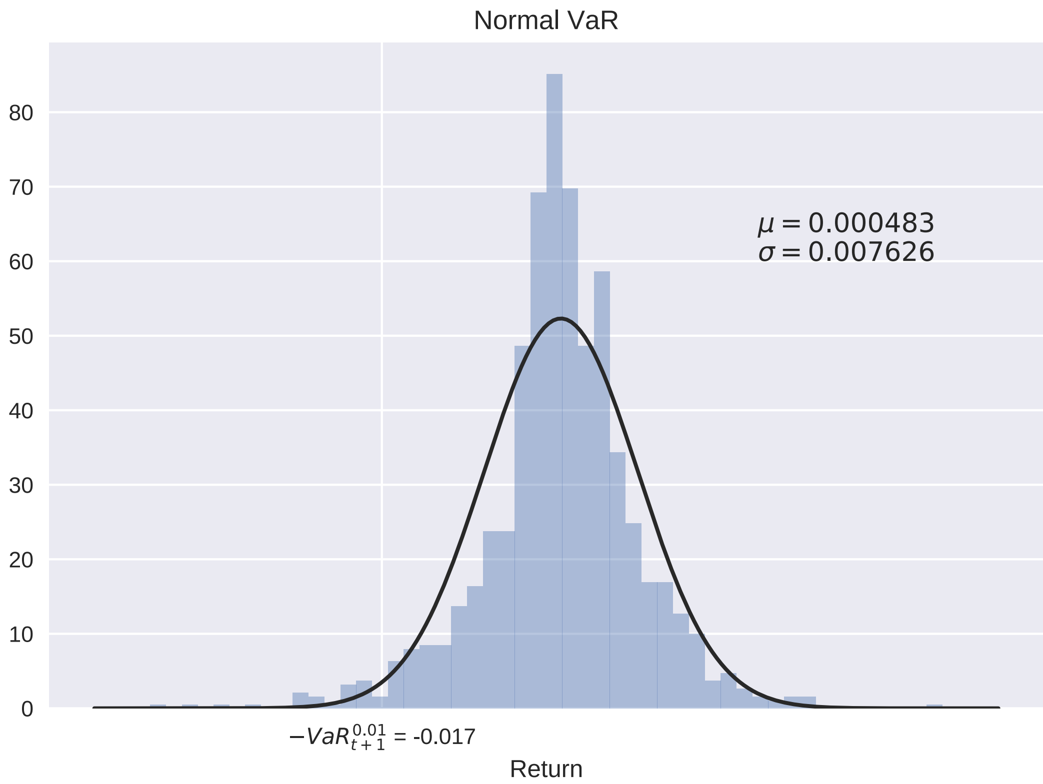
- Thus,

$$VaR_{t+1}^{p}=-\mu-\sigma\Phi^{-1}(p),$$

where $\Phi^{-1}(p)$ is the inverse distribution function of the standard normal, a.k.a. the *percentage point function* (ppf).
- In Python:

In [12]:
```
mu, sig=stats.norm.fit(r) #fit a normal distribution to r
VaR_norm=-mu-sig*stats.norm.ppf(0.01)
VaR_norm
```

