V-Lab: Real-time Financial Volatility, Correlation, And Risk...

https://vlab.stern.nyu.edu/en/

The Volatility Laboratory (V-Lab) provides real time measurement, modeling and forecasting of financial volatility, correlations and risk for a wide spectrum of assets. V-Lab blends together both classic models as well as some of the latest advances proposed in the financial econometrics literature. The aim of the website is to ...

Correlation Analysis · Fixed Income Analysis · Liquidity Analysis · Volatility Analysis
Volatility Analysis
There are few guarantees in financial markets. However, we do know that volatility clusters and mean-reverts. But how long will it take to mean revert and, on average, to what level? Where are the ‘hot spots’ of volatility in the world and in what sectors? We attempt to answer these questions and more in our Volatility Analysis section of V-Lab. Come see the many models meant to explain volatility and explore volatility dynamics.

Systemic Risk Analysis
The Global Financial Crisis of 2008 revealed the degree of interconnectedness and fragility of the global financial system at the time. How badly would the equity values of financial institutions decline if there were another crisis today? What degree of capital shortfall would financial institutions suffer? Our Systemic Risk Analysis section of V-Lab simulates crises in domestic markets, as well as another global financial crisis, in an attempt to answer these questions.

Correlation Analysis
The co-movement of asset prices is important in many financial market decisions, such as portfolio allocation, diversification, and hedging. In our Correlation Analysis section, we use econometric models to determine how these time series co-move, which assets are particularly correlated, and which are diverging in direction.

Long-Run VaR Analysis
Often, volatility is assumed to grow with the square root of time. However, this assumes independence between observations each day (i.e. today’s volatility has no bearing on what volatility will be tomorrow). Since this is not the case, one must defer to more sophisticated methods in order to estimate long-run volatility. Our Long-Run Value-at-Risk section simulates the 1 month and 1 year risk of holding financial assets, both using only returns and also conditioning average future volatility on current options market data.
Liquidity Analysis

The liquidity of a financial asset reflects transaction costs and the ability to unwind large trades at reasonable prices. 'Liquidity spirals' often exacerbate stock market declines, such as what we saw in the last Global Financial Crisis. In the liquidity section we estimate and forecast the liquidity of a broad spectrum of financial assets.

Fixed Income Analysis

The future direction of interest rates has large implications for the the determination of discount rates, asset pricing, and firm capital structure. In addition, interest rates and their term structure are often used to infer economic forecasts of inflation, recession, and other key indicators. But where are rates headed in the long term? We forecast the distribution of treasury rates up to 5 years ahead from a 6-month bill to 30-year bond in the Fixed Income Section. We show upper and lower confidence intervals for future rates.

Climate Risk Analysis

Climate change is effecting the world via stronger, more severe weather events, rising sea levels, and in many other ways. Are these events and the risks imposed by climate change properly reflected in asset prices? Environmental risks can be thought of as long run risks which influence portfolio decisions. In our Climate Risk Analysis section. We examine the performance of publicly traded environmental portfolios, which can serve as a measure of the new information on environmental risk and a mechanism to hedge these risks.
VOLATILITY MAP IN JANUARY 2018

GREEN MEANS PREDICTED VOLATILITY IS LOW RELATIVE TO PAST.
V-LAB VOLATILITY MAP FOR FEB 9, 2018
JUNE 28, 2016 ~ BREXIT

Global Volatility

Region: World

8 Days Ago
NOVEMBER 14, 2016
# United States Volatility Summary

**Last Update: 2018-04-28 00:56:19 GMT**

## Volatility by Industry

<table>
<thead>
<tr>
<th>Industry</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>35.17%</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>36.64%</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>35.83%</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>36.16%</td>
</tr>
<tr>
<td>Financials</td>
<td>25.80%</td>
</tr>
<tr>
<td>Health Care</td>
<td>50.22%</td>
</tr>
<tr>
<td>Industrials</td>
<td>35.94%</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>40.11%</td>
</tr>
<tr>
<td>Technology</td>
<td>39.52%</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>35.96%</td>
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<tr>
<td>Utilities</td>
<td>19.95%</td>
</tr>
</tbody>
</table>

## Market Summary

### Equities

<table>
<thead>
<tr>
<th>Index</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500 Index</td>
<td>16.70%</td>
</tr>
<tr>
<td>Dow Jones Industrial Average</td>
<td>17.63%</td>
</tr>
<tr>
<td>NASDAQ Composite Index</td>
<td>20.25%</td>
</tr>
<tr>
<td>Russell 2000 Index</td>
<td>14.76%</td>
</tr>
<tr>
<td>Russell Midcap Index</td>
<td>14.82%</td>
</tr>
</tbody>
</table>

### Currencies

<table>
<thead>
<tr>
<th>Index</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States Dollar Index</td>
<td>6.20%</td>
</tr>
</tbody>
</table>

**Note:** The volatility percentages indicate the degree of price fluctuation in the mentioned sectors and indices.
## United States Volatility Summary

**Last Update: 2017-11-03 23:39:29 GMT**

### Volatility by Industry

<table>
<thead>
<tr>
<th>Industry</th>
<th>Volatility</th>
</tr>
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<tbody>
<tr>
<td>All</td>
<td>35.04%</td>
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<tr>
<td>Basic Materials</td>
<td>32.76%</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>37.39%</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>35.85%</td>
</tr>
<tr>
<td>Financials</td>
<td>25.83%</td>
</tr>
<tr>
<td>Health Care</td>
<td>52.45%</td>
</tr>
<tr>
<td>Industrials</td>
<td>34.07%</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>37.89%</td>
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<tr>
<td>Technology</td>
<td>40.25%</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>40.54%</td>
</tr>
<tr>
<td>Utilities</td>
<td>20.28%</td>
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</table>

### Market Summary

#### Equities

<table>
<thead>
<tr>
<th>Index</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500 Index</td>
<td>7.61%</td>
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<tr>
<td>Dow Jones Industrial Average</td>
<td>7.59%</td>
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<tr>
<td>NASDAQ Composite Index</td>
<td>10.41%</td>
</tr>
<tr>
<td>Russell 2000 Index</td>
<td>10.72%</td>
</tr>
<tr>
<td>Russell Midcap Index</td>
<td>8.90%</td>
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</table>

#### Currencies

<table>
<thead>
<tr>
<th>Index</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States Dollar Index</td>
<td>6.36%</td>
</tr>
</tbody>
</table>
FACEBOOK VOLATILITY

FACEBOOK INC GJR-GARCH VOLATILITY GRAPH

Volatility Prediction for Monday, April 30, 2018: 39.53% (-0.68)

Date Range: from 4-27-2016 to 4-27-2015

Facebook Inc - GJR-GARCH Volatility

Facebook Inc Return
Facebook Inc Price

 Jul ’16     Oct ’16     Jan ’17     Apr ’17     Jul ’17     Oct ’17     Jan ’18     Apr ’18

45%        40%        35%        30%        25%        20%        15%        10%        5%        0%        -5%        -10%        -15%
FACEBOOK VOL MODELS

Other Facebook Inc Analyses
- GARCH
- EGARCH
- APARCH
- AGARCH
- Spline-GARCH
- Zero Slope Spline-GARCH
- GAS-GARCH Student T
- MEM
- Asy. MEM
- Asy. Power MEM

Parameter Estimates
- \( \omega = 0.0185, t\text{-stat} = 3.36 \)
- \( \alpha = 0.0121, t\text{-stat} = 6.79 \)
- \( \beta = 0.9635, t\text{-stat} = 262.61 \)
- \( \gamma = 0.0454, t\text{-stat} = 4.60 \)

Estimation Period:
May 18, 2012 to Apr 27, 2018

Volatility Forecasts

News Impact Curve
FACEBOOK VOLATILITY

Volatility Prediction for Monday, April 30, 2018: 39.53% (-0.68)

FACEBOOK INC GJR-GARCH VOLATILITY GRAPH

Date Range: from 4-27-2018 to 4-27-2018

Window: 5m - 1y - 2y - 5y - 10y - all

V-Lab (2018)
CORRELATION
MODELS AND DATA

- USER CAN SELECT
  - GARCH-DCC,
  - GJR-DCC,
  - GARCH-DECO,
  - GJR-DECO,
  - EWMA-COV

- PLANS TO IMPLEMENT ENGLE, LEDOIT, WOLF “NL-GARCH-DCC” FOR MATRICES UP TO 1000X1000

- DATA SETS OF Equities, Currencies, Commodities, Sectors, International Equities, Asset Classes
GARCH-DCC CORRELATION PLOT BETWEEN GSCI INDICES

Average Correlation for Friday, April 27, 2018: 0.17% (0.00)