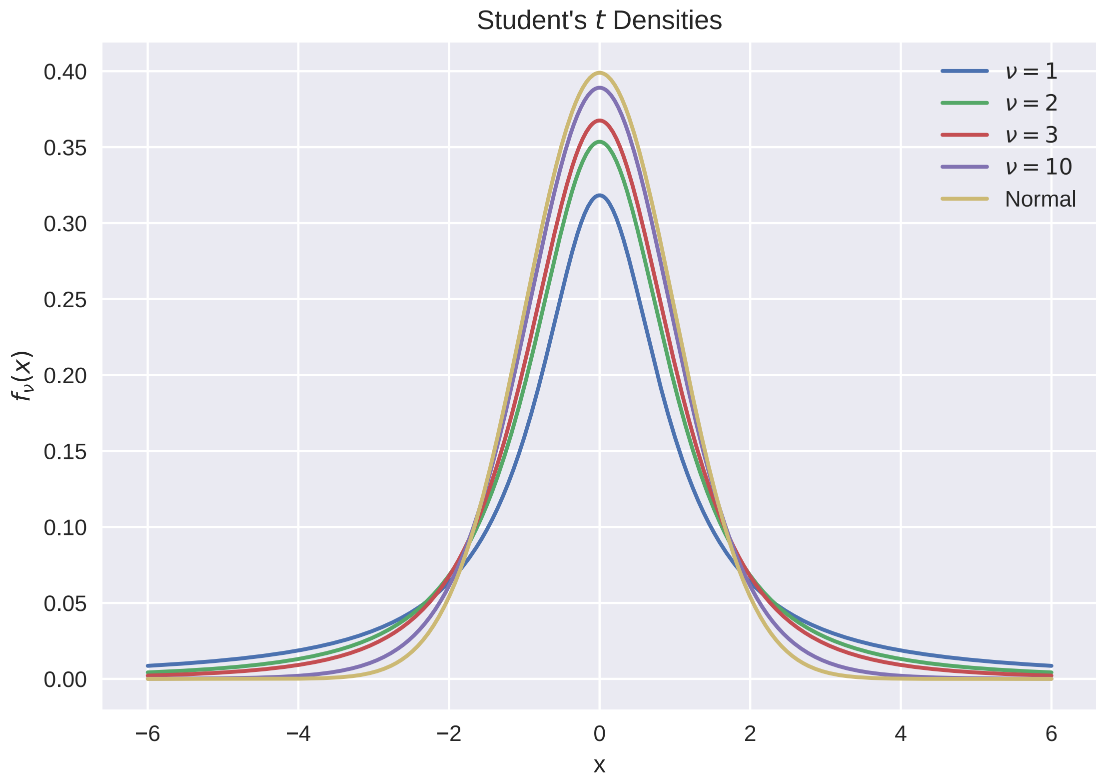
Out[12]:
```
0.017257996794445292
```



Normal VaR
80
70
60
50
40
30
20
10
0
$\mu = 0.000483$
$\sigma = 0.007626$
$-VaR_{t+1}^{0.01}$ = -0.017
Return

- Problems:
  - Variance of the past year(s) of data not necessarily representative for the future.
  - Returns typically have heavier tails than the normal.
- The solution to the second point is to use another distribution. The Student's t distribution is a popular choice.

- The Student's t distribution with ν degrees of freedom, t_ν, is well known from linear regression as the distribution of t-statistics, where $\nu = T - k$.
- Can be generalized to allow $\nu \in \mathbb{R}_+$.
- Smaller values of ν correspond to heavier tails. As $\nu \to \infty$, we approach the $N(0, 1)$ distribution.
- It only has moments up to but not including ν:
  - The mean is finite and equal to zero if $\nu > 1$.
  - The variance is finite and equal to $\nu/(\nu - 2)$ if $\nu > 2$.
  - The excess kurtosis is finite and equal to $6/(\nu - 4)$ if $\nu > 4$.
- The distributions are symmetric around 0, hence mean and skewness are 0 if they exist.