Date Range: from 1-12-1999 to 4-27-2018

Window: 6m · 1y · 2y · 5y · 10y · all
V-Lab(2018)
LIQUIDITY

CONDITIONAL ESTIMATE OF AMIHUD ILLIQ USING MEM MODEL AUGMENTED FOR TRENDS AND ASYMMETRY. ILLIQ IS THE RATIO OF ABSOLUTE RETURN/DOLLAR VOLUME
## LIQUIDITY ANALYSIS

<table>
<thead>
<tr>
<th>Sector</th>
<th>Average Level</th>
<th>Change</th>
<th>% Down/Up Illiq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil &amp; Gas</td>
<td>1,119.66</td>
<td>+10.12</td>
<td></td>
</tr>
<tr>
<td>Basic Materials</td>
<td>970.22</td>
<td>-15.70</td>
<td></td>
</tr>
<tr>
<td>Industrials</td>
<td>1,204.64</td>
<td>-26.39</td>
<td></td>
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<tr>
<td>Consumer Goods</td>
<td>996.69</td>
<td>-8.34</td>
<td></td>
</tr>
<tr>
<td>Health Care</td>
<td>1,417.23</td>
<td>-13.22</td>
<td></td>
</tr>
<tr>
<td>Consumer Services</td>
<td>941.99</td>
<td>-21.31</td>
<td></td>
</tr>
<tr>
<td>Telecommunications</td>
<td>1,425.55</td>
<td>+28.72</td>
<td></td>
</tr>
<tr>
<td>Utilities</td>
<td>523.53</td>
<td>-7.99</td>
<td></td>
</tr>
<tr>
<td>Financials</td>
<td>1,250.67</td>
<td>-61.97</td>
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</tr>
<tr>
<td>Technology</td>
<td>1,066.06</td>
<td>-18.02</td>
<td></td>
</tr>
</tbody>
</table>
FACEBOOK ILLIQUIDITY
LONG RUN VALUE AT RISK

TO COMPUTE VaR OVER A MONTH OR A YEAR, NEED ESTIMATE OF THE “RISK THAT THE RISK WILL CHANGE”

GARCH PROVIDES SUCH AN ESTIMATE.

Simulate 1000 sample paths and calculate quantile.

Use option term structure rather than GARCH for more forward guidance.
FIXED INCOME
FIXED INCOME SCENARIO GENERATION

- Many equally likely scenarios generated out 5 years
- Forward yield spread follows dynamic three factor Nelson Siegel
- Shocks are GARCH-DCC
- Data are spline transformed to a log model for rates below 50bp.
- Short rate is regime switching
  - Unit root with positive intercept in upward regime
  - Mean reverting in middle regime
  - Unit root with negative intercept in downward regime
- Model is chosen by back test accuracy of quantiles.
Term Structure Forecast

Horizon: 255 Days Ahead

V-Lab (2018)

Term Structure Forecast

Horizon: 1240 Days Ahead

V-Lab (2018)
A FINANCIAL APPROACH TO CLIMATE RISK
NEW INITIATIVE of the VOLATILITY INSTITUTE
FIND AND EVALUATE
HEDGE PORTFOLIOS AND MAKE THIS PUBLIC

PRINCIPLE INVESTIGATORS: JOHANNES STROEBEL AND MYSELF
WITH HEEBUM LEE AND KONHEE CHANG
IN COLLABORATION WITH BRYAN KELLY AND STEFANO GIGLIO AT YALE

SUPPORTED BY GENEROUS GRANTS FROM:
GLOBAL RISK INSTITUTE, TORONTO
NORGES BANK UNDER THE NFI PROGRAM, OSLO
EVALUATION OF ENVIRONMENTAL FUNDS
VLAB.STERN.NYU.EDU/WELCOME/CLIMATE

GREEN ETFs
- ALTERNATIVE ENERGY
  - WIND
  - SOLAR
  - NUCLEAR
- LOW CARBON

MORNINGSTAR SELECTED FUNDS
- LOW EXPOSURE TO FOSSIL RESERVES
- CARBON FOOTPRINT < .5*SP500
- HIGH RANKING ON E MEASURE OF ESG
- INTERNATIONAL SUSTAINABLE
### ALTERNATIVE ENERGY ETFs (RANKED BY 3Y RETURN)