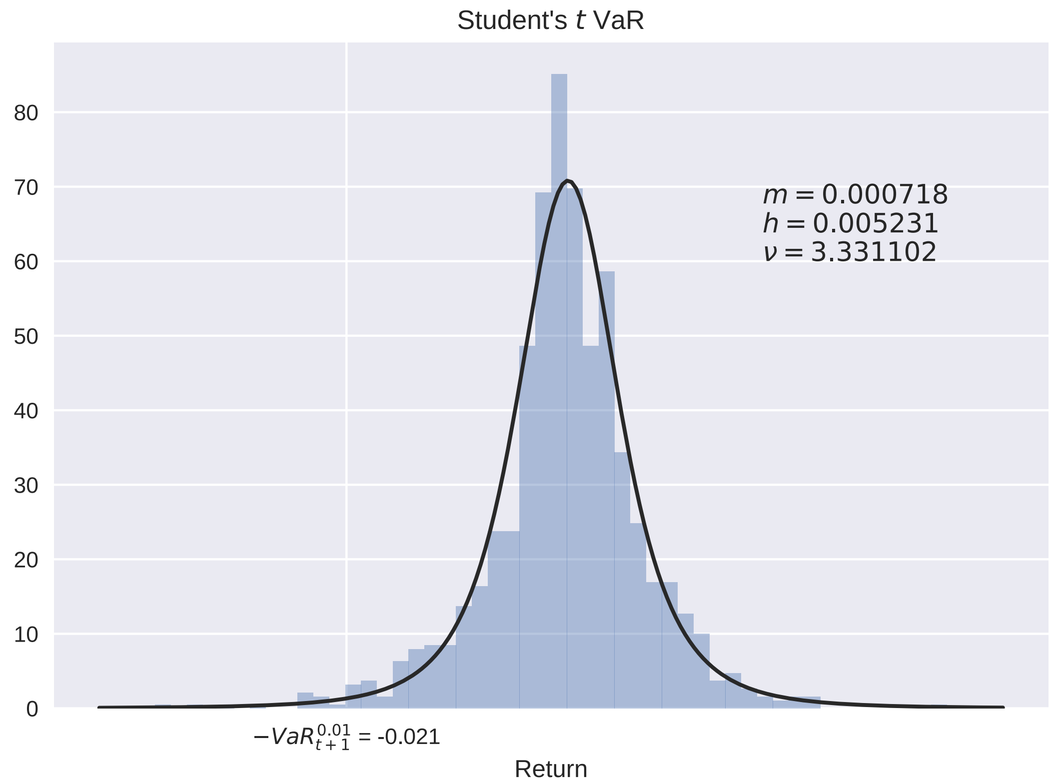


Student's t Densities
$\nu = 1$
$\nu = 2$
$\nu = 3$
$\nu = 10$
Normal
$f_\nu(x)$
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−6
−4
−2
0
2
4
6
x

- For financial applications, we need to allow for a non-zero mean, and a variance different from $\nu/(\nu-2)$.
- This is achieved by introducing a *location parameter* m and a *scale parameter* h. We'll write $f_\nu(x;m,h)$ for the resulting density, $F_\nu(x;m,h)$ for the distribution function, and $F_\nu^{-1}(p;m,h)$ for the percentage point function.
- Note that if $x \sim t_\nu(m,h), \nu > 2$, then $\mathbb{E}[x]=m$ and $\mathrm{var}[x]=h^2\nu/(\nu-2)$.
- The VaR becomes \begin{equation} VaR{t+1}^{p}=-m -h F^{-1}\nu(p;0,0). \end{equation}
- In Python:

In [15]:
```
df, m, h=stats.t.fit(r) #fit a location-scale t distribution to r
VaR_t=-m-h*stats.t.ppf(0.01, df)
VaR_t
```

Out[15]:
```
0.021244629280331669
```


Student's t VaR
80
70
60
50
40
30
20
10
0
$m = 0.000718$
$h = 0.005231$
$\nu = 3.331102$
$-VaR^{0.01}_{t+1}$ = -0.021
Return

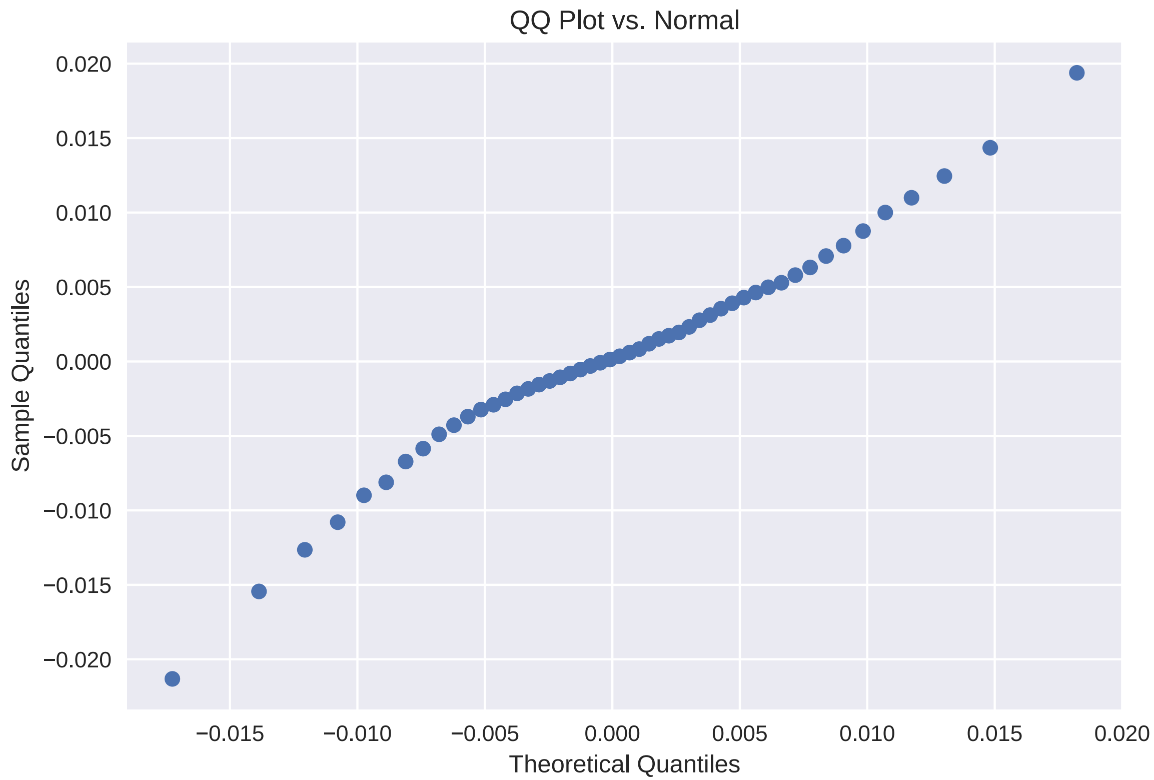
- There are several ways to assess whether a distributional assumption is adequate.
- One is to use a *goodness of fit test*. Many such tests exist.
- Hilpisch discusses the D'Agostino-Pearson test, available as `stats.normaltest`.
- Here we use the Jarque-Bera test. The test statistic is
$$JB = N\left(S^2/6 + (K-3)/24\right),$$
where S and K are respectively the sample skewness and kurtosis.
- Intuitively, it tests that the skewness and excess kurtosis are zero.
- It is distributed as χ_2^2 under the null of normality. The 5% critical value is