#### Climate Risk

**Last Update: April 27, 2018 at 12:46:04 AM GMT**

<table>
<thead>
<tr>
<th>Security</th>
<th>Return</th>
<th>Vol</th>
<th>Sharpe Ratio</th>
<th>α</th>
<th>β</th>
<th>SMB</th>
<th>HML</th>
</tr>
</thead>
<tbody>
<tr>
<td>iShares MSCI EAFE ETF</td>
<td>4.51%</td>
<td>15.20%</td>
<td>0.12</td>
<td>1.65</td>
<td>0.92</td>
<td>0.30</td>
<td>0.08</td>
</tr>
<tr>
<td>SPDR S&amp;P 500 ETF Trust</td>
<td>10.03%</td>
<td>13.23%</td>
<td>0.56</td>
<td>-6.63</td>
<td>0.93</td>
<td>-0.10</td>
<td>0.03</td>
</tr>
<tr>
<td>SPYUS - XLE-US</td>
<td>9.84%</td>
<td>15.69%</td>
<td>0.63</td>
<td>-9.46</td>
<td>-0.88</td>
<td>0.12</td>
<td>-0.11</td>
</tr>
<tr>
<td>Stranded Assets</td>
<td>4.28%</td>
<td>14.70%</td>
<td>0.26</td>
<td>-11.25</td>
<td>-1.49</td>
<td>0.24</td>
<td>-0.13</td>
</tr>
<tr>
<td>PowerShares Cleantech Portfolio</td>
<td>12.18%</td>
<td>16.00%</td>
<td>0.60</td>
<td>1.65</td>
<td>0.92</td>
<td>0.30</td>
<td>0.08</td>
</tr>
<tr>
<td>First Trust Global Wind Energy ETF</td>
<td>10.34%</td>
<td>17.25%</td>
<td>0.45</td>
<td>-6.38</td>
<td>-0.88</td>
<td>0.12</td>
<td>-0.11</td>
</tr>
<tr>
<td>VanEck Vectors Uranium+Nuclear Energy ETF</td>
<td>4.45%</td>
<td>13.04%</td>
<td>0.13</td>
<td>-9.46</td>
<td>-1.37</td>
<td>0.51</td>
<td>-0.24</td>
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<tr>
<td>First Trust NASDAQ Clean Edge Green Energy Index Fund</td>
<td>1.27%</td>
<td>21.04%</td>
<td>-0.06</td>
<td>-11.25</td>
<td>-1.49</td>
<td>0.56</td>
<td>-0.13</td>
</tr>
<tr>
<td>VanEck Vectors Global Alternative Energy ETF</td>
<td>0.18%</td>
<td>19.98%</td>
<td>-0.13</td>
<td>-12.55</td>
<td>-1.75</td>
<td>0.24</td>
<td>0.08</td>
</tr>
<tr>
<td>Powershares Global Clean Energy Portfolio</td>
<td>-0.77%</td>
<td>17.71%</td>
<td>-0.19</td>
<td>-12.58</td>
<td>-1.95</td>
<td>0.09</td>
<td>-0.04</td>
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<tr>
<td>Powershares WilderHill Clean Energy Portfolio</td>
<td>-3.27%</td>
<td>23.34%</td>
<td>-0.26</td>
<td>-18.50</td>
<td>-2.05</td>
<td>0.07</td>
<td>-0.07</td>
</tr>
<tr>
<td>PowerShares WilderHill Progressive Energy Portfolio</td>
<td>-3.71%</td>
<td>22.84%</td>
<td>-0.28</td>
<td>-16.05</td>
<td>-2.24</td>
<td>0.67</td>
<td>-0.80</td>
</tr>
<tr>
<td>PowerShares WilderHill Progressive Energy Portfolio</td>
<td>-3.71%</td>
<td>22.84%</td>
<td>-0.28</td>
<td>-16.05</td>
<td>-2.24</td>
<td>0.67</td>
<td>-0.80</td>
</tr>
</tbody>
</table>