In [17]:
```
stats.chi2.ppf(0.95, 2)
```
Out[17]:
```
5.9914645471079799
```

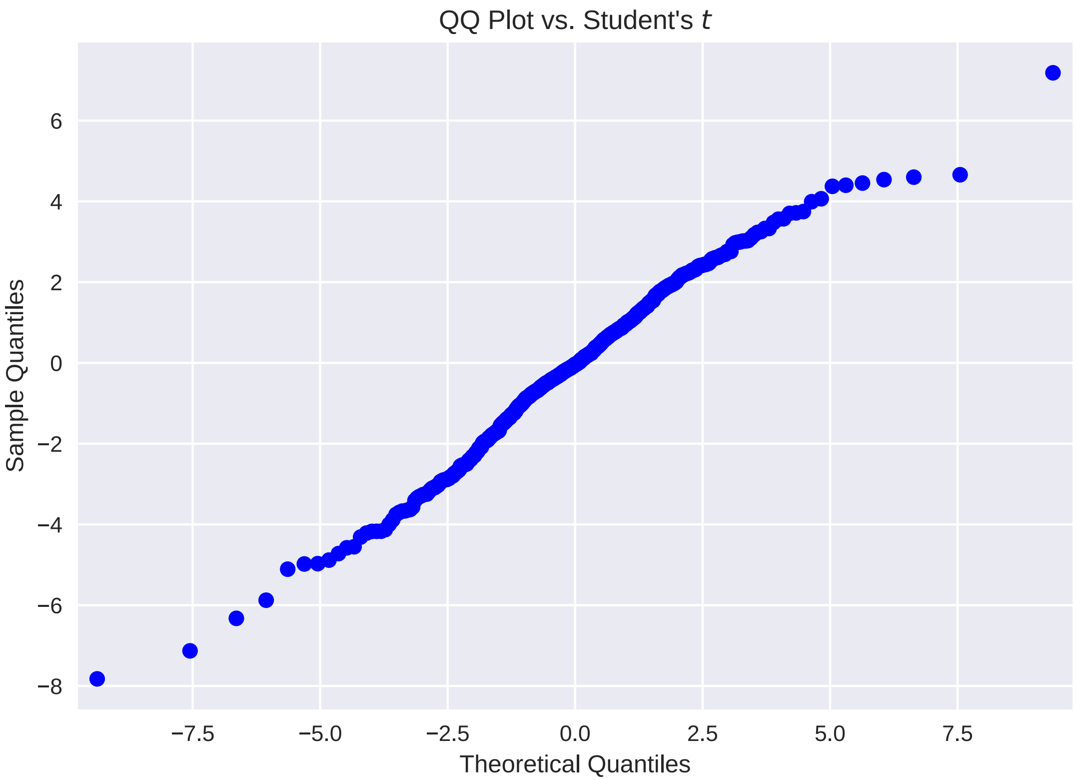
- In Python:

In [18]:
```
stats.jarque_bera(r) #returns (JB, p-val)
```
Out[18]:
```
(410.78923631633768, 0.0)
```

- Another option is to use a QQ-plot (quantile-quantile plot).
- It plots the empirical quantiles against the quantiles of a hypothesized distribution, e.g. $\Phi^{-1}(p)$ for the normal.
- If the distributional assumption is correct, then the plot should trace out the 45 degree line.



QQ Plot vs. Normal
Sample Quantiles
Theoretical Quantiles
0.020
0.015
0.010
0.005
0.000
−0.005
−0.010
−0.015
−0.020
−0.015
−0.010
−0.005
0.000
0.005
0.010
0.015
0.020


QQ Plot vs. Student's t
Sample Quantiles
Theoretical Quantiles
6
4
2
0
−2
−4
−6
−8
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5

VaR Methods: Filtered

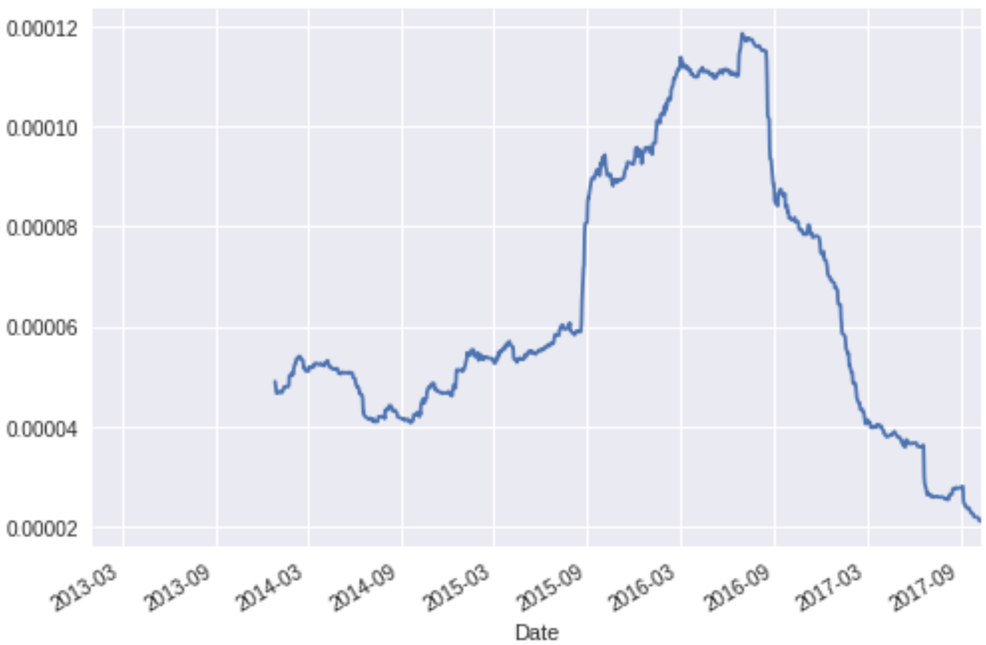
- All methods discussed so far share one drawback: they assume that the volatility is constant, at least in the estimation (and forecast) period.
- Implicitly, the Normal and Student's t method use the *historical volatility*:

$$\sigma^2_{t+1,HIST} = \frac{1}{m}\sum_{j=0}^{m-1} R^2_{t-j}.$$

  (Note: volatility usually means standard deviation, not variance. I'll be sloppy here).
- Here we assumed a zero mean, which is realistic for daily returns.
- Some adaptability is gained by choosing a smaller m such as 250 (one trading year), but there is a tradeoff because doing so decreases the sample size.
- A general solution requires a *volatility model*, which will be discussed in *Advanced Risk Management*.

- A Pandas `Series` object has a `rolling` method that can be used to construct historial volatilities for an entire series, using, at each day, the past m observations.
- The method returns a special window object that in turn has a method `var` (for variance).

In [21]:
```
sig2_hist=r.rolling(window=250).var()
sig2_hist.plot();
```



- A partial solution to the drawbacks of historical volatility is given by the RiskMetrics model, which is a special case of a more general framework known as *GARCH* models.
- The idea is to replace the equally weighted moving average used in historical volatility by an exponentially weighted moving average (EWMA):

$$\begin{aligned}\sigma^2_{t+1,EWMA} &= (1-\lambda)\sum_{j=0}^{\infty}\lambda^j R^2_{t-j}\\ &= \lambda\sigma^2_{t,EWMA} + (1-\lambda)R^2_t, \qquad 0<\lambda<1.\end{aligned}$$

- This means that observations further in the past get a smaller weight.

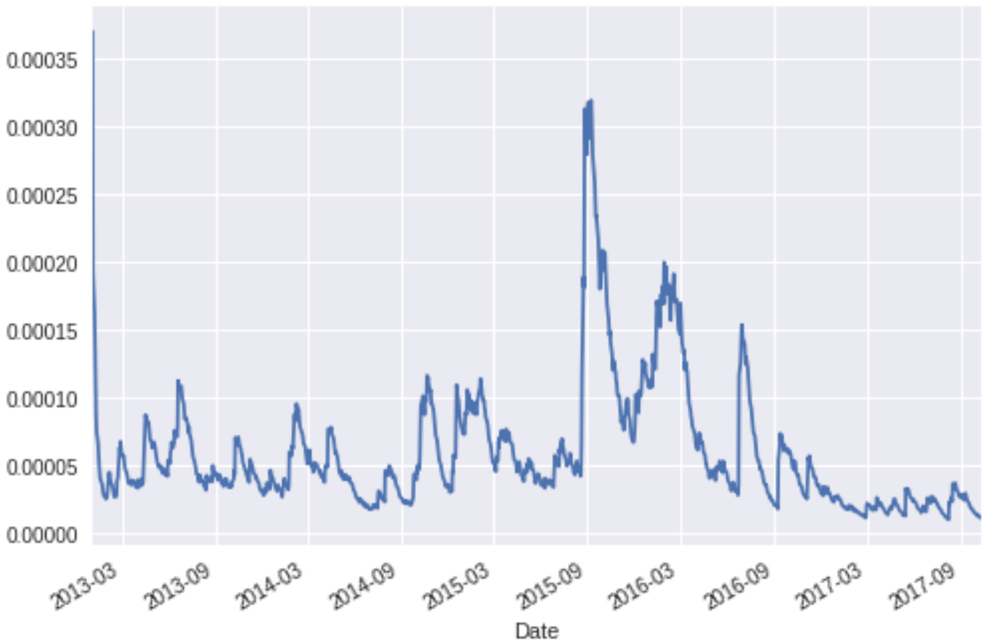
- Smaller λ means faster downweighting; for $\lambda \to 1$ we approach historical volatility (with an expanding window).