**Category:** Alternative Energy

**Time period:** 1Y, 3Y, 5Y, Max, Exp. Weight
### Top 10 Holdings

<table>
<thead>
<tr>
<th>Company Name</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABB Ltd</td>
<td>3.13%</td>
</tr>
<tr>
<td>Schneider Electric SE</td>
<td>3.13%</td>
</tr>
<tr>
<td>Siemens AG</td>
<td>3.08%</td>
</tr>
<tr>
<td>Kingspan Group PLC</td>
<td>3.05%</td>
</tr>
<tr>
<td>ANSYS Inc</td>
<td>3.05%</td>
</tr>
<tr>
<td>Xylem Inc</td>
<td>3.03%</td>
</tr>
<tr>
<td>Intertek Group PLC</td>
<td>3.02%</td>
</tr>
<tr>
<td>Sensata Technologies Holding PLC</td>
<td>3.02%</td>
</tr>
<tr>
<td>BorgWarner Inc</td>
<td>3.02%</td>
</tr>
<tr>
<td>Autodesk Inc</td>
<td>3.01%</td>
</tr>
</tbody>
</table>
LINKS TO VINSIGHT
波动率排名 - Volatility Ranking

(点击柱状图查看历史数据 - click the bar to view history)
HOW TO FORECAST VOLATILITY?

Simple approaches commonly used

- Tomorrow’s volatility will be the same as the last month’s volatility: historical volatility.
- Tomorrow’s volatility will the exponentially weighted average of daily squared returns. Riskmetrics

Statistical approaches, ARCH, GARCH and many more

- Tomorrows volatility will be a weighted average of past daily squared returns where the weights can be estimated econometrically.

\[ r_{t+1} = \mu + \sqrt{h_{t+1}} \varepsilon_{t+1} \quad \varepsilon \sim IID(0,1) \]
\[ h_{t+1} = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t+1-i}^2 \quad ARCH \]
\[ h_{t+1} = \omega + \alpha r_t^2 + \beta h_t \quad GARCH \quad (\alpha_i = \alpha \beta^{i-1}) \]
ASYMMETRIC VOLATILITY FTSE/JSE 25

Negative returns predict higher volatilities than positive returns of the same size.

GJR-GARCH is for Glosten, Jaganathan and Runkle

\[ h_{t+1} = \omega + \alpha r_t^2 + \beta h_t + \gamma r_t^2 I_{r_t<0} \]
ESTIMATION

For any set of parameter values and starting assumptions, we can compute the volatility forecast for each observation.

Using Maximum Likelihood as a criterion, we can numerically compute the MLE under normality.

\[
\log \text{likelihood}_t(\mu, \omega, \alpha, \beta) = -0.5 \log(h_t) - \frac{(r_t - \mu)^2}{2h_t} - 0.5 \log(2\pi)
\]

\[
(\hat{\mu}, \hat{\omega}, \hat{\alpha}, \hat{\beta}) = \arg \max \left\{ -0.5 \sum_{t=1}^{T} \left[ \log(h_t) + \frac{(r_t - \mu)^2}{h_t} \right] \right\}
\]

For non-normal densities, this remains a Quasi-Maximum Likelihood estimator. Often an MLE is available too.
COMPARE MODELS

Models which achieve the highest value of the log likelihood are preferred

If they have different numbers of parameters—this is not a fair comparison.

◦ Use aic or bic (schwarz) instead. The smallest value is best.
DIAGNOSTIC CHECKING

Time varying volatility is revealed by volatility clusters

These are measured by the Ljung Box statistic on squared returns

The standardized residuals \( \left( \frac{r_t}{\sqrt{h_t}} \right) \) no longer should show significant volatility clustering. Check this.
NEW ARCH MODELS
see Bollerslev glossary

<table>
<thead>
<tr>
<th>GJR-GARCH</th>
<th>FIGARCH</th>
</tr>
</thead>
<tbody>
<tr>
<td>TARCH</td>
<td>FIEGARCH</td>
</tr>
<tr>
<td>STARCH</td>
<td>Component</td>
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<tr>
<td>AARCH</td>
<td>Asymmetric Component</td>
</tr>
<tr>
<td>NARCH</td>
<td>SQGARCH</td>
</tr>
<tr>
<td>MARCH</td>
<td>CESGARCH</td>
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<td>SWARCH</td>
<td>Student t</td>
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<td>SNPARCH</td>
<td>GED</td>
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<td>APARCH</td>
<td>SPARCH</td>
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<tr>
<td>TAYLOR -SCHWERT</td>
<td>Autoregressive Conditional Density</td>
</tr>
<tr>
<td></td>
<td>Autoregressive Conditional Skewness</td>
</tr>
</tbody>
</table>
MEASURING RISK
Value at Risk

The future value of a portfolio is uncertain

VaR is a number of $ that you can be 99% sure, is worse than what will happen.