- In practice we do not have $R_{t-\infty}$, but the second equation can be started up by an initial estimate / guess $\sigma^2_{0,EWMA}$.

- For daily data, RiskMetrics recommends $\lambda = 0.94$.

- The `ewm` (exponentially moving average) method of a Pandas `Series` can be used to achieve something similar (the exact definition is slightly different, see here (http://pandas.pydata.org/pandas-docs/stable/computation.html#exponentially-weighted-windows)).
- As before, the method returns a window object that has a `var` method.

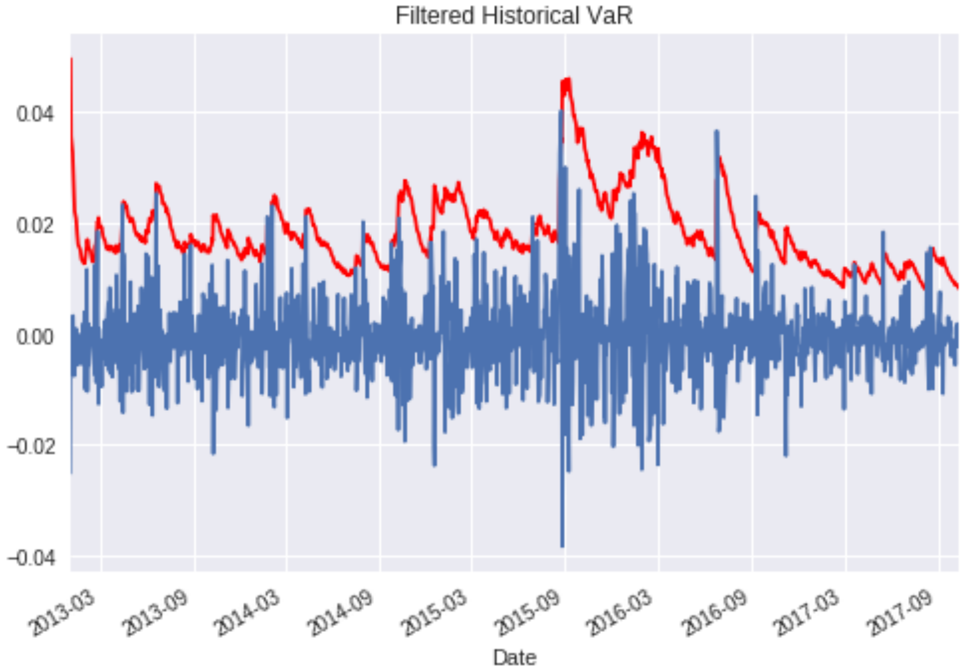
In [22]:
```
sig2_ewma=r.ewm(alpha=0.06).var() #alpha=(1-lambda)
sig2_ewma.plot();
```



- The idea behind a filtered VaR method is to decompose the returns as
$$R_t = \mu + \sigma_t z_t, \quad z_t \overset{\text{i.i.d}}{\sim} (0,1),$$
so that $\mathbb{E}[R_t] = \mu$ and $\text{var}[R_t] = \sigma_t^2$. In principle, μ could be time-varying as well.
- Let z_p denote the $100p\%$ percentile of
$$z_t = \frac{R_t - \mu}{\sigma_t}.$$
It can be estimated by applying any of the VaR methods above (historical, normal, or Student's t) to the *filtered* (demeaned and devolatized) returns
$$\hat{z}_t = \frac{R_t - \hat{\mu}}{\hat{\sigma}_t}$$
- Finally, $VaR_{t+1}^p = -\mu - \sigma_{t+1} z_p$.

In [23]:

```
sig_ewma=np.sqrt(sig2_ewma)
mu=np.mean(r)
z=(r-mu)/sig_ewma #assuming mu=0
VaR_filtered_hist=-mu-sig_ewma*z.quantile(0.01)
VaR_filtered_hist.plot(color='red');
plt.plot(-r)
plt.title('Filtered Historical VaR');
```



Backtesting

- The Basel accords require that banks' internal VaR models be *backtested*.
- They recommend constructing the 1% VaR over the last 250 trading days and counting the number of *VaR exceptions* (times that losses exceeded the day's VaR figure).
- A method is said to lie in the:
    - Green zone, in case of 0-4 exceptions;
    - Yellow zone, in case of 5-9 exceptions;
    - Red zone, in case of 10 or more exceptions.
- Being in one of the latter two incurs an extra capital charge.

- A more advanced method is the *dynamic quantile* (DQ) test by Engle and Manganelli (2004).
- It is based on the *hit series*

$$I_t = \begin{cases} 1, & \text{if } r_t < -VaR_t^p, \\ 0, & \text{if } r_t > -VaR_t^p. \end{cases}$$

- If the VaR model is correctly specified, then $\mathbb{E}[I_t] = p$ (there should be $p \cdot T$ exceptions in a sample of size T, on average). This is known as the *unconditional coverage hypothesis*.
- It can be tested by regressing $I_t - p$ on an intercept and testing that it is zero.
- In addition, it is desirable that the exceptions not be correlated. This is the *independence hypothesis*. It can be tested by including lags of I_t in the regression and testing their significance.
- Jointly testing both (with an F test) tests the *conditional coverage* hypothesis.

In [24]:
```
import statsmodels.formula.api as smf
y=(r<-VaR_filtered_hist)*1 #multiplication by 1 turns True/False into 1/0
y.name='I'
data=pd.DataFrame(y)
model=smf.ols('I.subtract(0.01)~I.shift(1)', data=data)
res=model.fit()
print(res.summary2())
```

```
                  Results: Ordinary least squares
===================================================================
Model:              OLS                Adj. R-squared:     0.020
Dependent Variable: I.subtract(0.01) AIC:                -2069.9720
Date:               2017-10-19 17:25 BIC:                -2059.7852
No. Observations:   1204               Log-Likelihood:     1037.0
Df Model:           1                  F-statistic:        25.67
Df Residuals:       1202               Prob (F-statistic): 4.68e-07
R-squared:          0.021              Scale:              0.010475
---------------------------------------------------------------------
              Coef.    Std.Err.     t      P>|t|    [0.025   0.975]
---------------------------------------------------------------------
Intercept    -0.0008    0.0030   -0.2576   0.7967   -0.0066   0.0051
I.shift(1)    0.1446    0.0285    5.0669   0.0000    0.0886   0.2006
-------------------------------------------------------------------
Omnibus:            1816.402     Durbin-Watson:         2.014
Prob(Omnibus):      0.000        Jarque-Bera (JB):      382361.558
Skew:               9.218        Prob(JB):              0.000
Kurtosis:           88.334       Condition No.:         10
===================================================================
```

- Conclusions:
  - Unconditional coverage is not rejected. This is by construction; note that $r_t \lessgtr -VaR_t^p \iff z_t \lessgtr z_p$.
  - Independence is rejected; apparently our model is dynamically misspecified. May need to use a more general GARCH model instead of EWMA.
- The latter finding is likely driving the rejection of the conditional coverage test:

In [25]:
```
print(res.f_test('Intercept=0, I.shift(1)=0'))
```

```
<F test: F=array([[ 12.87315967]]), p=2.93962494772e-06, df_denom=1202, df_num=2
>
```