It is the 99% of the loss distribution (or the 1% quantile of the gain distribution)

Simple idea, but how to calculate this?
PREDICTIVE DISTRIBUTION OF PORTFOLIO GAINS

1\%  $ GAINS ON PORTFOLIO
EXPECTED SHORTFALL OR CONDITIONAL VALUE AT RISK

This is the expected loss if the VaR is exceeded

It can be written as

$$ES = E \left( Loss \mid return < -VaR \right)$$
CONCERNS

This single number (a quantile) is used to represent a full distribution. It can be misleading.

What happens in the 1% tail? The example of CDS and other insurance products. ES is better.

VaR fails to satisfy some basic principles called “coherence”. ES is OK.

Both assume that you do not change your portfolio over the next day
- Bad assumption for day traders and proprietary trading desks
- Do not recognize role of dynamic hedging
- But can be calculated on a higher frequency too.
TIME CONCERNS

This is a measure of risk over one day.
  ◦ Even if it is defined over a 10 day period, the one day VaR is simply multiplied by square root of 10.

It does not correspond to the risk of holding illiquid long term assets. We will come back to this.
HOW TO ESTIMATE VaR

Assume tomorrow will be the same as last year. *Historical VaR*

Assume the data are GARCH with Normal Errors
• Forecast volatility and multiply by Normal quantile such as 2.33 for 1%

Assume the data are GARCH with non-Normal Errors
• Forecast volatility and multiply by non-parametric quantile of the standardized residuals
SP 1%VaR USING ONE YEAR HISTORICAL QUANTILES

HISTVAR

0 10 20 30 40 50 60 70 80 90 100

0 20,000 40,000 60,000 80,000 100,000
VOLATILITY BASED VaR

With a good volatility forecast, predict the standard deviation of tomorrow's return.

Assume a Normal Distribution. Then

\[ \text{VaR is } 2.33 \times \sigma_t \times \text{notional} \]

- But what do we use for the volatility?
- GARCH forecasts!
- Other volatility estimates?
GARCH MODEL FOR SPY

Use for example data for 10 years (05-15)

Forecast out of sample and record the daily standard deviation

Multiply by 2.33
### Variance Equation

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<td>C</td>
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<td>2.85E-07</td>
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<td>RESID(-1)^2</td>
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<td>GARCH(-1)</td>
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<td>0.010132</td>
<td>87.64687</td>
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</table>

<table>
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<th>DATEID</th>
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<th>SPVOL</th>
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<td>2015-01-09</td>
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<tr>
<td>2015-01-20</td>
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<td>0.010255</td>
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</table>
VOLATILITY BASED VaR WITHOUT NORMALITY or T

What is the right multiplier for the true distribution? Maybe neither the normal nor the student t are correct!

If:

\[ r_t = \sqrt{h_t} \varepsilon_t, \quad \varepsilon_t \sim i.i.d. \]

Then 1% quantile of the standardized residuals should be used. This is the bootstrap estimator or Hull and White’s volatility adjustment.
HISTOGRAM OF STANDARDIZED RESIDUALS

1% quantile = -2.72

Series: Standardized Residuals
Sample 1/03/2005 1/16/2015
Observations 2528

Mean 0.026783
Median 0.085196
Maximum 3.357119
Minimum -6.583583
Std. Dev. 0.999555
Skewness -0.486358
Kurtosis 4.501972
Jarque-Bera 337.2876
Probability 0.000000
SHOULD WE HAVE KNOWN?
That the financial crisis was coming?
Would a good econometrician or risk manager have predicted this?

Or was this a Black Swan event? Completely unpredictable?
Did these risk models “break”? 
BE PREPARED
3 Sigma Bands before Aug 2007
Out-of-Sample 3 Sigma Bands after Aug 2007

DJRET

-3*DJSD

3*DJSD
Crisis Out-of-sample Standardized Returns

Series: DJRET/DJSD
Sample 7/31/2007 7/16/2010
Observations 773

- Mean: -0.021212
- Median: 0.013111
- Maximum: 3.261659
- Minimum: -3.671674
- Std. Dev.: 1.046813
- Skewness: -0.367987
- Kurtosis: 3.543005
- Jarque-Bera: 26.94260
- Probability: 0.000001
FORECAST PERFORMANCE IN VLAB

During the financial crisis, the short run forecasts were just as accurate as during the low volatility period.

One month ahead forecasts were less accurate during the crisis but were still within the 1% confidence interval of historical and theoretical experience.

See Brownlees, Engle, Kelly,”A Practical Guide to Forecasting in Calm and Storm”
FUNDAMENTAL CAUSES OF FINANCIAL CRISIS

*Risk was underestimated* by many market participants (traders, money managers, bank ceo’s and boards, ratings agencies, regulators, investors and probably risk managers)

*Many of these had strong incentives to ignore risks.*
IMPROVING RISK MEASUREMENT
SHORT RUN VS. LONG RUN RISK

Widely used risk measures are Value at Risk and Expected Shortfall. These measure risk at a one day horizon (or 10 day which is calculated from 1 day)

However, many positions are held much longer than this and many securities have long horizons. 

*There is a risk that the risk will change!!*
LONG TERM INVESTING

If markets have low risk, it is natural to increase your risk.
  ◦ Increase leverage
  ◦ Invest in illiquid assets with long horizons

This is called “risk myopia” - Using short term risk measures to make long term investment decisions
WHAT HAPPENED?

In 2006 financial firms invested in illiquid sub-prime mortgage securities

These were often CDOs which seemed very safe

When volatility rose, many of these were put up for sale and the price dropped!!!!
WHAT IS NEEDED?

Risk management should consider both long run and short run risks. Scenario Analysis and *Stress Tests* are tools. Term structure of VaR is another tool.

Some assets that are designed to do well in a crisis can be added to portfolios. "*Hedge portfolios*" or options. These can reduce long run risks if correctly managed.
HOW TO MEASURE TERM STRUCTURE OF RISK?

Calculate VaR and ES for long horizons.
Volatility models measure the speed at which volatility can change.
Simulate many times and examine the quantiles of outcomes.

Use derivative prices to improve these estimates.
Use economic information to improve these estimates.
Two period return is the sum of two one period continuously compounded returns.

Look at binomial tree version.

Asymmetry gives negative skewness.
1 DAY RETURNS ON D.J.

Series: RSP
Sample 1/02/1990 6/05/2015
Observations 6312

Mean       0.000276
Median   0.000553
Maximum  0.109572
Minimum -0.094695
Std. Dev.   0.011419
Skewness  -0.239708
Kurtosis   11.74163
Jarque-Bera  20157.88
Probability  0.000000
10 DAY RETURNS ON SP

Series: LOG(SP/SP(-10))
Sample 1/02/1990 6/05/2015
Observations 6312

Mean       0.002793
Median   0.005514
Maximum  0.195882
Minimum -0.299547
Std. Dev.   0.031740
Skewness  -0.963744
Kurtosis  9.463876
Jarque-Bera  11965.69
Probability  0.000000
50 DAY RETURNS

Series: LOG(SP/SP(-50))
Sample 1/02/1990 6/05/2015
Observations 6312

Mean 0.014129
Median 0.021337
Maximum 0.294411
Minimum -0.506817
Std. Dev. 0.068754
Skewness -1.322785
Kurtosis 8.413585
Jarque-Bera 9548.463
Probability 0.000000
ONE YEAR RETURNS

Series: LOG(SP/SP(-252))
Sample 1/02/1990 6/05/2015
Observations 6312

Mean 0.071638
Median 0.102202
Maximum 0.522201
Minimum -0.669877
Std. Dev. 0.169837
Skewness -1.321885
Kurtosis 5.251106
Jarque-Bera 3170.990
Probability 0.000000
EVIDENCE FROM DERIVATIVES

The high price of out-of-the-money equity put options is well documented.

This implies skewness in the risk neutral distribution.

Much of this is probably due to skewness in the empirical distribution of returns.

Data matches evidence that the option skew is only post 1987.
CALCULATION BY SIMULATION

EVALUATE ANY MEASURE BY REPEATEDLY SIMULATING FROM THE ONE PERIOD CONDITIONAL DISTRIBUTION: $f_t(r_{t+1})$

**METHOD:**
- Draw $r_{t+1}$
- Update density and draw observation $t+2$
- Continue until $T$ returns are computed.
- Repeat many times
- Compute measure of downside risk
100 step simulation

Series: Y
Sample 1 10000
Observations 10000

Mean       0.000435
Median   0.012593
Maximum  0.444148
Minimum -0.870962
Std. Dev.   0.125104
Skewness  -0.953848
Kurtosis   5.674819
Jarque-Bera  4497.483
Probability  0.000000
HOW MUCH SRISK IS TOO MUCH?
Come back tomorrow to see?